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REVIEW

Machine learning and deep learning techniques for breast cancer diagnosis and classification: a comprehensive review of medical imaging studies

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Abstract

Background Breast cancer is a major public health concern, and early diagnosis and classification are critical for effective treatment. Machine learning and deep learning techniques have shown great promise in the classification and diagnosis of breast cancer.

Purpose In this review, we examine studies that have used these techniques for breast cancer classification and diagnosis, focusing on five groups of medical images: mammography, ultrasound, MRI, histology, and thermography. We discuss the use of five popular machine learning techniques, including Nearest Neighbor, SVM, Naive Bayesian Network, DT, and ANN, as well as deep learning architectures and convolutional neural networks.

Conclusion Our review finds that machine learning and deep learning techniques have achieved high accuracy rates in breast cancer classification and diagnosis across various medical imaging modalities. Furthermore, these techniques have the potential to improve clinical decision-making and ultimately lead to better patient outcomes.

Keywords Breast cancer · Deep learning · Machine learning · Medical imaging · Mammography · Ultrasound · MRI · Histology · Thermography · Nearest neighbor · SVM · Naive Bayesian network · DT · ANN · Convolutional neural network

Introduction

Computer-aided diagnosis (CAD) is an advanced computer-based technology utilized by radiologists to diagnose medical conditions with a higher degree of precision. By utilizing a computer system to assist with the identification and diagnosis of diseases, CAD can increase the accuracy of photo interpretation and minimize the occurrence of errors and misinterpretations.

CAD has demonstrated particular efficacy in the early and rapid diagnosis of breast cancer through the use of mammography. The integration of CAD into mammography analysis has resulted in improved diagnostic accuracy, thereby facilitating prompt and effective medical interventions that may ultimately improve patient outcomes. This innovative technology represents a significant advance in the field of medical imaging and has the potential to improve patient care across a range of medical specialties (Henriksen et al. 2019). Cancer diagnosis relies on a range of techniques, including laboratory tests, biopsy, imaging tests, and physical examination. As such, the diagnosis of breast cancer may involve various procedures such as biopsy, mammography, magnetic resonance imaging (MRI), and ultrasound. The biopsy is a well-established method of obtaining tissue samples for examination and analysis to identify the presence of cancerous cells. Mammography is a specialized X-ray imaging technique that generates images of breast tissue and can help detect early-stage breast cancer. Similarly, MRI uses a strong magnetic field and radio waves to create detailed images of the breast and surrounding tissues. Ultrasound employs high-frequency sound waves to produce images of breast tissue and can aid in the detection of breast cancer. The use of a combination of these diagnostic methods can improve the accuracy of breast cancer diagnosis and facilitate timely and appropriate medical interventions. The

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development and application of such diagnostic approaches continue to enhance our ability to detect and treat breast cancer, ultimately improving patient outcomes (Wang 2017). Breast cancer represents a significant global health concern, particularly for women over the age of 40 years. The American Cancer Society recommends regular screening for women in this age group, with an emphasis on annual mammograms beginning at age 45 and continued annual screening at age 55 and beyond. Breast cancer is a serious disease that poses a considerable threat to women, particularly those aged 50 and over, and is the leading cause of mortality among women. Early detection and prompt intervention are essential to improving patient outcomes, reducing mortality rates, and minimizing disease-related complications. The development and implementation of effective screening programs, along with advancements in diagnostic and therapeutic interventions, represent significant strides toward improving breast cancer care. While breast cancer remains a complex and challenging disease, ongoing research efforts are aimed at enhancing our understanding of the disease and improving treatment options to benefit patients worldwide (Smith et al. 2018). Imaging techniques have proven to be highly effective in the early detection of tumors, both in breast cancer and other internal organs. These methods play a critical role in the diagnostic process and can help identify the presence of cancerous growth at an early stage.

In this regard, the use of computer-aided diagnosis (CAD) has demonstrated significant effectiveness in the diagnosis and treatment of cancer. CAD employs advanced image analysis software that enables radiologists and other medical professionals to more accurately identify and analyze suspicious features within medical images. This approach can help reduce the likelihood of misdiagnosis or missed diagnoses, ultimately leading to more effective treatment options and improved patient outcomes.

The continued development and refinement of imaging and CAD technologies hold great promise for the early detection and treatment of cancer and are essential components of comprehensive cancer care.

Medical images

The integration of machine learning techniques and conflict processing into medical imaging analysis is a significant advancement in diagnostic medicine that has the potential to improve patient outcomes in various medical specialties by enabling more accurate and efficient tumor detection and diagnosis (Akbar et al. 2018). Each imaging technology provides detailed information about the part of the body being examined or treated (Rajinikanth et al. 2017). Medical imaging serves to measure, categorize the position, and investigate the characteristics of the target organ. Numerous researchers are currently focused on developing and analyzing medical images to classify a significant percentage of disorders (Khan et al. 2019). Medical imaging has proven to be one of the most successful diagnostic methods for breast cancer, utilizing a variety of techniques such as MRI, mammography, CT, PET, as

Fig. 1 The most common diagnostic methods for breast cancer

well as duplex ultrasound, and radiography (Fig. 1) (Salh and Ali 2022).

3-D mammography

In recent years, there have been significant advancements in imaging modalities, particularly the adoption of 3-D mammography and the integration of multiple imaging techniques through fusion imaging. These innovations have shown great promise in enhancing the accuracy and effectiveness of breast cancer diagnosis, staging, and treatment planning.

3-D Mammography: 3-D mammography, also known as digital breast tomosynthesis (DBT), is an advanced imaging modality that provides a three-dimensional representation of the breast. It overcomes some limitations of traditional 2-D mammography by capturing multiple low-dose X-ray images from different angles. The acquired images are reconstructed to create a detailed 3-D image of the breast tissue, allowing radiologists to view the breast in thin slices. This enables improved detection and characterization of breast lesions, reducing false positives and improving overall diagnostic accuracy (Pöhlmann et al. 2017; Üncü et al. 2022).

3-D mammography offers several benefits in breast cancer diagnosis and screening. It provides better visualization of breast tissue, particularly in dense breasts, enhancing the detection of small tumors and reducing recall rates (Malekmohammadi et al. 2023). Furthermore, it helps in localizing and characterizing lesions, aiding in biopsy guidance and treatment planning. Studies have shown that 3-D mammography improves cancer detection rates, especially in cases of invasive cancers and interval cancers (Ryser et al. 2022).

Fusion of imaging modalities

Fusion imaging involves the combination of multiple imaging modalities, such as mammography, ultrasound, magnetic resonance imaging (MRI), and molecular imaging techniques. By integrating complementary information from different modalities, fusion imaging offers a more comprehensive and accurate assessment of breast lesions (Kavita et al. 2022).

Fusion imaging techniques can be categorized into two approaches: sequential fusion and simultaneous fusion. In sequential fusion, images from different modalities are acquired separately and then aligned and overlaid for analysis (Kavita et al. 2022). Simultaneous fusion, on the other hand, involves the use of hybrid imaging systems that capture multiple modalities simultaneously (Paramanandham & Rajendiran 2018).

The fusion of imaging modalities enables better characterization of breast lesions by combining anatomical and functional information. For example, the fusion of mammography with ultrasound or MRI provides complementary details about the morphology, vascularity, and tissue composition of breast lesions. This integration improves the accuracy of lesion characterization, especially in cases where mammography alone may be inconclusive (Becker et al. 2018; Opieliński et al. 2018). The combined use of imaging modalities also has implications for breast cancer prognosis. Fusion imaging techniques, such as positron emission tomography-computed tomography (PET-CT), allow for the assessment of metabolic activity and tumor biology (Romeo et al. 2021). By integrating functional and anatomical information, these modalities assist in staging, treatment response evaluation, and monitoring of disease progression.

