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Review

Deep and machine learning techniques for medical imaging-based breast cancer: A comprehensive review

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A R T I C L E I N F O

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Ultrasound images
Thermography images

A B S T R A C T

Breast cancer is the second leading cause of death for women, so accurate early detection can help decrease breast cancer mortality rates. Computer-aided detection allows radiologists to detect abnormalities efficiently. Medical images are sources of information relevant to the detection and diagnosis of various diseases and abnormalities. Several modalities allow radiologists to study the internal structure, and these modalities have been met with great interest in several types of research. In some medical fields, each of these modalities is of considerable significance. This study aims at presenting a review that shows the new applications of machine learning and deep learning technology for detecting and classifying breast cancer and provides an overview of progress in this area. This review reflects on the classification of breast cancer utilizing multi-modalities medical imaging. Details are also given on techniques developed to facilitate the classification of tumors, non-tumors, and dense masses in various medical imaging modalities. It first provides an overview of the different approaches to machine learning, then an overview of the different deep learning techniques and specific architectures for the detection and classification of breast cancer. We also provide a brief overview of the different image modalities to give a complete overview of the area. In the same context, this review was performed using a broad variety of research databases as a source of information for access to various field publications. Finally, this review summarizes the future trends and challenges in the classification and detection of breast cancer.

1. Introduction

1.1. Breast cancer

Breast cancer is a group of diseases in which the breast tissue cells modify and split in an uncontrolled manner, usually producing mass or lump. Most breast cancers start in the lobules (mammary glands) or in the channels that connect the lobules to the nipple (Society, 2019). Breast cancer is the most common cancer among women and is the second leading cause of death. Throughout the years, the incidence of breast cancer has risen worldwide, and throughout one million new cases are reported annually (Hamidinekoo, Denton, Rampun, Honnor, & Zwiggelaar, 2018). Relative to other cancers it has a high prevalence in women. This disease leads to death if it is not diagnosed early (Arevalo, González, Ramos-Pollán, Oliveira, & Lopez, 2016). Breast cancer can be divided into two groups: normal and abnormal and it can be divided into two categories: benign (not dangerous) and cancer (malignant). Benign tumors grow fairly slowly and do not invade neighboring tissues and do not spread into different parts of the body (Mohammed et al., 2018). Breast cancer is typically detected before signs occur during screening, or after a woman finds a lump. The largest of the masses contained on a mammogram is considered to be mild (not cancerous), and most breast lumps. If cancer is detected, the tissue is typically collected for microscopic examination from a needle biopsy (fine needle or larger heart needle) and less frequently from a surgical biopsy (Society, 2019). The early and reliable identification of this disease is focused on reviewing prior diagnostic data and collecting valuable information from previous data. Machine learning techniques and medical imaging will help the process.

1.2. Medical imaging

Nowadays, rapid detection and diagnosis of tumors using image processing and machine learning techniques can be an important aid in

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enhancing the accuracy of a breast cancer diagnosis. Medical imaging plays a major role in clinical disease diagnosis, treatment assessment and identification of defects in different body organs such as the eye (Akbar, Akram, Sharif, Tariq, & Khan, 2018), the lungs (Akbar et al., 2018), the brain (Rajinikanth, Satapathy, Fernandes, & Nachiappan, 2017), the breast (Fonseca et al., 2015), and the stomach (Khan, Sharif, Akram, Yasmin, & Nayak, 2019). Medical imaging refers to specific techniques that are used to analyze the human body to diagnose, track, or treat a disorder. Every type of technology offers specific details about the region of the body being investigated or handled, about the illness, injury, or the efficacy of the medical care in which the human body has been investigated for illness detection and monitoring (Ashour, Dey, & Mohamed, 2016). Medical imaging studies seek to classify the location, size, and characteristics of the organ in question, which has been considered an effective method for extracting useful information from the enormous amount of information. Consequently, several researchers focused intensively on the production and interpretation of medical images to identify the majority of diseases. Medical images thus promote disease identification and help the detection of pathological lesion, the patient's clinical treatment, and the presumption of multiple medical conditions. Machine learning and artificial intelligence have made substantial progress in recent decades and played a major role in the medical field, such as the analysis of medical images. Medical imaging is the most effective way to detect breast cancer, with regular use of different modalities such as MRI, PET, mammography, and CT, radiography ultrasound and duplex ultrasound (Deserno, 2010; Dhawan, 2011; Pluim, Maintz, & Viergever, 2003) are frequently used for breast cancer. This review provides an overview of the most commonly used types of medical images (i.e. Mammography, Ultrasound, MRI, Histological, and Thermography images).

1.2.1. Mammography images

A mammography test called a mammogram helps detect and diagnose breast cancer in women early (Society, 2019). It is a human breast x-ray that uses small dose x-rays to produce a breast image (Dheeba, Singh, & Selvi, 2014). Screening mammograms are effective in assessing the cancer risk in women with no noticeable symptoms, whereas diagnostic mammograms in patients with irregular symptoms or breast nodules are performed. This produces a picture that shows the soft tissue, dense tissue, pectoral muscle, and fibro-gland area, etc. These mammograms can be examined by professional radiologists to find out if there are any anomalies in the breast. Some improvement over one or two years in two or more mammograms may imply early cancer. A mammogram can display breast changes up to a year or two before the patient or doctor has seen the symptoms (Dhawan, 2011). When significant changes are verified at an early stage of cancer, more intensive therapies can be prevented and the probability of breast survival increased.

The American Cancer Society recommends once a year mammography for all women over 40 years old. Dense breast tissue during a mammogram can appear white or light gray. This can make it easier to view mammograms in younger women who appear to have thicker breasts. Most breast diseases resemble cancer signs and require testing to identify them, and often a biopsy. Mammography stays the cornerstone of population breast cancer screening and can detect more in situ lesions and smaller invasive cancers than other screening approaches such as MRI and Ultrasound (Shen, Yan, Tian, Jiang, & Zhou, 2019).

1.2.2. Ultrasound images

Another method of breast cancer screening is ultrasound imaging, which often uses a low dose of frequencies to create images of the breast, but keeps the contrast image very small. Ultrasound imaging can be used to assist in screening mammography in examining abnormalities, particularly in women with large breasts. Ultrasound can detect and identify breast mass nodes and is mostly used for ease, volume, non-invasiveness, and low-cost (Qi et al., 2019).

1.2.3. Magnetic resonance imaging

Magnetic resonance imaging (MRI) is another technique to detect cancer cells early, in addition to ultrasound and mammography techniques. Instead of X-rays, MRI uses magnetic fields to construct very accurate three dimensional (3D) transverse images. Human body MRI requires a high dose of radiation to get accurate breast 3D images. So, the differences in the infected region are very vivid when we use an MRI and thus reveal no cancer that cannot be seen in any other way. On the contrary, this alone is not enough for MRI screening because compared with mammography, the technology is costly. As demonstrated by mammography and calcification, MRI will neglect the first type of breast cancer, too. MRI seems to have the advantage of the benefit that the risks of angiography and, in particular, clearer information on abdominal masses than CT in some situations. With high spatial precision, specific variations between soft tissues can be seen by changing the data acquisition parameters (Wilkinson & Graves, 0000).

1.2.4. Histological images

Despite rapid advancements in medical research, the benchmark for cancer diagnosis remains the histopathologic diagnosis. Histopathological images are microscopic images of the tissues used in disease analysis. The nature of histopathological images and the drastic rise in work, therefore, make this job lengthy and the findings may be subject to the pathologist's subjectivity. Therefore, the production of automated and precise methods of histopathological image analysis is crucial for the area (Sudharshan et al., 2019).

1.2.5. Thermography images

Another modality for breast cancer imaging, called thermography emerged in 1982 (Prabha, Sujatha, & Ramakrishnan, 2014). Breast thermography or thermal imaging is a pain-free, non-invasive method that often used to detect changes in the breast that may indicate breast cancer. Thermography is an effective screening test that can detect breast cancer by showing the body parts displaying an irregular temperature shift by using a thermal infrared camera that transforms this infrared radiation into electrical signals by shows it as a thermogram. Hossam, Harb, and Abd El Kader (2018)

1.2.6. Motivation

The motivation for this review is to enable radiologists to use deep and machine learning techniques to increase the rate of rapid and reliable detection and classification of breast cancer. This review aims at identifying various studies in the literature related to the classification of breast cancer using multiple modalities of medical imaging based on deep and machine learning techniques. In summary, the main contributions of this research are to look for replies to these questions:

1. Which imaging modalities are demonstrated in classifying breast cancer?
2. What databases are used in the classification models for medical images?
3. Which types of deep and machine learning techniques are currently applied to classifying breast cancer using modalities of medical imaging?
4. What type of CNN architecture is used to classify breast cancer?
5. What evaluation metrics are used to evaluate the efficiency of the classification models?

1.3. Paper structure

This review provides an overview of various machine learning and deep learning techniques used in mammography, ultrasound, MRI, histological, and thermography breast cancer detection and classification. The rest of this paper is structured as follows: basics and background for machine learning and deep learning techniques will be discussed in-depth in Section 2, ML applications for different image modalities will be discussed in Section 3, DL applications for different image modalities will be given in Section 4, future trends, and challenges will be presented in Section 5. Finally, the research review is concluded under Section 6.

2. Basics and background

2.1. Machine learning overview

In medicine, machine-learning is also used to diagnose breast cancer. Fig. 1a presents the statistics for machine learning and breast cancer classification and detection studies from 2010 to 2019 based on information from the Scopus databases. Fig. 1b shows the distribution of machine learning for breast cancer research area.

Machine learning is regarding as an artificial intelligence branch, which connects the learning problem from data samples to the general principle of inference (Tapak et al., 2019) and uses mathematical, statistical, and logical techniques to allow the machine to learn from data without programming (Montazeri, Montazeri, Naji, & Faraahi, 2013). By incorporating artificial intelligence in gaming and pattern recognition algorithms, Arthur Samuel came up with the term machine learning in 1959 to make the computer learn from experience. The key goals of machine learning are predictions or decisions guided by the data. Machine learning has become a powerful modeling tool for difficulties that are difficult to communicate correctly (Rahman, 2019). Through using numerous machine learning algorithms, solid machine learning techniques have replaced several parts of human involvement (Goodfellow, Bengio, & Courville, 2016). The machine learning science has become very successful over the years as the volume of data has increased, and due to the availability of computing power. Throughout various studies, different methods of machine learning were implemented (Alkım, Gürbüz, & KıLıç, 2012; Das & Sengur, 2010; Zheng, Yoon, & Lam, 2014).

A publication in Montazeri, Montazeri, Montazeri, and Beigzadeh (2016) compared the accomplishments of Naive Bayes, Trees Random Forest, 1-Nearest Neighbor, AdaBoost, Support Vector Machine, RBF Network and multi-layer perceptron techniques for machine learning. In Chao, Yu, Cheng, and Kuo (2014) Support Vector Machine, Logistic Regression, and a C5.0 Decision Tree model used to predict the survival of British Columbia. The SVM method is the most common classification of breast cancer. ML techniques widely used for developing CAD systems are Decision Tree (DT), Naive Bayes, nearest neighbor, Artificial Neural Network (ANN), Support Vector Machines, and set classifiers (Saxena & Gyanchandani, 2019).

2.1.1. Support vector machine

Support Vector Machine (SVM) is a widely used method in machine learning for classification and problem regression. It was originally introduced by Vapnik in the last decade of the 20th century (Drucker, Wu, & Vapnik, 1999). SVM was used in many applications, for example in biometrics (Vatsa, Singh, & Noore, 2005), bioinformatics (Byvatov & Schneider, 2003), and chemoinformatics (Doucet, Barbault, Xia, Panaye, & Fan, 2007). Training data is used in the SVM classifier to construct the model for the classification. Classification of an unknown sample is performed later. SVM's principal concept is to use hyperplanes to distinguish various groups. SVM has achieved high precision levels when data can be divided linearly. SVM output cannot non-linearly separate separable data, though. This problem can be solved by mapping the data to a different, high dimensional space using kernel functions, and then the data can be separated linearly. The selection of the correct kernel function and its parameters are two key problems when using SVM (Tharwat, Hassanien, & Elnaghi, 2017).

2.1.2. Decision tree

Decision Tree (DT) is regarding as a common classifying data approach as "divide and conquer". With this approach, the data may be represented in a tree format, the various characteristics are expressed by internal nodes and data sample labels expressed by the leaf nodes. The tree is traversed between root and leaf to identify the respective data set. The leaf node holds the final grading result (Witten & Frank, 2002). For classification, the most widely used DT algorithm is C4.5. Amin, Sibaroni, et al. (2015). In the method discussed in Lim, Loh, and Shih (2000), a comparison of C4.5 with other DT algorithms is made. Ruggieri (2002) introduced a more robust variant of C4.5, known as EC4.5, which provides five times better efficiency over C4.5 for the same decision tree. It has the same tree of decision as C4.5.

2.1.3. k-nearest neighbor

In the K-Nearest Neighbor (k-NN), a sample of data is compared using a distance measure with other data samples. A distance metric can be used to minimize the distance between two identical data samples, and to increase the distance between two separate data samples (Kotsiantis, Zaharakis, & Pintelas, 2007). In general, the standard Euclidean distance is used to measure the distance between two data samples. Eq. (1) will give the Euclidean distance between x and y. This method is known as the closest k-method (Witten & Frank, 2002).

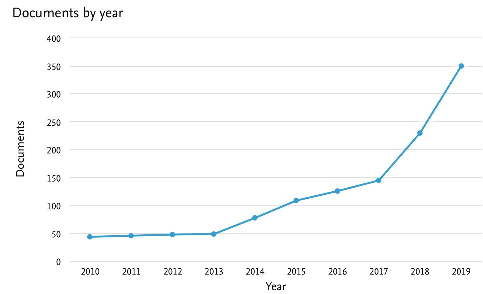
$$D(X,Y) = \sqrt{(\sum_{i=1}^{n} |x_i - y_i|^2)} \tag{1}$$

2.1.4. Naïve Bayesian Network

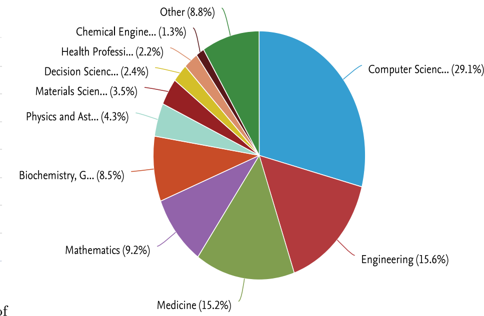
The Bayesian Network (BN) is a directed acyclic graph that described a relationship between many variables (features) using probabilities. The graph nodes represent the variables, and the arcs represent the relations between the variables. It is a particular case of BN, where there is only one parent and several children in the DAG. Child nodes within their parent node remain independent of each other. BN classifiers are used to make projections of likelihood and not predictions (Kourou, Exarchos, Exarchos, Karamouzis, & Fotiadis, 2015).