Problems and challenges of breast cancer diagnosis

Although literature shows promising results, there are still limitations and challenges in breast cancer diagnosis and classification that can be addressed using machine learning (ML) techniques. One of the main challenges is the lack of comprehensive training datasets for training deep learning models in medical imaging. The automatic detection and identification of breast cancer using deep learning models from CT or MRI images is a challenging task due to the appearance of lesions anywhere and their different intensity distributions, leading to the misidentification of malignant abnormalities as benign conditions. However, there are various datasets available for building computer-aided diagnosis (CAD) systems using traditional machine learning or deep learning models for breast cancer (Salh and Ali 2022). Here are some challenges that are faced in breast cancer diagnosis using machine learning methods:

1. Generating large medical imaging datasets is a difficult task as it requires extensive time and effort for data annotation by multiple experts to eliminate human error.
2. The analyzed studies used different datasets, which makes it difficult to compare the results.
3. Overfitting can be a major challenge when using transfer learning techniques, so data augmentation approaches may be necessary to address this issue.
4. Training machine learning models for large breast cancer datasets can be time-consuming and computationally expensive, which can be a significant challenge.

Breast cancer dataset

There are eight publicly available datasets used for this purpose, which include Digital Database for Screening Mammography (DDSM), Breast Cancer Data Repository (BCDR), INBreast, Mammography Image Analysis Society (MIAS), mini-MIAS, Wisconsin Breast Cancer Dataset (WBCD), Wisconsin Diagnostic Breast Cancer (WDBC), Image Retrieval in Medical Applications (IRMA), and Breast Cancer Histology Image (BreakHis) (Houssein et al. 2021).

Fundamentals and background for machine learning and deep learning

Machine learning overview

Machine learning is a subfield of artificial intelligence that involves using statistical, mathematical, and logical methods to enable machines to learn from data without being explicitly programmed. It utilizes inference principles to solve problems by learning from sample data (Houssein et al. 2021). The primary objective of machine learning is to make decisions and predictions based on data. It is a highly effective modeling tool that has been advanced to solve problems that are challenging to solve through traditional methods (Rahman 2019). Advancements in computing power and the availability of large amounts of data have led to the success and reliability of machine learning, allowing it to replace several areas that previously required human involvement. The field has evolved over time and has become a powerful tool for solving complex problems using various machine learning algorithms (Houssein et al. 2021).

There are several ML techniques used to develop CAD systems for breast cancer, including decision tree (DT), naive Bayes, nearest neighbor, artificial neural network (ANN), support vector machines (SVM), and group classification. These techniques are used for data classification and prediction based on specific features extracted from medical images. Each technique has its own strengths and weaknesses and can be used depending on the specific requirements of the CAD system. For instance, DT is suitable for dealing with categorical data, Naive Bayes is suitable for dealing with high-dimensional data, and SVM is suitable for handling non-linear data (Saxena and Gyanchandani 2020).

Support vector machine (SVM)

In 2013, researchers proposed a method using MATLAB bioinformatics software to train the SVM algorithm for identifying benign or malignant tumors, achieving an accuracy of approximately 95% in grouping the obtained data. Another study in 2017 proposed an automated diagnostic method combining a two-stage clustering algorithm and SVM for detecting and identifying hidden patterns of benign and malignant tumors with a classification accuracy of 99.1%. The researchers demonstrated that this method leads to an increase in cancer prediction accuracy and a decrease in misclassification errors. Hence, the type of breast cancer diagnosis and classification algorithm plays a crucial role in achieving optimal results and accuracy (Fig. 2) (Yassin et al. 2018).

Naïve Bayesian network

A Bayesian network is a type of directed acyclic graph that represents the relationships between multiple variables. Nodes in the graph represent the variables, and the arcs represent the relationships between them. A simple classifier based on Bayes' theorem is a special type of Bayesian network. Bayes' theorem is a fundamental concept in probability theory that underlies the simple Bayes algorithm. The following equation expresses Baye's theorem:

$$P\left(\frac{A}{B}\right) = \frac{P\left(\frac{B}{A}\right)P(A)}{P(B)},$$

where P (A/B) is an event occurring probability if event B occurs, P (A) and P (B) are event A and B probabilities, respectively, and P (B/A) is the B event occurring probability if the A event occurs (Chaurasia et al. 2018).

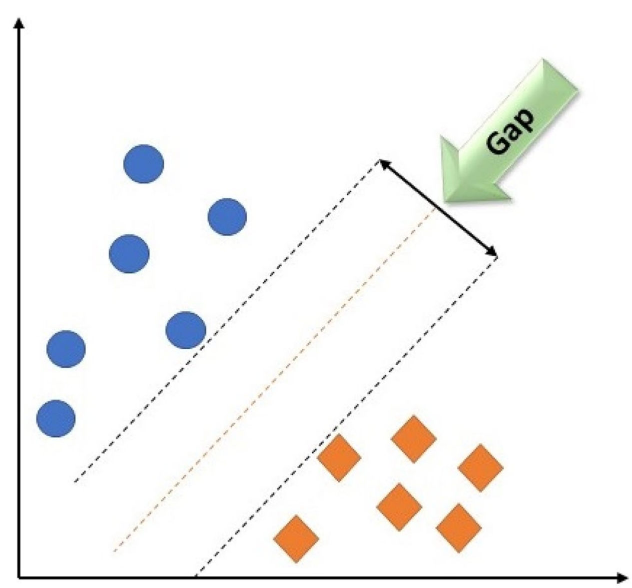

Fig. 2 SVM successfully classifies benign and malignant tumors with an accuracy of 99.1%

k-nearest neighbor (KNN)

While KNN is a commonly used algorithm in classification tasks, it may not be the best option for breast cancer classification due to the complexity of the disease and the large number of variables involved. Other machine learning algorithms, such as support vector machines, random forests, and artificial neural networks, have shown promising results in breast cancer classification tasks. The choice of algorithm depends on the specific problem and the available data (Sharma et al. 2018).

Decision tree (DT)

DT technology is utilized for the early detection of breast cancer. It works by creating a tree-like structure where classifications or regressions are reported. The dataset is divided into smaller subsets, which are then further divided into even smaller subsets (Tahmooresi et al. 2018).

Artificial neural network (ANN)

An artificial neural network (ANN) mimics the biological neural network in the human brain, where all neurons are interconnected. ANN uses a backpropagation training technique to classify problems. Direct effect ANN represents the basic anatomy of a single neuron, where it receives input from other neurons, multiplies the data by the corresponding weight and uses an activation function to produce a weighted output (Fig. 3) (Murtaza et al. 2020).

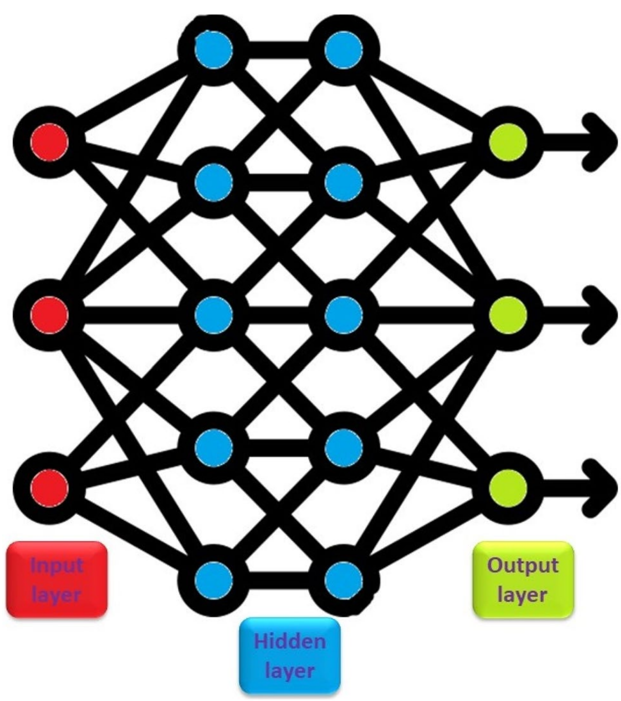

Fig. 3 Integration of multiple types of data via ANN

Random forest (RF) algorithm

To ensure maximum model accuracy during sorting stages, it is essential to utilize the RF method, which minimizes bias and variance risks. To overcome the limitations of DTs, a large number of trees are constructed using random samples and replacements. The observations are categorized by each tree, and the final decision is made based on the majority vote of the trees (Elgedawy 2017).

AdaBoost classifier

The mentioned algorithm utilizes classification and regression techniques to predict the existence of breast cancer. By combining weak learners into a powerful rule, it is able to enhance prediction accuracy. The algorithm also adjusts the weight of the node to obtain more precise results. However, it can be affected by poor-quality features and noise (Senkamalavalli and Bhuvaneswari 2017).

Methods used for breast cancer in machine learning

The author of this review collected information from various sources such as Internet sources, books, magazines, and articles to evaluate investigations on the medical diagnostic aspect of breast cancer imaging using machine learning and the challenges associated with it. The author examined the arguments of researchers who supported the use of machine learning for breast cancer imaging and evaluated the challenges facing this process. The review aimed to explain the evolution of machine learning in medical diagnostics for breast cancer imaging over time, and it explored several machine learning algorithms used to detect breast cancer tumors. The review concludes that SVM is the best algorithm for breast cancer diagnosis due to its high accuracy and results (Salh and Ali 2022).

Machine learning techniques for MRI (magnetic resonance imaging)

Several machines learning algorithms, including k-nearest neighbor, SVM, ANN, and Bayesian network, have been used to classify and diagnose breast cancer in MRI images. Researchers have proposed various approaches to distinguish between benign and malignant breast tumors using these algorithms. In one study, three machine learning algorithms (support vector machine, k-nearest neighbor, and decision tree) were used, and their performances were compared to identify the best algorithm for breast cancer classification. The algorithm with the highest accuracy (98.1%) and the lowest false discovery rate was selected. Other classification techniques, such as gradient boosting, XGBoost, random forest, RBF, naive Gaussian Bayes, linear support vector machine, and logistic regression, were also utilized. The study demonstrated that semi-supervised learning (SSL) achieves good accuracy (90–98%) using only half of the training data, making it a promising approach (Obaid et al. 2018). Al-Azzam and Shatnavi employed the DNN technique in their research and found that machine learning methods can be applied to detect breast cancer. Apart from DNN, other algorithms like KNN, SVM, ANN, and others can also be utilized. Nonetheless, DNN demonstrated a higher superiority in terms of accuracy compared to other methods. The average accuracy improved to 89.77%, while the high accuracy increased to 96%. Machine learning techniques have essential characteristics, including binary dependent and independent variables, and their primary objective is to create a classification model from a data set containing named classes. In machine algorithms, dataset training and validation are two critical phases. Table 1 illustrates various machine learning techniques for detecting breast cancer (Salh and Ali 2022).

Deep learning (DL) overview

DL is a type of machine learning that is capable of autonomous learning and differs from traditional ML techniques because of its ability to learn complex image feature hierarchies. DL uses multi-level neural networks to create a hierarchical structure of features from raw input images. Unlike conventional ML algorithms, DL algorithms are not affected by changes in the images and can be trained on a large number of images. DL has gained significant attention due to its recent achievements in image classification and segmentation. DL is utilized for various purposes, including disease diagnosis and classification (Dargan et al. 2020). Neural networks are frequently used in this device to facilitate data prediction. Due to the intricacies of neural networks and other components involved, it is evident that this form of machine learning demands comprehensive and profound understanding and training. According to Korotcov et al. (2017), ensemble learning is a collection of diverse algorithms that work together to create a system capable of handling any challenge and providing accurate predictions or diagnoses. DL uses a deep neural network that consists of multiple layers of processing to detect and diagnose the existence of a disease (Chen et al. 2017). The effectiveness of DL in predicting diseases is not always guaranteed as machines are not perfect and may not be 100% efficient in all cases, despite its capability to predict and solve many diseases (Salh and Ali 2022). A neural network is utilized to distinguish between normal and cancerous cells with a high level of confidence. The network has two possible outcomes, either a cell is normal or cancerous. The results have demonstrated high accuracy and low false negatives. Among deep learning techniques, CNN is a popular approach due to its ability to effectively use local connections with common weights, making it well suited for image processing. Deep convolutional networks are considered one of the most effective DL algorithms for analyzing medical images (Salh and Ali 2022).

Table 1 The evaluation of various machine learning algorithms for breast cancer detection and diagnosis

Author	Algorithms/techniques used	Dataset	Accuracy of machine learning in medical diagnosis	Implementation tool
Sharma et al. (2018)	KNN	Wisconsin Diagnosis Breast Cancer (WDBC)	95.90%	Machine learning libraries in Python
Chaurasia et al. (2018)	Naïve Bayes	Uci machine learning repository datasets	97–36%	
Benhassine et al. (2020a)	ANN, SVM, NB	MIAS	100% 94.1% 92.6%	MATLAB
Arafah et al. (2019)	SVM	MIAS	91%	MATLAB
Benhassine et al. (2020b)	ANN,SVM, RF, NB	MIAS	99.1% 99.4% 98.2% 97.7%	MATLAB
Silva et al. (2020)	GRNN and FFBPN, SVM, DT and naive Bayes	MIAS	GRNN 83.33%, FFBPN 85.18%, NB 72.2%, DT 70.83% & SVM: 77.77%	MATLAB

Convolutional neural network

A convolutional neural network (CNN) is a type of deep neural network primarily utilized for analyzing visual images in the field of deep learning. CNNs operate in a feedforward manner and are capable of identifying the topological features of images. They are also known as multilayer perceptron models (Yap et al. 2017). A fully connected network is one in which each neuron in a layer is connected to every neuron in the preceding and following layers. In contrast, CNNs are a type of neural network that consists of three main layers: the convolution layer, the integration layer, and the fully connected layer. Each layer serves a specific purpose and is shaped accordingly (Fig. 4) (Stenroos 2017).

1. Convolutional layers: These layers create feature maps using the theory of weight distribution and the concept of local connectivity. Each unit in a feature map is connected to local patches in the previous layer through a weight group called a filter bank, which is responsible for local connectivity (Salh and Ali 2022).
2. Integration layer: The integration layer in CNN combines the features extracted by the convolutional layer using a subsampling method. This layer merges the features from the same convolutional layer to create a single layer (Salh and Ali 2022).
3. Fully connected layer: The fully connected layer is made up of individual units that function like a standard neural network, where each unit is connected to all the units in the previous layer (Salh and Ali 2022). CNN architecture: The accuracy and speed of CNN depend on its architecture, which includes the parts used in each level, the organization of the levels, and how they are structured. In recent years, CNN has experienced rapid growth and has achieved significant success. There are various CNN architectures such as ImageNet, LeNet-5, AlexNet, GoogleNet, VGGNet, Inception-v4, ResNet-50, Inception-ResNet, Xception, Inception-v3, Inception-v1, and ResNetXt-50 (Stenroos 2017).

Recurrent neural networks (RNNs)

The model employs multiple RNNs to extract features from various clinical texts such as MRI, CT, ultrasound, and X-ray images and then integrates them over time. This results in a network layer that is larger than the recurrent neural network, which can then be used to identify benign and malignant breast tumors based on the extracted features (Chen et al. 2017).

Deep belief networks (DBNs)

The DBN (deep belief network) incorporates active contour segmentation to detect abnormal images that can be classified by the network. In the low-dose-rate medical image reconstruction method, the proposed algorithm is utilized to eliminate the scatter point function feature and enhance the quality of the reconstructed image (Malathi et al. 2021).

Long short-term memory networks (LSTMs)

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) that can learn and remember long-term dependencies and solve the problem of vanishing gradients.