2.1.5. Artificial neural network

Artificial Neural Network (ANN) is analogous to the interconnected neuronal biologic network in the human brain (Ripley, Harris, & Tarassenko, 1998). Feedback is the most widely used ANN for classifying ANN problems with the training algorithm for backpropagation. Fig. 2 shows the basic structure of a single neuron in a direct-acting ANN (Murtaza et al., 2019). A unique neuron in ANN receives input Xi from other neurons, and multiplies each date by the corresponding weight Wij, and uses an activation function to produce a weighted output f (Xj). This weighted output is again transferred in the next layer as input to another neuron and the same process is repeated before reaching the output layer. The neurons are organized in the form of strata in this type of network. A typical direct action ANN may have one input layer, one output layer, and several hidden layers. The training algorithm for backpropagation provides the method for weight shifts in Feedforward ANN during preparation. In the output layer, the actual output produced by ANN is compared to the desired output. The error is then determined by determining the difference between the real (determined) output and the expected (target) output. Finally, during the next iteration, the error updating the weights is re-transmitted to the network (Saxena & Gyanchandani, 2019).



(a) Histogram of machine learning for classification and detection of breast cancer publications.



(b) Distribution of machine learning for breast cancer research area.

Fig. 1. The machine learning techniques for breast cancer classification researches performed in the last decade [2010–2019] according to the Scopus database.

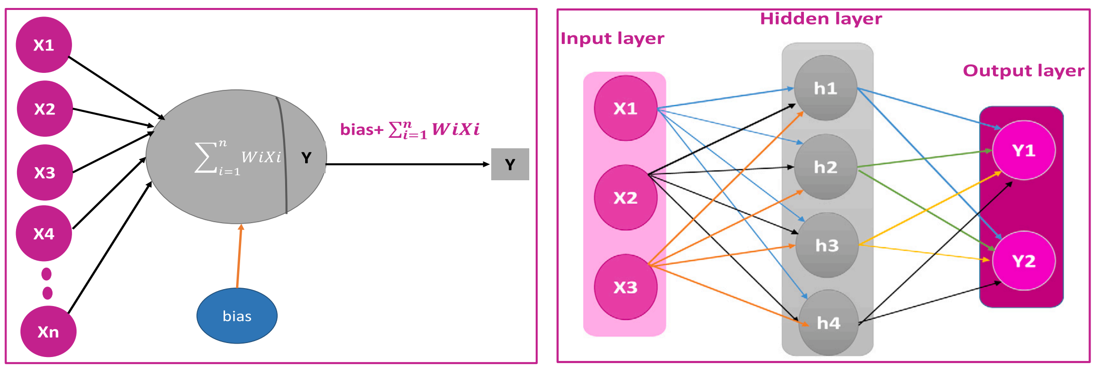


Fig. 2. The left side: shown an artificial neuron, the right side: the basic ANN.

2.2. Deep learning overview

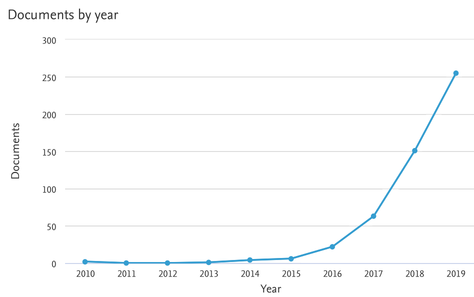
Deep learning (DL) is a subcategory of machine learning and AI that concentrates a complex hierarchy of image characteristics due to its ability to learn on its own, unlike traditional ML extraction algorithms. Deep learning algorithms apply to many recently used computer models to make remarkable progress in the way computers extract information from images. Such algorithms have been applied to tasks in a variety of medical specialties, especially radiology and pathology, and have achieved comparable performance in some cases with that of human experts. DL may also be used to extract data from medical images that would not be identifiable by human analyses and to gain information on molecular status, prognosis, or treatment sensitivity (Akkus, Galimzianova, Hoogi, Rubin, & Erickson, 2017).

DL consists of multilevel neural networks deriving a hierarchical structure of features through raw input images. Rapid improvement in graphics processor processing power has allowed the development of advanced DL algorithms able to practice with millions of images and are insensitive to image variations. DL became better known due to the latest success particularly in image segmentation and classification applications. Numerous types of DL methods were developed for various purposes, e.g. Recognition and segmentation of objects into images, speech recognition, the recognition of genotypes and phenotypes, and disease classification. Several common DL-algorithms include stacked autoencoders, deep Boltzmann machines, deep neural networks, and convolution neural networks (CNN) (Yap et al., 2017). Fig. 3a, illustrates the statistics for DL and breast cancer classification and detection studies from 2010 to 2019 based on the information from the Scopus databases. Fig. 3b, shows the distribution of DL for breast cancer research area.

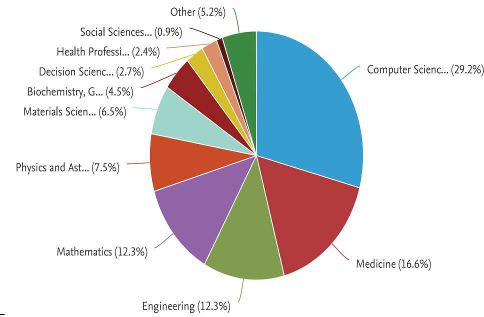
2.2.1. Convolutional neural network

Convolutional Neural Networks (CNNs) have become an important technique in image analysis, particularly when faces, text, human bodies, and biological images are detected or recognized (Yap et al., 2017). The CNNs are the most widely used imaging algorithms. Since its initial release in 1989 (LeCun et al., 1989), The CNNs were used with great success for the classification and segmentation of images (Deng et al., 2009; Krizhevsky, Sutskever, & Hinton, 2012; Russakovsky et al., 2015). A convolutional neural network in deep learning is a form of deep neural networks most widely used to classify visual images. CNN is a feed-forward network able to extract an image's topological properties. CNNs are Multilayer Perceptron driven models. Generally, the layered perceptron refers to completely linked networks, whereby each neuron in one layer is linked to all neurons in the next layer. CNNs are more like a neural network with three different types of layers that are ***convolutional***, ***pooling,*** and ***fully connected.*** Every layer has a different task. The ***convolutional layer*** has served as an extractor of features. ***Fully connected layer*** uses the extracted function to identify which category belongs to the current entry. ***A pooling layer*** is charged with reducing the dimensions of feature maps and network parameters. Fig. 4, shows an example of CNN (Stenroos et al., 2017).

1. *Convolutional Layers:* The convolutional layers are organized into feature maps based on the local connectivity principle and weight distribution theory. Local connectivity refers to the fact that each unit (neuron) in a feature map is only connected through a weight group called a filter bank to local patches of the feature map at the previous stage. Each of the units on a feature map shares a filter row. This is the model for weight distribution. Various filter banks are also used for various feature maps, too. The explanation for local connectivity and weight distribution is to minimize the number of parameters, thus taking advantage of the fact that the local pixel neighborhood is highly correlated and the local image statistics are independent of the location. Then the weighted sum of each unit is passed on to a nonlinear transformation function called the activation function. The activation function enables the nonlinear transformation of the transmitted information to the subsequent processing stages (Guo et al., 2016).



(a) Histogram of deep learning for breast cancer classification and detection publications.



(b) Distribution of deep learning research area.

Fig. 3. The deep learning techniques for breast cancer classification researches performed in the last decade [2010–2019] according to the Scopus database.

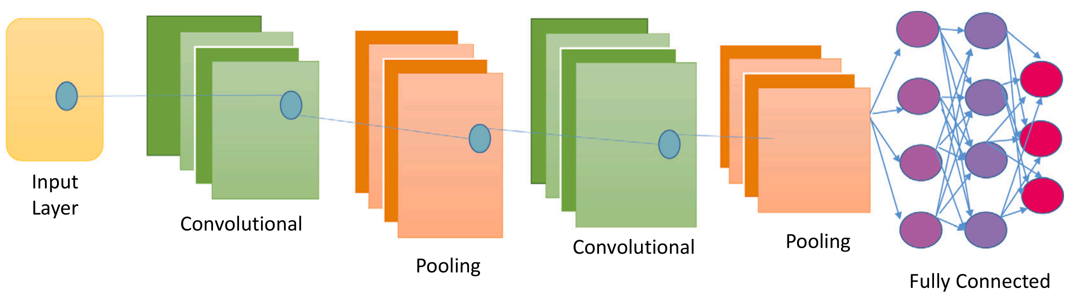


Fig. 4. An example of a convolutional neural network.