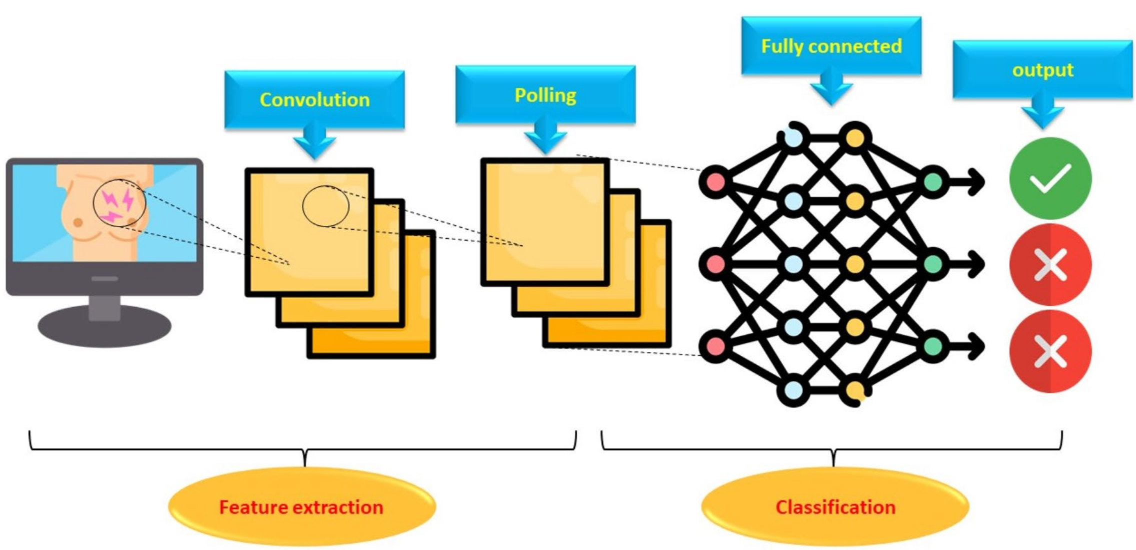

Fig. 4 An example of a convolutional neural network

It includes a memory unit and a gate mechanism to capture extensive dependencies in a sequence (Malathi et al. 2021).

Deep learning techniques for breast cancer

This section provides a summary of the advancements made in identifying, diagnosing, prognosis, and classifying breast cancer using DL. Several studies have employed DL techniques to classify and diagnose breast cancer using medical imaging techniques such as MRI, mammography, and ultrasound. In Malathi et al. (2021) study, the authors presented the evaluation results of breast abnormality detection using the YOLO detector. The results showed that the detector achieved an overall detection accuracy of 99.17% and 97.27% and an F1 score of 99.28% and 98.02% for the breast and DDSMs datasets, respectively. The YOLO detector was able to achieve high detection accuracy and F1 scores for both the breast and DDSM datasets in a study by Malathi et al. The detector also had a high prediction rate of 71 frames per second for DDSM and INbreast datasets during the testing phase. In addition, researchers used InceptionResNet-V2, ResNet-50, and CNN classification models to achieve good average accuracies for DDSM, with the CNN model having the highest accuracy at 97.50%. Another study proposed an automated method for classifying breast cancer histopathology images by combining deep features and an improved routing approach (Salh and Ali 2022). The researchers have developed a new architecture called FE-BkCapsNet, which can extract convolutional and capsule features simultaneously and integrate semantic and spatial features to provide more accurate results for the BreaKHis dataset. The method has been tested and found effective in classifying breast cancer in clinical settings, with experimental results showing an accuracy of 93.54% at 400× magnification, 94.03% at 200× magnification, 94.52% at 100× magnification, and 92.71% at 40× magnification. Wang (2017) utilized strong CNNs and achieved improved outcomes compared to other advanced techniques for categorizing similar general data. The accuracy and AUC were reported to be 96.67% and 0.96 for the BCDR database, 95.50% and 0.97 for the INbreast database, and 97.35% and 0.98 for the DDSM database. The CNN model-based breast cancer screening framework demonstrated the most exceptional results, with an accuracy of 98.94% (Feng et al. 2020). Table 2 displays various deep-learning methods for the diagnosis of breast cancer.

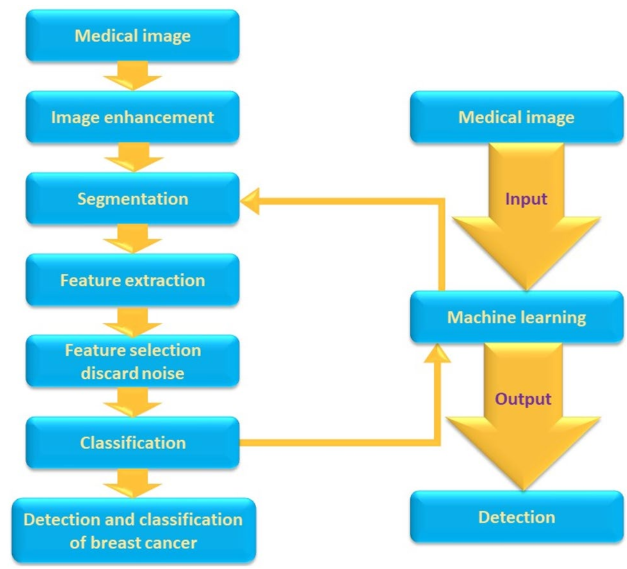

Fig. 5 The process of using machine algorithms and deep learning for diagnosing breast cancer through medical imaging

Table 2 Comparison of the results of various deep learning algorithms for diagnosing breast cancer

Authors	Algorithms/techniques used	Dataset	Accuracy of deep learning in medical diagnosis	Implementation tool
Ahmed et al. (2020)	Deep Lab Mask-RCNN	MIAS CBISDDSM	95.0% 98.0%	Libraries in Python
Baffa and Lattari (2018)	CNNs	DMR	98% for static and95% for dynamic protocol	Libraries in Python
Roslidar et al. (2019)	enseNet201ResNet101 MobileNetV2 ShuffleNetV2	Database for Mastology Research (DMR)	MobileNetV2 has an accuracy of 100% for static datasets and 99.6% for dynamic datasets	MATLAB
Zuluaga–Gomez et al. (2020)	Proposed CNNs	DMR-IR database	92%	Libraries in Python
Yari et al. (2020)	CNN, DensNet, ResNet	BreakHis dataset	100%	Libraries in Python
Kim et al. (2020)	CRNN	Breast Ultrasoun d Image-Mendeley Data	99.75%	OpenCV-python

Steps in machine learning and deep learning in breast cancer

Machine learning and deep learning algorithms are essential for diagnosing breast cancer based on CT and MRI images (Fig. 5). Image quality enhancement algorithms are typically applied to improve the visual appearance of remote sensing data and generate newly enhanced images. Image segmentation simplifies the process by dividing the images into meaningful components. Extracting features from medical images is crucial for accurate diagnosis by medical professionals. Medical image classification is a significant challenge in the field of image recognition, with the objective of grouping medical images into different categories. Therefore, the classification of breast cancer-related images involves two stages: benign and malignant breast masses.

This section compares the results of the proposed method with various machine learning and deep learning methods. The comparison demonstrates that the proposed model outperforms other methods, as presented in Tables 1 and 2. The study employed different machine learning and deep learning techniques for detecting and diagnosing breast cancer using MRI, CT, and mammography images. The accuracy achieved by the proposed deep learning method was better than that of machine learning methods. Researchers (Yari et al. 2020) developed a DL-based approach for breast cancer classification, which achieved 100% accuracy using the BreakHis dataset with DensNet, CNN, and ResNet. In another study, the authors employed a CNN-based model for breast cancer classification using various datasets, including CBIS-DDSM DMR, MIAS, DMR-IR Research Database, Database for Mastology, BreakHis dataset, and Mendelian breast ultrasound image data, color images. The proposed method achieved an accuracy of 95.0%, 98.0%, and 98% for the static dataset and 95% for the dynamic dataset. The MobileNetV2 protocol obtained 100% accuracy for the static dataset and 99.6% for the dynamic dataset. Although the CNN model had many layers, the architecture did not produce satisfactory results.

Performance evaluation

This section discusses the evaluation criteria used to test CAD systems for breast cancer. The diagnosis of breast cancer can be classified as true negative (TN) or true positive (TP) if correctly diagnosed and as false negative (FN) or false positive (FP) if misdiagnosed. The evaluation criteria commonly used for breast cancer classification include accuracy, sensitivity, AUC (area under the curve), FMeasure, and volume under the ROC surface (Murtaza et al. 2020). These evaluation criteria are summarized as follows: Accuracy (Acc): This calculation measures the number of samples that are completely classified as right. It is shown by Eq. 2:

$$\mathrm{ACC} = \frac{(\mathrm{TP} + \mathrm{TN})}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})}.$$

Sensitivity (Sn): This item indicates the total number of positive cases correctly calculated. In this way, how many of the total abnormal breast cancer patients have been correctly identified is shown and can be measured using the following equation:

$$\mathrm{Sn} = \frac{(\mathrm{TP})}{(\mathrm{TP} + \mathrm{FN})}.$$

Specific metric (Sp): It shows the number of negative predictions and how many normal predictions are correct and can be measured using the following equation:

$$\mathrm{Sp} = \frac{\mathrm{TN}}{(\mathrm{TN} + \mathrm{FP})}$$

Precision metric (Pr): This shows how accurate the prediction of abnormal breast cancer is. For medical image recognition, both Sn and Pr should be high to avoid the misdiagnosis of cancer patients. It can be measured using the following equation:

$$\mathrm{Pr} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FP})}.$$

F-Measure metric: represents Sn and Pr simultaneously, which is created by adding more penalties by the harmonic tool over extreme values. It can be measured using the following equation:

$$\mathrm{F-measure} = \frac{(1 + \mathrm{B2})(\mathrm{Pr} * \mathrm{Sn})}{(\mathrm{B2} * \mathrm{Pr} * \mathrm{Sn})}.$$

AUC: The area under the curve is a numerical value that shows how the model will perform in different conditions. The AUC value can be measured using the following equation:

$$\mathrm{AUC} = \frac{\sum \mathrm{Ri}(\mathrm{Ip}) - \mathrm{Ip}(\mathrm{Ip} + 1)/2}{\mathrm{Ip} + \mathrm{In}},$$

where Ip and In represent the number of positive and negative breast cancer images, and Ri is the ranking of the first positive image.

Use of ML and DL in BC-related images

Various machine learning methods are utilized to diagnose and classify breast cancer by extracting features from medical imaging. This section focuses on the examination of different techniques for breast cancer diagnosis based on five types of medical imaging: ultrasound images, mammography images, MRI, histological images, and thermography.

Machine learning techniques for mammogram images

A research study conducted by Wang et al. (2018) aimed to examine a generalized learning algorithm that utilizes a support vector machine for the purpose of diagnosing breast cancer. The proposed model was applied to a diverse set of datasets such as Wisconsin Breast Cancer (WBC), WDBC, and the US National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) program, all of which are widely used in breast cancer research. Researchers conducted a study in which they utilized the Hough transform to extract features from mammography images for classification purposes. The extracted features were then classified using a support vector machine (SVM) algorithm (Houssein et al. 2021). In addition, a study conducted by researchers reported a different approach for classifying breast cancer as either normal or abnormal. The method involved using SVM on the DDSM dataset and achieved an impressive AUC metric value of 94.4%. Furthermore, another study conducted by researchers utilized a semi-supervised SVM on the DDSM dataset to classify tumors into two categories, malignant or benign. The accuracy metric of this approach was reported as 93.1%.

Another research group utilized SVM to classify clusters in mammography images and reported an AUC of 0.7 for their model. The dataset used in their study consisted of mammography images from the DDSM dataset. Furthermore, another study used a similar approach as the aforementioned research to conduct a simulation experiment on 44 mammography images from the MIAS database. The results indicated that the mass classification accuracy was as high as 95% (Houssein et al. 2021).

Researchers developed a model using the rough set (RS) and classifier SVM (RSSVM) to identify and diagnose breast cancer. They used RS to select the best features from the dataset and found that using SVM improved the performance of the detection system. The effectiveness of RS was investigated in the WBCD dataset. The researchers also proposed a least square support vector machine (LS-SVM), which used cross-validation to evaluate the equality and classification accuracy of the model. The results showed that the LS-SVM had a classification accuracy of 98.53% (Houssein et al. 2021).

The researchers proposed modified regression functions to replace SVM and a standard selection method for mutual information functions. They applied this method to simulated mammography images from the DDSM database and reported an accuracy rate of 93%. Another model based on K-SVM for cancer detection was also presented. In this model, the K-means clustering method was used to extract symbolic objects from tumors. The accuracy of this method was determined to be 97.38% based on the WDB dataset (Houssein et al. 2021).

Multiple studies have demonstrated that SVM outperforms other automated detection systems in detecting breast cancer. To further enhance the detection and identification of breast cancer, researchers have employed a hybrid intelligence system that combines both feature selection and clustering techniques (Houssein et al. 2021).

In the following publication, an alternative classification method is proposed where the authors utilize artificial neural networks (ANN) to categorize breast cancer. This technique is compared to a conventional multilayer backpropagation perceptron through testing on the WBCD dataset (Houssein et al. 2021). In a study, a method was proposed to address the breast cancer classification problem using the neural network (NN) method on the Wisconsin Breast Cancer Database (WBCD) by researchers. In another study, researchers proposed a method for crime detection using an artificial neural network with neural fuzzy. They reported an accuracy of 95.42% for this method, and they utilized the MIAS dataset (Houssein et al. 2021).

Mabrouk et al. (2019) proposed a computer-aided diagnosis (CAD) system that utilizes image processing techniques to detect breast cancer changes with a higher degree of accuracy and at an earlier stage than traditional CAD inspection systems. The proposed system includes several stages, such as preprocessing, segmentation, feature extraction, and identification, which together improve the system's performance in breast cancer detection. The research proposed a computer-aided detection (CAD) system for detecting breast cancer changes with higher certainty and earlier than traditional methods. The system employed image processing methods starting with preprocessing, segmentation, feature extraction, and classification. The study focused on integrating different features, such as static moment form, texture, and features. The MIAS dataset was used, and the proposed system achieved an accuracy of 96% in automatic ANN mode.

Another study presented a hybrid approach for breast cancer detection and identification, combining machine learning methods of nearest neighbor and fuzzy artificial immune system into one model. The model was then tested on the WBCD dataset, and the accuracy was reported to be 99.14% (Houssein et al. 2021). Researchers have proposed the use of fuzzy neural methods for breast cancer detection and identification and have tested this method on the WBCD dataset. According to their results, the accuracy of this system was found to be equal to 95.06% (Houssein et al. 2021).

The authors introduced a method for breast cancer detection utilizing a decision tree based on the C4.5 algorithm. The WBCD dataset was used, and the model was evaluated with cross-validation. The accuracy of the classification system was reported as 94.74% (Houssein et al. 2021).

The detection of breast cancer was proposed by researchers using a PSO-KDE method, which utilized particle swarm optimization for bandwidth and KDE classifiers. The accuracy of the PSO-KDE model was evaluated using WBCD and WDBC datasets (Houssein et al. 2021). Another study introduced a hierarchical hybrid intelligent model consisting of three main phases: sample selection, function selection, and classification. The WBCD dataset was used to test the accuracy of this model, which was found to be 99.7151% (Houssein et al. 2021). A study utilized PSOWNN, a particle swarm-optimized wavelet neural network, to develop a classification method for breast abnormality detection. The approach involved extracting mammography rules from tissue energy measurements and classifying suspicious areas using a model classifier. The study used a real clinical database of 216 mammograms obtained from mammography screening centers. The proposed algorithm had an area under the ROC curve of 0.96853, with a sensitivity of 94.167% and specificity of 92.105%

The researchers proposed a weighted naive Bayesian approach for breast cancer diagnosis using the BCDB. They achieved high accuracy rates of 99.1%, 98.2%, and 98.5% for sensitivity, specificity, and precision, respectively, using fivefold cross-validation (Houssein et al. 2021).

The authors of the study (Kaur et al. 2019) proposed a method for breast cancer diagnosis using a small dataset of 322 MIAS images. Their method involved preprocessing and feature extraction using K-means clustering, as well as the use of speeded-up robust features (SURF) for feature selection. Additionally, the authors presented a knowledge-based approach for breast cancer diagnosis that involved noise reduction and classification methods (Nilashi et al. 2017). The researchers utilized the expectation maximization (EM) algorithm to cluster the data into related categories, followed by using classification and regression trees (CART) to create fuzzy rules for breast cancer classification based on process knowledge. The system was tested using WDBC and mammographic mass data, achieving accuracies of 0.93 and 0.94, respectively.

Mohanty et al. (2020) proposed a computer-aided diagnosis (CAD) system to classify digital mammograms as normal or abnormal and benign or malignant. The system uses a block-based discrete wavelet transform package to extract features, which are then subjected to principal component analysis (PCA) to extract distinct features from the main feature vector. A classifier called an envelope-optimized extreme learning machine using weighted salp chaos swarming algorithm is then used to classify the mammograms. The method was tested on three standard datasets, including MIAS, DDSM, and BCDR.