2. *Pooling layer:* The pooling layer conducts a subsampling procedure to merge similar characteristics of the convolutional layer into one (semantically). A unit within a pooling layer uses a local patch at the input from a preceding entity map (convolutional layer) and calculates the maximum or average patch value at the output. It decreases the size of the representation by reducing parameter numbers needed at the following stages and increases the robustness of the representation by providing an invariance against small displacements and distortions (Guo et al., 2016).
3. *Fully connected layer:* As can be seen in a normal neural network (i.e. a multilayer perceptron), the units in this layer are completely connected to all the units in the previous layer. Guo et al. (2016).

CNN Architectures: The CNN architecture is a major factor of its efficiency and performance. How the layers are organized, the elements used in each layer, and how they are constructed, all of these factors influences the speed and precision at which different tasks can be performed. Table 1 shows the common architectures; the 10 CNN architecture, the year their paper was published, and its configuration.

2.3. Breast cancer classification dataset analysis

This section includes an overview of the public datasets that were used in the various breast cancer classification studies in this review. Fig. 5, and Table 2 show that eight public documents were used to breast cancer classification, included the breast cancer data repository (BCDR), a Digital Database for Screening Mammography (DDSM), INBreast, Mammographic Image Analysis Society (MIAS)/mini-MIAS, Wisconsin Breast Cancer Dataset (WBCD), Wisconsin Diagnosis Breast Cancer (WDBC), Image Retrieval in Medical Applications (IRMA), and Breast Cancer Histopathological Image (BreakHis).

2.4. Performance evaluation

This section explains the performance metrics used to test CAD systems. Breast cancer can be categorized as true-positive (TP) or true-negative (TN) if it is diagnosed right/correctly and it can be categorized

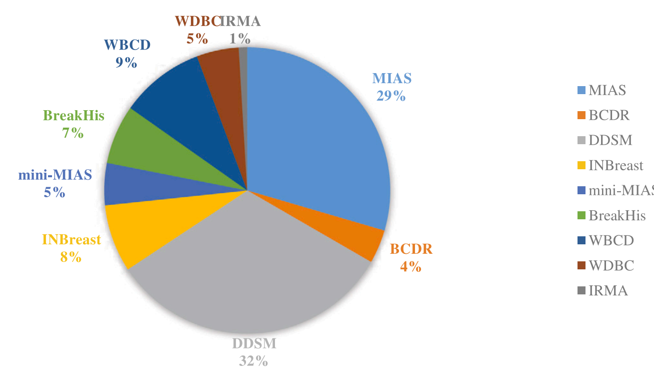


Fig. 5. A pie chart of the datasets used in the studies in this review.

as false-positive (FP) or false negative (FN) if it is diagnosed incorrectly. Accuracy, sensitivity, precision, FMeasure, AUC (Area under the curve), and volume under the ROC surface are the most common assessment measures adopted for breast cancer classification (Murtaza et al., 2019). These metrics are described briefly as:

Accuracy (Acc): This calculation measures how many instances are completely classified Right. It represented by Eq. (2)

$$ACC = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{2}$$

Sensitivity (Sn): This test reveals only how many of the overall positive cases are only right estimated. In simple words, it reflects how much of the total abnormal breast cancer patients are correctly estimated. This can be measured using Eq. (3)

$$Sn = \frac{TP}{(TP + FN)} \tag{3}$$

Specificity metric (Sp): It demonstrates how accurate the overall negative forecasts are and depicts how much of the usual predicted is right. It can be denoted by Eq. (4)

$$Sp = \frac{TN}{(TN + FP)} \tag{4}$$

Table 1
CNN architecture and configuration.

CNN architecture	Publication	Configuration
LeNet-5	LeCun, Bottou, Bengio, and Haffner (1998)	2 convolutional layers and 3 fully-connected layers.
AlexNet	Krizhevsky et al. (2012)	AlexNet has eight layers: five convolutional, and three entirely connected.
VGG-16	Simonyan and Zisserman (2014)	Thirteen convolutional and three fully connected layers, taking the ReLU from AlexNet.
Inception-v1	Szegedy et al. (2015)	Twenty-two layer architecture with 5M parameters.
Inception-v3	Szegedy, Vanhoucke, Ioffe, Shlens, and Wojna (2016)	Inception-v3 is a predecessor to Inception-v1 with parameters of 24 M.
ResNet-50	He, Zhang, Ren, and Sun (2016)	Has 50 layers deep
Xception	Chollet (2017)	Has 36 convolutional layers.
Inception-v4	Szegedy, Ioffe, Vanhoucke, and Alemi (2017)	Inception-v4 has two parts, feature extractor, and fully-connected layers.
Inception-ResNets	Szegedy et al. (2017)	Has 164 layers deep.
ResNeXt-50	Xie, Girshick, Dollár, Tu, and He (2017)	Consists of five stages each with a block of identification and convolution. Every block of convolution has 3 layers, and each block of identity has 3 layers of convolution.

Table 2
List of publicly available datasets used in this review and corresponding URL.

Dataset name	Image modality	URL
MIAS (Suckling et al., 2015)	Mammogram	https://www.repository.cam.ac.uk/handle/1810/250394
BCDR (Moura & López, 2013)	Mammogram	https://bcdr.ceta-ciemat.es/information/about
DDSM (Bowyer et al., 1996)	Mammogram	http://marathon.csee.usf.edu/Mammography/Database.html
INBreast (Moreira et al., 2012)	Mammogram	http://medicalresearch.inescporto.pt/breastresearch/index.php/Get_INBreast_Database
mini-MIAS (SUCKLING J, 1994)	Mammogram	http://peipa.essex.ac.uk/info/mias.html
BreakHis (Spanhol, Oliveira, Petitjean, & Heutte, 2016)	Histological	https://web.inf.ufpr.br/vri/databases/breastcancer-histopathological-databasebreakhis/
WBCD (Wolberg & Mangasarian, 1990)	Multimodality	https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic)
WDBC (Wolberg, Street, & Mangasarian, 1992)	Multimodality	http://networkrepository.com/breast-cancer-wisconsin-wdbc.php
IRMA (Oliveira, Gueld, Araújo, Ott, & Deserno, 2008)	Mammogram	https://data.world/datasets/irma

Precision metric (Pr): This only reflects how much of the prediction of abnormal breast cancer is correct. For medical image diagnosis, both Sn and Pr should be high to prevent the misdiagnosis of cancer patients. It can be determined by Eq. (5)

$$Pr = \frac{TP}{(TP + FP)} \quad (5)$$

F-Measure metric: It represents the simultaneous Sn and Pr effected by adding more penalties by harmonic means over extreme values. It is measurable by Eq. (6)

$$F - Measure = \frac{(1+\beta^2)(Pr \times Sn)}{(\beta^2 \times Pr \times Sn)} \quad (6)$$

AUC: The area under the curve is a numerical value that tells us how will the model perform in different situations. AUC value is calculable by Eq. (7)

$$AUC = \frac{\sum R_i\left(I_p\right) - I_p(I_p+1)/2}{I_p + I_n} \quad (7)$$

where Ip and In, remark the number of positively and negatively images of breast cancer, and Ri is the rating of the ith positive image.