Various machine learning methods utilizing combined classification approaches have been introduced for the diagnosis and identification of breast cancer. In one study, a hybrid approach combining an artificial neural network (ANN) and support vector machine (SVM) was proposed to detect and identify breast masses. This approach was tested on 303 images from the DDSM dataset, and the area under the curve (AUC) value after SVM was found to be 0.932, which was improved to 0.925 after using ANN. In another study, researchers presented a computer-aided diagnosis (CAD) system based on SVM and ANN, which utilized 400 private images (Houssein et al. 2021). The researchers in a study used K-nearest neighbor and SVM algorithms for breast cancer clustering based on IRMA data. They also applied several classifiers, including naive Bayes, SVM, K-nearest neighbor, logistic regression (LR), random forest (RF), and decision tree, in the Mini-MIAS dataset to detect and identify breast masses. LR, which was developed by statisticians, was used by ML scientists in learning along with other classifiers (Houssein et al. 2021). Logistic regression (LR) is commonly used for binary classification and involves using a set of predictors to calculate the probability of an event occurring (Yassin et al. 2018). Random forest (RF) is a method that involves combining multiple decision trees to make predictions. The trees are constructed independently, and the final decision is based on a majority vote. However, when dealing with imbalanced data, RF may not yield optimal results (Yassin et al. 2018). In a different research, a method for predicting malignant and benign abnormalities in breast cancer was presented using random forest, SVM, and naive Bayes classifiers applied to data from BCDR and INBreast datasets (Houssein et al. 2021). Several classification methods have been proposed for distinguishing between malignant and benign breast cancer using the DDSM dataset, including decision tree, naive Bayes, K-nearest neighbor, probabilistic-ANN, AdaBoost, and SVM. Additionally, a CAD system that integrates random forest, decision tree, and SVM is presented to detect breast cancer using BCDR and DDSM data, achieving 100% accuracy. Other studies combine K-nearest neighbor, naive Bayes, decision tree, and support vector machine techniques on INBrest and MIAS data, as well as using Fisher's linear discriminant analysis (FLDA), decision tree, SVM, and K-nearest neighbor classifiers on the DDSM dataset to classify between masses and normal breast tissue (Houssein et al. 2021).

Yassin et al. (2018) conducted a systematic review on the use of machine learning techniques for the diagnosis of breast cancer using various imaging methods.

Machine learning techniques for ultrasound images

In a study, researchers proposed a method for grouping breast ultrasound images into normal and tumor cases using backpropagation neural networks and multifractal dimensions. They examined 184 ultrasound images consisting of 72 tumor cases and 112 normal cases. The proposed method achieved an accuracy value of 82.04%, a specificity value of 84.75%, and a sensitivity value of 79.39% (Mohammed et al. 2018).

Machine learning techniques for magnetic resonance imaging

Several studies have employed support vector machines (SVM) for MRI breast cancer classification and diagnosis. One study proposed an approach to classify cancer as natural or non-natural using SVM on a set of private data, achieving an accuracy rate of 98%. Another study utilized SVM for detecting mass anomalies, while another employed SVM to detect breast cancer on a private dataset, reporting an accuracy rate of 94% (Houssein et al. 2021). Some studies have utilized the SVM method to classify breast cancer into benign and malignant categories, utilizing private datasets. Other researchers have proposed subgroup classification using cross-validated k-NN on a dataset of 200 private images (Houssein et al. 2021).

Machine learning techniques for histological images

In their study, the researchers proposed a method for distinguishing breast cancer images into three classes: carcinoma in situ, normal carcinoma, and invasive carcinoma, using a three-class SVM classification approach. Another approach involved creating an efficient cascade classifier that used artificial neural networks and a sequence of parallel SVM classifiers. The weak classifiers in this approach were the ANN and SVM classifiers, which were combined to form a stronger final classifier (Houssein et al. 2021). In a study, the researchers used the local binary pattern (LBP) and the Curvelet transform method to extract learning characteristics and develop a set of SVM classifiers for computer-aided diagnosis (CAD) of breast cancer. They also investigated the importance of multi-sample learning (MIL) for CAD. The study compared their CAD approach with other advanced MIL approaches such as ARR, citation-k-NN, diverse density, MI-SVM, as well as newer methods such as deep learning (MIL-CNN) and non-parametric approaches using BreaKHis public data (Sudharshan et al. 2019).

The researchers proposed various models to examine the primary components of a core class, which were created by utilizing specific characteristics associated with each type of breast cancer. These models were tested on the UCI breast cancer dataset (Houssein et al. 2021).

In a study, researchers used the Grossman vector local cumulative descriptor (VLAD) method to identify local features of breast cancer and present them in a spatially variable multidimensional signal that can be effectively modeled. The BreaKHis dataset was used in this method (Dimitropoulos et al. 2017). In a study, researchers proposed a method that aimed to differentiate between feature vectors of benign and malignant breast cancer cases by maximizing the learning of the constant domain space. They achieved an average classification rate of 88.5% on the BreaKHis dataset using this approach (Alirezazadeh et al. 2018).

Machine learning techniques for thermography images

Several studies have explored the use of thermography for breast cancer classification and diagnosis. SVM has been used in some studies for classification, while other studies have combined multiple classifiers, such as SVM, K-nearest neighbor, and naive Bayes, to achieve higher accuracy in classification (Sánchez-Ruiz et al. 2020). In addition to using traditional machine learning techniques, some researchers have proposed new methods for breast cancer detection and identification. For example, one group proposed a feature extraction method, while another proposed using swarm algorithms to detect breast cancer. These methods may offer unique advantages and should be further explored. da Silva et al. (2020) proposed a technique called "neural network with multiple classifiers" for breast cancer detection and diagnosis.

Deep learning techniques for different image modalities

Recently, several deep learning (DL) methods have been developed to enhance the effectiveness of medical image analysis and extract significant features. In this section, DL methods used for the classification and diagnosis of breast cancer are described for five different types of medical imaging, namely ultrasound, mammography, histology, MRI, and thermography.

Deep learning techniques for mammogram images

Chougrad et al. (2018) developed a recognition system for breast cancer based on deep convolutional neural networks, including ResNet50, VGG16, and Inception v3. The system used transfer learning with pre-trained weights and achieved high accuracy and AUC scores on three different databases: DDSM, INbreast, and BCDR. The system also preprocessed and standardized regions of interest (ROI) from mammograms, combined the data to create image sets, and achieved a high accuracy metric of 98.94%. In a different study, deep convolutional neural networks were utilized by researchers to classify different types of breast cancer tumors as either benign or malignant. The researchers developed a deep metric learning neural network for grouping breast tumors based on their characteristics (Houssein et al. 2021). The researchers presented a method that combines deep convolutional neural networks (CNN) with support vector machines (SVM) for crime detection (Houssein et al. 2021). In a study by Dontchos et al. (2021), a deep learning (DL) method was used to predict mammographic breast density on 2174 images. The researchers created a convolutional neural network (CNN) model on the mammography points and used the data from the last fully connected layer as a high-level feature representation of an image to develop a classification support vector machine (SVM). They also employed ResNet-18 in their DL approach.

In a study, researchers proposed an advanced DenseNet neural network model for the classification of malignant and benign tumors. The model, called DenseNet II, was created by preprocessing mammography images and replacing the first convolutional layer of the original DenseNet model. The processed data was then connected to several other neural network models, including AlexNet, GoogLeNet, VGGNet, and DenseNet. The proposed model achieved an accuracy rate of 94.55% (Li et al. 2019). A method for breast cancer grouping called CNNI-BCC was proposed by researchers to improve the classification of breast cancer abnormalities. This method utilizes convolutional neural networks to classify mammography images into three groups: benign, malignant, and persistent (Ting et al. 2019). The researchers proposed a method for distinguishing different pathological degrees in digital mammography by developing an end-to-end learning algorithm based on hybrid multilevel functions. The method involves extracting and selecting low-level features using guided logistic regression in LASSO and then developing a CNN model to extract high-level features. The proposed algorithm integrates multi-level derived functions to automate the current end-to-end functions of CNN, which allows different parts of the network to address different functional levels (Hai et al. 2019).