3. Machine learning techniques for different image modalities

Several techniques of machine learning are used to detect, classify, and diagnose breast cancer based on the characteristics extracted from medical imaging. This section discusses and reviews the techniques of breast cancer detection for five medical imaging types; Mammogram, Ultrasound, MRI, Histological, and Thermography images.

Fig. 6 illustrates a chart of different machine learning techniques used for breast cancer classification discussed in this review.

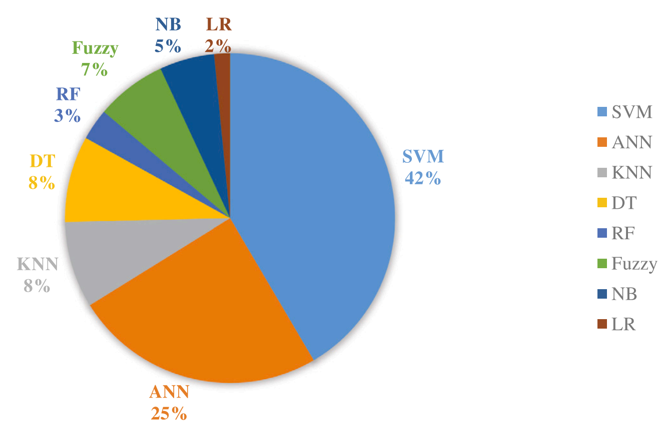


Fig. 6. Different machine learning techniques used in breast cancer classification discussed in this review.

3.1. Machine learning techniques for mammogram images

According to the work in Wang, Zheng, Yoon, and Ko (2018), the authors explored a general learning algorithm based on a support vector machine for breast cancer diagnosis. The proposed model is applied on different datasets; Wisconsin Breast Cancer (WBC), WDBC, and the U.S. National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) program breast cancer. In Vijayarajeswari, Parthasarathy, Vivekanandan, and Basha (2019), authors presented the mammogram classification according to the characteristics derived with the Hough transformation to identify the characteristics of the mammograms and classified them using SVM. This method was tested on 95 mammography images. In Quellec, Lamard, Cozic, Coatrieux, and Cazuguel (2016), the authors provided a technique for classifying breast cancer as normal or abnormal using the SVM on the DDSM dataset. The AUC metric measurement is 94.4%. Also in Zemmal, Azizi, and Sellami (2015), a semi supervised SVM is used on the DDSM dataset for tumors classification into benignity or malignancy, the accuracy metric is 93.1%. In Liu, Liu, Zhou, and Tang (2010), another method used SVM to classify the masses. Experiments showed the area under the ROC curve was 0.7. The study employed mammography images from the DDSM dataset. The authors in Anitha and Peter (2012) used the same concept as the previous study to perform a simulation experiment with 44 mammography images in the MIAS database and the authors indicated that the mass classification accuracy was as high as 95%.

A model based on the Rough Set (RS) and SVM classifier (RSSVM) for breast cancer diagnosis were built in Chen, Yang, Liu, and Liu (2011). The authors used RS as the technique for selecting the best features from the dataset. SVM has made another increase in the performance of the diagnostic system. On the WBCD dataset the efficacy of RS has been tested. while authors in Polat and Güneş (2007) proposed Least Square Support Vector Machine, classifying the development of a breast cancer diagnostic method, testing LS-SVM's robustness using k-fold cross-validation and the accuracy of the classification is 98.53%.

Authors in Liu and Tang (2013) presented modified regression functions to eliminate SVM and a standard selection procedure for mutual information functions. Simulated mammography images from the DDSM database showed that the method's accuracy was 93%. The developed of a K-SVM-based model for cancer diagnosis proposed in Zheng et al. (2014), using the K-means clustering technique to extract symbolic objects from tumors. The accuracy was 97.38% by K-SVM based on the WDBC dataset. In Übeyli (2007), the classification details of the different classifiers were reviewed on WBCD. The authors showed that SVM achieves greater precision in the diagnosis than other automated diagnostic systems. Researchers at (Chen, 2014) used both a grouping method and a characteristic selection technique to develop a hybrid intelligence system for breast cancer diagnosis.

Other classifier techniques proposed in the following publications, where the authors presented a model in Marcano-Cedeño, Quintanilla-Domínguez, and Andina (2011) which used an ANN for classification of breast cancer. Through testing the methods on WBCD, this technique was contrasted with the normal multi-layer perceptron with backpropagation. In Bhardwaj and Tiwari (2015), the authors proposed a method to solve the breast cancer classification problem based on the NN technique, using the WBCD database. Furthermore, the authors in Mahersia, Boulehmi, and Hamrouni (2016), propose a mass detection method using an Artificial Neural Network with Neuro-fuzzy, and the performance evaluation of this method is 95.42% accuracy, and they used MIAS dataset. In Singh and Urooj (2016) and Xie, Li, and Ma (2016), the authors using Artificial Neural Network hybrid with Extreme Machine Learning and wavelet ANN to classify the breast cancer tumor, and using the MAIS and DDSM datasets.

In Mabrouk, Afify, and Marzouk (2019), the researchers proposed a CAD system that diagnoses and detects changes in breast cancer earlier, more reliably and faster than traditional CAD inspection systems based on image processing techniques that begin with the preprocessing step, segmentation, extraction of characters and finally the classification stage. The analysis described in this work is focused on the integration of various features, such as invariant moment form, texture, and characteristics. The used dataset is MIAS, the accuracy of the proposed system reached 96% in automatic ANN mode. While in Şahan, Polat, Kodaz, and Güneş (2007), researchers proposed a hybrid approach for detecting breast cancer using machine learning techniques, integrated the fuzzy artificial immune system and the k-nearest neighbor into the model and tested the model in WBCD, accuracy was 99.14%. And also, the authors introduced neuro-fuzzy techniques in Nauck and Kruse (1999) and tested the process on WBCD. Their system has got a 95.06% accuracy.

The authors built a breast cancer approach using decision tree C4.5 in Quinlan (1996). They used a ten fold cross validation for the WBCD dataset. Their accuracy in the classification system was 94.74%.

Sheikhpour, Sarram, and Sheikhpour (2016) presented a PSO–KDE technique for breast cancer diagnosis using the PSO (Particle Swarm Optimization for determining bandwidth) and KDE classifiers. They measured PSO–KDE's results on two datasets on breast cancer, WBCD, and WDBC. In Onan (2015), the authors proposed a classified hybrid intelligent model building on 3-main phases: the instance selection phase, the functionality selection phase, and the classification phase, which was used by the WBCD dataset to evaluate this model. Their method's classification accuracy was 99.7151%. Furthermore, in Dheeba et al. (2014) PSOWNN (Particle Swarm Optimized Wavelet Neural Network) is used to examine a classification approach for detecting breast anomalies. The proposed anomaly detection technique is based on extracting mammogram laws from texture energy measurements and the classification of suspect regions using a model classifier. A true clinical database of 216 mammograms obtained in mammography screening centers were used to implement the procedure. The result shows that the area under the proposed algorithm's ROC curve is 0.96853 with a 94.167% sensitivity and a 92.105% specificity.

The authors have created a Naïve Bayesian (weighted-NB) application for detecting breast cancer in Karabatak (2015). This approach is tested using the Breast Cancer Database (BCDB). Their method obtained 99.1%, 98.2%, and 98.5% for sensitivity metric, specificity metric, and precision metric, respectively, using five fold cross validation.

Kaur, Singh, and Kaur (2019) presented an approach applied to the 322-image MIAS mini-dataset and a pre-processing method and integrated feature extraction using K-mean clustering to pick Speed-Up Robust Features (SURF) functions. While, the authors proposed a knowledge-based method to diagnosis breast cancer diseases by classification, noise elimination, and classification techniques in Nilashi, Ibrahim, Ahmadi, and Shahmoradi (2017). Expectation Maximization (EM) acts as a grouping tool to divide data into related categories, then the authors use the Classification and Regression Trees (CART) to produce the Fuzzy rules for classifying breast cancer in the system based on knowledge of the argumentation process. For system assessment, WDBC and Mammographic Mass datasets are used. The method's accuracies are 0.93 and 0.94 for WDBC and Mammographic Mass datasets, respectively.

Mohanty, Rup, Dash, Majhi, and Swamy (2020) propose a CAD system to classify digital mammograms as normal or abnormal, and also as benign or malignant. The proposed system uses a block-based discrete wavelet transformation packet to extract features. Then, the Principal Component Analysis (PCA) technique is used to extract the discriminating characteristics from the original vector feature. An optimized wrapper based extreme learning machine using a weighted chaotic salp swarm algorithm is subsequently proposed as a classifier for classifying the digital mammograms. The proposed method is evaluated on three standard datasets, namely, MIAS, DDSM, and BCDR.

Also, other machine learning approaches proposed in the following publications used hybrid classification approaches to detect and identify breast cancer as in Choi (2015), the authors proposed a hybrid approach combining SVM and ANN to identify breast masses, 303 DDSM dataset images are used, and the AUC value after SVM is 0.932 and improved with ANN to 0.925. Similarly, the researchers in Sun, Tseng, Zhang, and Qian (2016) proposed a CAD based on SVM and ANN used 400 private images. In Elmanna and Kadah (2015), SVM and K-nearest neighbor are hybrid to classify breast cancer using the IRMA dataset. Moreover, in Radovic, Milosevic, Ninkovic, Filipovic, and Peulic (2015), multiple classifiers are applied on the Mini-MIAS dataset to detect the breast mass; these classifiers are SVM, Naive Bayes, K-nearest neighbor, decision tree, Logistic Regression (LR), and Random Forest (RF). LR was created by statisticians and is frequently used by ML scientists in Learning like the other classifiers. LR is primarily used for issues related to binary classification. The probability of an occurrence is calculated based on a series of values used as predictors (Yassin, Omran, El Houby, & Allam, 2018). RF combines many trees for predictive decisions and created by combining multiple classification trees. Each of these trees is standalone. RF yields sub-optimal outcomes when the data is highly unbalanced (Yassin et al., 2018). In addition, the authors in Diz, Marreiros, and Freitas (2016) provided a technique to predict the benign and malignant lesions using SVM, Random Forest and Naive Bayes on INBreast, and BCDR datasets. In Raghavendra et al. (2016), many techniques are applied

Table 3
Summary of the papers for Mammogram images using SVM classifier from 2015–2017; AUC: area under the curve; Sn: sensitivity.

Reference	Dataset used	Contribution	Performance evaluation
Abdel-Nasser, Rashwan, Puig, and Moreno (2015)	– Mini-MIAS – INBreast	– Classification of breast density and mass or normal and classification	– Mini-MIAS: – Accuracy: 99%, AUC value: 0.9325
Liu and Zeng (2015)	– DDSM	– Mass detecting for diagnosis of disappointing areas	– Sn value: 82.4%
de Oliveira, de Carvalho Filho, Silva, de Paiva, and Gattass (2015)	– DDSM	– Classification of regions extracted as mass/non-mass	– Accuracy: 98.88%
Wajid and Hussain (2015)	– MIAS – INBreast	– Differentiating between abnormality (mass or microcalcifications) and (benign or malignant)	– Accuracy: 99% ± 0.50 – AUC value: 0.9900 ± 0.0050
de Nazaré Silva, de Carvalho Filho, Silva, De Paiva, and Gattass (2015)	– DDSM	– Masses detection	– Accuracy: 83.53%
Liu, Mei, Liu, and Hu (2015)	– INBreast: 410 images	– Detection of microcalcifications	– AUC value: 0.8676
Sharma and Khanna (2015)	– IRMA – DDSM	– Classify vector features as malignant or non-malignant	– IRMA: Sn value: 99%, Sp value: 99% – DDSM: Sn value: 97%, Sp value: 96%
Ponomaryov (2015)	– MIAS	– Breast cancer classification	– Accuracy: 96.3%
Khalaf and Yassine (2015a)	– MIAS – DDSM	– Breast cancer classification	– MIAS: Accuracy: 95.80% – DDSM: Accuracy: 95.78%
Khalaf and Yassine (2015b)	– DDSM	– Breast cancer classification	– Accuracy: 94.44%
Addioui, Benabbou, El Filali, and El Aroussi (2015)	– Private cases	– Breast cancer classification	– Accuracy: 98.33%
Phadke and Rege (2016)	– MIAS	– Classify abnormalities using fusion functions	– Accuracy: 93.17%
Hiba, Hamid, and Omar (2016)	– DDSM	– Classification of breast cancer	– Accuracy: 91.25%
Khan, Hussain, Aboalsamh, and Bebis (2017)	– MIAS : 109 cases	– Normal and masses classification	– Accuracy value from 68% to 100%

Table 4
Summary of the papers for Mammogram images using ANN: Artificial Neural Network classifier.

Reference	Dataset used	Contribution	Performance evaluation
Pratiwi, Harefa, Nanda, et al. (2015)	– MIAS	– Normal or abnormal classification then classify the abnormal into benign or malignant	– RBF(normal/abnormal): – Accuracy: 93.98, Sn value: 97.22% – RBF(benign/malignant): – Accuracy: 94.29%, Sn value: 100%
Mina and Isa (2015)	– MIAS	– Breast tissues classification into normal and abnormal groupings	– Classification rate: 91.64%
Tan, Qian, Pu, Liu, and Zheng (2015)	– Private:1896 cases	– Breast cancer detection	– Sn value: 68.8% – Sp value: 95% – AUC value: 0.851 ± 0.046
Rouhi and Jafari (2016)	– MIAS: 57 images – 37 benign – 20 malignant	– Tumors classification; malignant and benign	– Accuracy: 90.94% – AUC value: 96.89%
Peng, Mayorga, and Hussein (2016)	– MIAS – BancoWeb: 100 images	– Classification as a benign or malignant tumor	– Accuracy: 96%

to classify breast cancer to normal, benign, and malignant (decision tree, K-nearest neighbor, Naive Bayes, Probabilistic-ANN, SVM, and AdaBoost) using 690 images from the DDSM dataset. Also in Bruno et al. (2016) the authors proposed a CAD system that merges decision tree, Random Forest, and SVM to detect the breast cancer on the DDSM and BCDR datasets, the performance of this system is 100% accuracy. The authors in Burling-Claridge, Iqbal, and Zhang (2016) combined the Naive Bayes, decision tree, K-nearest neighbor, and support vector machine techniques on the MIAS and INBreast datasets. Also in Esener, Ergin, and Yüksel (2015), the Fisher's Linear Discriminant Analysis (FLDA), SVM, decision tree, and K-nearest neighbor classifiers are used in the DDSM dataset to classifying between masses and normal breast tissue.

Yassin et al. (2018) have presented a systematic review for breast cancer computer-aided diagnosis using various imaging modalities using the machine learning techniques, but they take up the topic in a specific older period and have analyzed the studies introduced according to the published journals only. Therefore, in this study, we try to introduce a comprehensive review comprises the machine learning techniques and the medical image modalities of breast cancer to help the researcher. Our review was classified depending on the type of machine learning technique beside the medical image type and presented it according to each machine learning for each medical image type and the date of publication as reported in the tables from Tables 3–8 divided by multiple subsections according to its image modality. Furthermore, in this study, an attempt is made to summarize several deep learning methods for medical image modalities of breast cancer and this is considered as the major merit.

In Tables 3–5, more work uses more than one method for classifying machine learning to find the best way to classify mammogram images based on breast cancer problems. Table 3 presents the summary of publications adopts the SVM classifier dated from 2015–2017 which is 14 paper and mention the accuracy of each study and the used dataset.