The proposed review includes a quantitative analysis of various approaches used for detecting and identifying different masses, as well as a qualitative analysis of their strengths and weaknesses. Additionally, the review covers the use of deep learning techniques for diagnosing, detecting, and classifying breast cancer tumors from mammography images (Houssein et al. 2021). Another study proposed an optimized breast cancer classification model using deep learning (DL) to automatically extract distinctive features. The model utilized all necessary features in the feature extraction process (Dhungel et al. 2017; Kooi et al. 2017). Researchers presented a rapid region-based convolutional neural network (R-CNN) based computer-aided detection (CAD) method for mass detection in mammograms. The proposed deep learning model is capable of detecting, classifying, and localizing large objects in high-resolution mammographic images. The performance of the model was evaluated using the INbreast dataset (Ribli et al. 2018).

Other studies have introduced a computer-aided detection (CAD) system for crime detection that utilizes the You Only Look Once (YOLO) model (Al-Antari et al. 2018; Al-Masni et al. 2018). In a different study, a system for identifying and categorizing breast abnormalities was introduced. The INbreast and DDSM datasets were employed, and the YOLO detector was utilized for identifying and diagnosing breast abnormalities. The F1 score for DDSM was 99.2%, and for INbreast was 98.02%. After identification, three DL classifiers (CNN, ResNet-50, and InceptionResNet-V2) were employed for classification. The average accuracies for the CNN, ResNet-50, and InceptionResNet-V2 classifiers were 94.5%, 95.8%, and 97.5% for the DDSM dataset, and 88.7%, 92.5%, and 95.3% for the INbreast dataset, respectively (Al-Antari et al. 2020).

The researchers utilized a convolutional autoencoder (SCAE) in an automated manner to learn the features of mammography images at various scales. To increase the model's robustness, a low-density regulator was incorporated (Houssein et al. 2021) to evaluate the proposed system for population recognition. The results showed that the proposed system using SPL and DAL achieved high classification performance with an accuracy of 92.5%, outperforming other state-of-the-art methods. The researchers concluded that their proposed system could significantly reduce the annotation effort and improve the efficiency of mammography image analysis (Shen et al. 2019).

Researchers created a transfer learning approach to teach a convolutional neural network (CNN) to recognize and classify a mass (Suzuki et al. 2016). A technique was proposed by researchers to address overfitting in CNN models that occurs when training data is limited (Swiderski et al. 2017). The researchers utilized a structured SVM model that incorporated multiple potential functions, including deep belief networks and Gaussian mixture models, for the purpose of population grouping (Hu et al. 2018). Researchers employed an alternative approach for detecting crime, utilizing a DL cascade and random forest grouping in their method (Houssein et al. 2021).

Deep learning techniques for ultrasound images

Deep learning has been utilized in several studies for the diagnosis and classification of breast cancer with ultrasound. One approach used by researchers is a model based on deep convolutional neural networks with multiscale kernels and jump connections (Qi et al. 2019). The researchers developed a model that consisted of two parts: the first part determined the presence of malignant tumors in an image, and the second part detected large nodules in the image. They used a neural network with three convolutional layers and two fully connected layers to classify breast cancer using 292 benign masses and 166 malignant tumors. The mean AUC was 0.912, with an accuracy of 83.0% and a sensitivity of 82.4% (Michał Byra et al. 2017).

In this study, CNN was utilized to classify breast ultrasound images into four distinct groups, namely, fat tissue, 3D mass, fibro glandular tissue, and skin. Quantitative analysis of the results showed that the segmentation process had a positive impact on the performance measures such as recall, precision, and F1 score, which all exceeded 80%. These findings suggest that the proposed approach is capable of accurately detecting functional tissue in breast ultrasound images (Xu et al. 2019). A group of researchers introduced a computer-aided diagnosis (CAD) system that utilizes convolutional neural networks (CNN) to classify breast abnormalities as either malignant or benign. To achieve efficient feature extraction, the researchers modified the Inception-v3 architecture, allowing the network to extract multi-view features from both views. The system was tested on 316 breast lesions and achieved an AUC value of 0.9468, with a specificity of 0.876 and a sensitivity of 0.886 (Wang et al. 2020a, b).

In a study, DL was utilized by researchers to diagnose and identify ultrasound abnormalities through an investigation of three different methods: patch-based LeNet, U-Net, and transfer learning approach utilizing FCN (fully convolutional network). Additionally, AlexNet has already been constructed using fully convolutional networks (Yap et al. 2017). Researchers developed a CNN system with a focus on transfer learning to diagnose benign and malignant breast abnormalities. The system was tested on 150 cases and achieved an AUC of 93.6%. To train the model, the researchers used the VGG19 CNN model, which was pre-trained on ImageNet data, and configured it with 882 ultrasound images of breast masses (Michal Byra et al. 2019). The researchers in a study utilized GoogleNet to train on a dataset comprising 7408 ultrasounds and then tested the model on 829 images. They implemented an S-Detect program component algorithm on RS80A and found that their model had a sensitivity of 86%, an accuracy of 90%, and a specificity of 96% on experimental data (Han et al. 2017). The researchers employed a stacked autoencoder model for classifying breast abnormalities, and they achieved an AUC of 89.6%. This model exhibited superior performance compared to conventional machine learning-based methods (Houssein et al. 2021). The researchers utilized a deep learning model consisting of two layers to classify breast lesions from SWE images. The first layer of the model was a fully connected neural network used for feature extraction, while the second layer was a constrained Boltzmann machine employed to provide a better representation of the features. This approach resulted in improved outcomes in breast lesion classification (Houssein et al. 2021). The researchers also utilized U-net for the detection of criminal activities (Kumar et al. 2018).

Deep learning techniques for magnetic resonance imaging

The researchers proposed a CNN-based grouping approach combined with image quality assessment (IQA). They utilized a CNN architecture to compute the number of pixels in lesions with maximum pooling layers. Subsequently, high-quality pixel regions were identified with a high density of texture and grayscale features. Finally, they designed a multi-SVM image kernel for breast cancer grouping by leveraging the obtained quality values (Fang et al. 2019). In a separate study, researchers introduced the NiftyNet framework, an open-source platform for deep learning in medical imaging. The framework is designed to provide a flexible and scalable pipeline for various medical imaging tasks, including classification, visualization, and regression. Built on top of the TensorFlow system, NiftyNet supports standard functions such as 3D image visualization and 2D TensorBoard, as well as calculation graphs (Gibson et al. 2018). The authors of a different study presented a method for distinguishing between benign and malignant breast abnormalities using a knowledge-based feature learning and integration approach. They used 100 magnetic resonance imaging (MRI) scans and achieved a specificity of 85.7%, sensitivity of 84.6%, and accuracy of 85.0% with their method (Feng et al. 2020).

Deep learning techniques for histological images

The researchers developed a deep cascade network for identifying and detecting mitosis. Firstly, they created an FCN model to extract a mitosis candidate from all the histological slides. Then, they optimized a pre-existing CaffeNet model for mitosis classification on large-format ImageNet images (Houssein et al. 2021). Researchers created a deep learning algorithm to detect meteors, in which they utilized a CNN model to extract features that were then utilized to form an SVM to identify mitosis (Houssein et al. 2021). In a separate study, scientists utilized multi-scale convolutional neural networks (EMS-Net) to classify histopathological breast tissue stained with hematoxylin–eosin into three categories: carcinoma, benign lesions, and normal tissue. The image was transformed into various scales, and the training contexts were employed at each level to fine-tune the pre-trained models DenseNet-161, ResNet-152, or ResNet-101. This algorithm achieved an accuracy of $91.75 \pm 2.32\%$ in a five-fold cross-validation with 400 training images (Yang et al. 2019).