Table 5
Summary of the papers for Mammogram images using k-NN classifier, and Fuzzy C-Means.

Reference	Machine learning technique	Dataset used	Contribution	Performance evaluation
Hamoud, Merouani, and Laimeche (2015)	– Fuzzy C-Means (FCM)	– DDSM	– Classifying tumor into benign or malignant tissue	– Accuracy: 87% – Sn value: 90 to 47% – Sp value: 84 to 84%
Dhahbi, Barhoumi, and Zagrouba (2015)	– k-NN	– 252 image from Mini-MIAS – DDSM	– Differentiate between normal and abnormal breast tissues	– Mini-MIAS – Abnormality detecting: Accuracy: 91.2, AUC value: 0.98 – Malignancy detecting: Accuracy: 81.35, AUC value: 0.841
Abubacker, Azman, Doraisamy, and Murad (2017)	– Associative classifier with fuzzy-ANN	– DDSM: – 170 benign – 130 malignant	– Breast tissue and mass classification	– Accuracy: 95.11% – Sn value: 92.22% – Sp value: 96.39
Aminikhanghahi, Shin, Wang, Jeon, and Son (2017)	– Fuzzy Gaussian Mixture Model (FGMM)	– 300 images from – DDSM	– Malignant or benign classification	– Accuracy: 93% – Sn value: 90% – Sp value: 96%
Gardezi, Faye, Bornot, Kamel, and Hussain (2018)	– k-NN	– IRMA – MIAS	– ROI categorized as normal or abnormal	– Accuracy: 92.81% ± 0.0093 – Sn value: 92.85% ± 0.0099 – AUC value: 0.9713

Table 6
Summary of the papers for Ultrasound images using the SVM classifier.

Reference	Dataset used	Contribution	Performance evaluation
Cai et al. (2015)	– 138 Privately owned cases	– Benign and malignant tumors discriminate	– Accuracy: 86.96% – Sn value: 86.96% – Sp value: 86.96% – AUC value: 0.894
Prabusankarlal, Thirumoorthy, and Manavalan (2015)	– 120 Privately owned images – Benign: 70 – Malignant: 50	– Breast masses detection and diagnosis	– Accuracy: 95.85% – Sn value: 96% – Sp value: 91.46% – AUC value: 0.9444
Wu, Lin, and Moon (2015)	– 210 Privately owned images – Benign: 120 – Malignant: 90	– Evaluating malignant breast cancers	– Accuracy: 96.67% – Sn value: 96.67% – Sp value: 96.67% – AUC value: 0.9827
Huang, Yang, Liu, and Li (2015)	– 46 Privately owned images	– Detecting the tumor regions	– Accuracy: 0.983 ± 0.013 – Sn value: 0.974 ± 0.035 – Sp value: 0.985 ± 0.019 – AUC value: 0.997 ± 0.003
Chmielewski, Dufort, and Scaranelo (2015)	– 105 Privately owned images	– Classification of lymph node	– Sn value: 95% – Sp value: 90% – AUC value: 95%
Moon et al. (2015)	– 169 Privately owned cases	– Differentiating normal from abnormal	– Accuracy: 94.81% – Sn value: 94.12% – Sp value: 96.72%

Table 7
Summary of the papers for Ultrasound images using k-NN, LR, and RF.

Reference	Machine learning	Dataset used	Contribution	Evaluation results
Shibusawa et al. (2016)	– k-NN	– 97 Privately owned images	– Diagnosis of non-mass lesions	– Sn value: 87.8% – Sp value: 89.5% – AUC value: 0.93
Lo et al. (2016)	– Binary-LR	– 18 Privately owned cases	– CAD tumor	– Accuracy: 80.39%
Moon et al. (2017)	– LR – ANN	– 156 Privately owned cases – Benign: 78 – Malignant: 78	– Classification of breast cancers by tumor size	– Accuracy: 81.8%, Sn value: 85.4%, – Sp value: 77.8%, AUC value: 0.855
Abdel-Nasser, Melendez, Moreno, Omer, and Puig (2017)	– RF	– 59 Privately owned images	– Classification of benign and malignant tumor	– AUC value: 99%

Table 4 presents the summary of publications adopting ANN, and the number of ANN publications for the mammogram images in this table are 6 papers. And, Table 5 presented the summary of papers using k-NN and Fuzzy c-means classifiers.

3.2. Machine learning techniques for ultrasound images

The researchers in Mohammed et al. (2018) were proposed a classification method by use of multifractal dimensions and backpropagation

Table 8
Summary of the papers for Ultrasound images using hybrid techniques.

Reference	Machine learning	Dataset used	Contribution	Performance evaluation
Venkatesh, Levenback, Sultan, Bouzghar, and Sehgal (2015)	– NB – LR – AdaBoost	– 246 Privately owned image	– Differentiating malignant and benign masses	– Sn value: 90% – Sp value: 97.5% – AUC value: 0.98
Lo et al. (2015)	– Binary LR	– 69 Privately owned case	– Classification tumor	– Accuracy: 83% – Sn value: 76% – Sp value: 88%
Shan, Alam, Garra, Zhang, and Ahmed (2016)	– DT – k-NN – RF – SVM	– 283 Privately owned case	– Differentiate between benign and troubling lesions	– The SVM Accuracy: 77.7%, AUC value: 0.84 – The RF Accuracy: 78.5%, AUC value: 0.83

neural networks. For this study, 184 breast ultrasonic images (72 irregular (tumor cases), and 112 normal cases) were analyzed. The results obtained showed the precision value was 82.04%, the sensitivity value was 79.39%, and the specificity value was 84.75%. Also, Chen and Huang (2016) is another approach that proposed the backpropagation neural networks to classify breast cancer on clinical data.

Table 6 provides an overview of 6 papers in which the SVM classifier was used to detect and classify breast cancer using ultrasound images. These publications contain more than one contribution and are applied to different datasets. Tables 7 and 8 present another classifier techniques and hybrid techniques to detect and classify the ultrasound-based breast cancer, which contains 7 publications.

3.3. Machine learning techniques for magnetic resonance imaging

Many studies used the support vector machine to diagnose and classify MRI breast cancer. The research (Hassanien & Kim, 2012) suggested an approach that classifies cancer as normal or non-normal by using the SVM technique on a private dataset. This technique's accuracy metric is 98%. Hoffmann, Shutler, Lobbes, Burgeth, and Meyer-Bäse (2013) also used SVM to detect no mass lesions. The study (Soares, Janela, Pereira, Seabra, & Freire, 2013) used SVM to identify breast cancer in a private dataset and this technique's output accuracy is 94%. Other studies such as Agner et al. (2014) and Yang, Li, Zhang, Shao, and Zheng (2015) used SVM on a private dataset where breast cancer is graded as malignant and benign. While authors in Waugh et al. (2016) propose a subtype classification using a cross-validated k-NN on 200 private images.

The authors proposed a computer-aided system for the detection of breast masses in Huang, Chang, Huang, Chen, and Chang (2014), and the system performance is checked on 61 images using Fuzzy C-Means. Furthermore, in Weiss, Medved, Karczmar, and Giger (2014) the fuzzy c-means on privately owned images is used to differentiating benign and malignant lesions. Also, authors in Gallego-Ortiz and Martel (2016) proposed CAD for optimizing function selection and training classifiers separately for mass and non-mass lesions using 240 clinical data.

The researchers in Bhooshan et al. (2014) presented a model to classify the breast cancer of clinical DCE-MRI and HiSS MRI using Bayesian artificial neural networks.