Researchers have developed a CNN model that automatically classifies invasive ductal carcinoma in whole-slide images (WSI) and identifies non-invasive and invasive images (Houssein et al. 2021). The researchers developed a system that categorizes whole-slide images (WSI) into five diagnostic categories using a detector and a convolutional network. The detector localizes diagnostic regions using four fully folded arrays, while the convolutional network classifies image fields into different categories. The map and grouping features are then used for pixel-by-pixel labeling and slide-level grouping. Experiments using 240 WSIs showed that the classifier and detector networks performed with an accuracy of 55% on five slides, which was comparable to the predictions of 45 pathologists (Gecer et al. 2018).

The researchers employed a pre-existing Inception-V3 model to generate four significant post-treatment groups. The Inception-V3 model is a pre-built software utilized for categorizing diverse images within the ImageNet data, and it can recognize up to 1000 image classes (Wang et al. 2018). The researchers created simulation software that allowed them to select the most suitable CNN from a range of CNNs in order to develop robust video recognition software (Houssein et al. 2021). Researchers employed a technique to enhance the lossy performance of convolutional neural networks (CNNs) (Houssein et al. 2021). The researchers introduced a CNN model to differentiate between mitotic and non-mitotic nuclei using a multi-scale CNN architecture. They added a pooling layer after the Softmax layer to merge the dense annotations with the CNN for improved prediction results from multiple participants (Wahab et al. 2017). The researchers introduced a sparse automatic encoder (SSAE) approach to classify nuclei in breast cancer histopathology. The SSAE is trained in a layer-wise manner, where each hidden layer is generated sequentially and employs the output of previous layers to construct the next hidden layer. The optimization process is performed to ensure the sparsity of the representation learned by the SSAE (Houssein et al. 2021).

Researchers developed a patch-based clustering (PBC) method using CNN to group breast histology images into four different groups: invasive, in situ, benign, and normal. The PBC method works in two forms: one patch in one decision (OPOD) and all patches in one decision (APOD). The OPOD technique achieved a classification accuracy of 77% for four histopathological classes in each patch and 84.71% for two classes. APOD achieved an image classification accuracy of 90.0% for class 4 and 92.51% for class 2. The proposed model achieved an overall accuracy of 87% for the ICIAR-2018 covert experiment (Roy et al. 2019).

The researchers introduced a hybrid architecture for breast cancer histopathological image analysis, utilizing the feature extraction abilities of CNN. The architecture included an intensive interaction learning machine (ICELM) and dual deep transfer learning (D2TL). They evaluated the performance of this model on 134 histopathological images of breast cancer (Wang et al. 2020a). The researchers developed a DL-based method to extract optimal visual features for grouping breast cancer (Houssein et al. 2021).

The researchers in their study used a combination of a Fisher feature layer and a convolutional neural network to create a more refined space where specific features of breast cancer are encoded, allowing for effective differentiation of different types of breast cancer (Song et al. 2017). In another study, they proposed the use of a deep recurrent neural network and a hybrid convolutional network for clustering breast cancer (Yan et al. 2020).

Deep learning techniques for thermography images

The use of thermography for breast cancer diagnosis offers several clinical benefits, such as the ability to detect and categorize breast cancer at an early stage. A list of DL

Table 4 WBCD attributes

Number	Attribute	Domain
0	Sample code number	Id number
1	Clump thickness	1–10
2	Uniformity of cell size	1–10
3	Uniformity of cell shape	1–10
4	Marginal adhesion	1–10
5	Single epithelial cell size	1–10
6	Bare nuclei	1–10
7	Bland nhromatin	1–10
8	Normal nucleoli	1–10
9	Mitoses	1–10
10	Class	2 for benign 4 for malignant

Table 3 Studies using deep learning: DWNN: deep wavelet neural network

References	Technique	Contribution	Performance metrics
Ekici and Jawzal (2020)	CNN	Extracting features of the breast based on biodata, image processing, and image statistics	Accuracy: 98.95%
de Freitas Barbosa et al. (2020)	DWNN	Detecting the breast masses	Accuracy: 98.95%
Cabıoğlu and Oğul (2020)	CNN	CAD system that uses a transfer learning to classify breast cancer	Accuracy: 94.3%

techniques related to this area is provided in Table 3 (Houssein et al. 2021).

ML Applications in WBCD data analysis

The WBCD dataset was introduced in the 1990s and has been analyzed using various ML algorithms. It consists of nine features, excluding the first (specimen code number) and the last (output class), to classify breast cancer. Table 4 provides a summary of the features. The dataset contains 699 samples, but some researchers remove 16 samples with missing values during preprocessing. Sometimes, additional samples are also removed during preprocessing (Yue et al. 2018).

ML techniques are applied in WBCD to predict whether tumors are benign or malignant. As there are variations in characteristic values among patients even within the same class, doctors can categorize breast cancer tumor classes into different scenarios based on these values. This aids in cancer prognosis, such as predicting susceptibility, progress, and survival rates and providing effective treatments (Yue et al. 2018).

ANNs

A feedforward network with the backpropagation (BP) algorithm was created in 1993 to predict if a patient had benign or malignant lesions using a mammographic atlas of breast cancer. This dataset was collected in 1985. The findings suggest that artificial neural networks (ANNs) can be beneficial in the early analysis of mammography (Yue et al. 2018).

The comparison between radiologists' classifications and the output of the neural network revealed that the neural network has a better diagnostic performance than the radiologists. This indicates that the neural network is highly beneficial in the diagnosis and prognosis of breast cancer (Yue et al. 2018).

SVMs

In the past, a simple SVM approach was utilized to analyze WBCD data, which resulted in a classification accuracy of 97.2%. The study revealed that SVM had a high accuracy when applied to high-quality breast cancer data. Later, in 2007, the least square SVM (LS-SVM) method was introduced, which improved the accuracy to 98.53%. The main difference between LS-SVM and SVM is that LS-SVM employs linear data instead of quadratic programming. Another study proposed an SVM-based model for WBCD classification, achieving a specificity of 99.51%. The model selected the optimal feature combination from five features by calculating the F score of different combinations (Yue et al. 2018).

DTs

In 1996, Quinlan proposed a modified C4.5 decision tree, which had high predictive accuracy and the advantage of smaller construction. In 2005, three features related to WBCD were extracted using the C4.5 decision tree with expert suggestions, while the remaining six features were used for clustering using an artificial immune recognition system (AIRS). AIRS-related new feature selection (FS-AIRS) achieved an accuracy of 98.51%. Later, a new fuzzy decision tree (FDT) was developed and tested on WBCD. Each characteristic was processed using fuzzy trapezoidal membership functions and then placed in an if–then fuzzy structure in a decision tree, providing a compact and interpretable appearance with a grouping accuracy of 95.27%. In 2011, a hybrid method for medical data clustering was proposed, which combined case-based reasoning methods and the fuzzy decision tree method (CBFDT) (Yue et al. 2018).

k-NNs

The k-NN algorithm and its fuzzy variant have been widely used in breast cancer diagnosis and prognosis. The choice of k significantly affects the quality of the clustering. In a study conducted in 2000, both k-NN and fuzzy k-NN algorithms were employed to cluster the WBCD dataset. The algorithms were tested for different values of k ranging from 1 to 15, and the best performance was achieved at $k = 1$. The k-NN algorithm resulted in an accuracy of 98.25% on the test data, while the fuzzy k-NN algorithm achieved an accuracy of 98.83% (Yue et al. 2018).

Conclusion

Breast cancer is a serious disease that requires early detection for successful treatment. In recent years, machine learning and deep learning techniques have shown great promise in the classification and diagnosis of breast cancer. This review aimed to explore the various methods used in this field and categorized them into five groups based on the medical imaging techniques used: mammography, ultrasound, MRI, histology, and thermography.

The review highlighted five popular machine learning techniques used in breast cancer diagnosis: nearest neighbor, SVM, naive Bayesian network, DT, and ANN. Additionally, deep learning architectures and convolutional neural networks were used to analyze the medical images and classify breast cancer.

Overall, the results of these studies demonstrate the potential of machine learning and deep learning techniques in the diagnosis and prognosis of breast cancer. These methods have the potential to improve accuracy and reduce the time and costs associated with traditional diagnostic methods. However, further research is needed to optimize these techniques and ensure their accuracy and reliability in real-world clinical settings.

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Declarations

Conflict of interest The authors declare that the study was carried out independently of any financial or commercial interests.

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