3.4. Machine learning techniques for histological images

A three-class SVM classifier was developed by the authors Brook et al. (2008) to differentiate images of breast cancer into three groups: normal, invasive carcinoma, and in situ carcinoma. Another approach in Zhang (2011) was to construct an efficient cascade classifier using a sequence of SVM parallel classifiers and a series of ANN. Throughout their work, the SVM and ANN classifiers were regarded to be weaker classifiers that could be merged into a stronger final classifier. The learning features derived from the Curvelet transformation and the methods of Local Binary Pattern (LBP) have been used in this algorithm to develop the set of SVM classifiers. While authors in Sudharshan et al. (2019) propose a learning system and research the importance of Multi-Instance Learning (MIL) for the computer-aided diagnosis of breast cancer patients. This CAD contrasts many states of the art MIL approaches, including pioneering approaches (APR, Diverse Density, MI-SVM, Citation-k-NN) and more recent methods such as a nonparametric method and a deep learning (MIL-CNN) approach. The tests were performed using the public dataset BreaKHis.

The researchers in Zhang, Zhang, Coenen, Xiao, and Lu (2014) introduced several models of primary component analysis of a class nucleus, which were constructed using different characteristics of each breast cancer type. On the UCI breast cancer dataset, the proposed approach has been tested.

The authors in Dimitropoulos et al. (2017) have been using the local aggregated descriptor (VLAD) Grassmann vector method to obtain the local characteristics of breast cancer tumors and present them as a collection of multidimensional and spatially changing signals that can be effectively modeled on a system's higher-order linear dynamic analysis. BreaKHis dataset is used in this method.

In Alirezazadeh, Hejrati, Monsef-Esfahani, and Fathi (2018), the authors proposed a method which attempts to distinguish the vectors of benign extracted characteristics from those more intelligent by learning as much as possible an invariant domain space. This approach in the BreaKHis dataset achieved an average classification rate of 88.5%.

Fig. 7 presents the number of machine learning techniques according to existing publications, with various modalities.

3.5. Machine learning techniques for thermography images

There are several publications on the detection and classification of thermography breast cancer. Table 9 presents a summary of some of this work. Acharya et al. (2012), Gaber et al. (2015) and Milosevic et al. (2014) used SVM for classification. Milosevic et al. (2014) on the other hand combined a multiple classifiers as SVM, Naive Bayes, and K-Nearest Neighbor to achieve better accuracy. Where Pramanik et al. (2015) and Sánchez-Ruiz et al. (2020) proposed a segmentation methods. In addition, Araújo et al. (2014) proposed a feature extraction method to detect breast cancer. Sayed et al. (2016) proposed a method that uses swarm algorithms for detection. Another method, which is Santana et al. (2018) proposed neural network with multiple classifiers.

4. Deep learning techniques for different image modalities

Deep learning techniques have recently been established to extract biased features and increase the efficiency of analyzing medical images. This section provides an overview of DL techniques for breast cancer detection and classification in five types of medical imaging; Mammogram, Ultrasound, MRI, Histological, and Thermography images.

Fig. 8 indicates the CNN used with different image modalities applied in the reviewed publications.

Table 9
Summary of the papers for Thermography images.

Reference	Machine learning	Dataset used	Contribution	Evaluation results
Acharya, Ng, Tan, and Sree (2012)	– SVM	– 50 breast images	– Classification using texture feature	– Accuracy: 88.10% – Sn value: 85.71% – Sp value: 90.48%
Milosevic, Jankovic, and Peulic (2014)	– SVM – Naive Bayes – K-Nearest Neighbor	– 40 images	– Breast cancer detection	– Accuracy: 92.5%.
Araújo, Lima, and De Souza (2014)	– Feature extraction	– 45 infrared (IR)	– Classification of benign and malignant tumor	– Sn value: 85.7% – Sp value: 86.5%
Pramanik, Bhattacharjee, and Nasipuri (2015)	– DWT	– 306 images	– Segmentation and detection	– Accuracy: 90.48% – Sn value: 87.6% – Sp value: 89.73%
Gaber et al. (2015)	– Fuzzy c-means – ROI – SVM	– 63 image	– Segmentation and classification	– Accuracy: 100%
Sayed, Soliman, and Hassanien (2016)	– Bio-inspired Swarm Techniques	– 63 thermography images	– Detection	– Accuracy: 85.71%, 84.12%, 85.71%, and 96.83% for each swarm technique
Santana et al. (2018)	– ANN – DT – Bayesian – ELM – MLP	– 1052 thermogram images	– Classification	– Accuracy: 76.01%
Sánchez-Ruiz, Olmos-Pineda, and Olvera-López (2020)	– ROI – ANN	– Mastology Research dataset	– Segmentation	– Accuracy: 90.17% – Sn value: 89.336% – Sp value: 91%

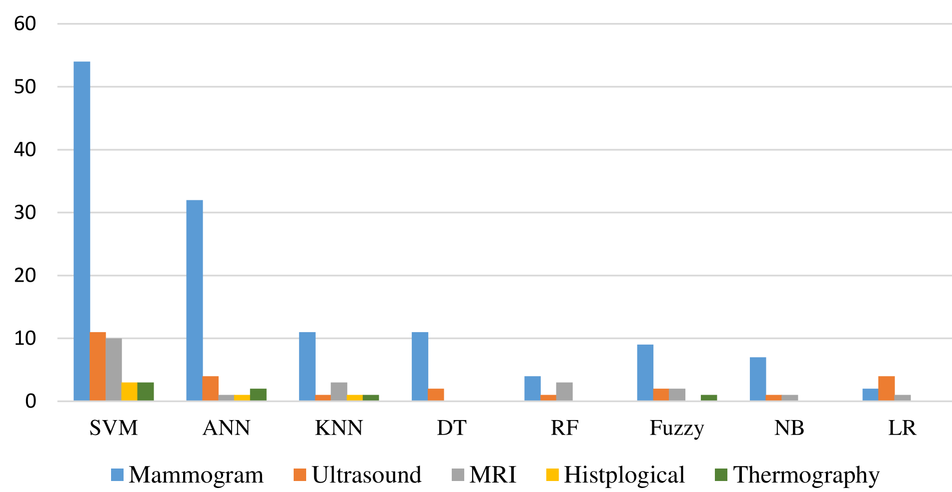


Fig. 7. The number of techniques used by machine learning with various modalities.

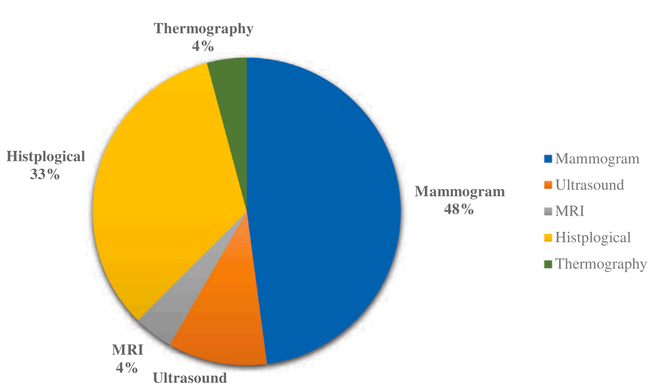


Fig. 8. Number of Convolutional Neural Network used with various image modalities.

4.1. Deep learning techniques for mammogram images

This subsection briefly describes the latest advances in breast cancer mammogram diagnosis and classification. The authors created a computer-assisted diagnostic system based on a convolutional network in Chougrad, Zouaki, and Alheyane (2018) focused on deeply convolutional neural networks that use three of the most impressive CNN models that VGG16, ResNet50, and Inception v3. Instead of random initialization, the transition of learning using pre-trained weights leads to better outcomes. The proposed system achieved 97.4% accuracy and 0.99 AUC on the DDSM database, 95.5% accuracy and 0.970 AUC on the INbreast database, and 96.60% accuracy and 0.96 AUC on the BCDR database. After all, the extracted Regions of Interest (ROIs) were pre-processed and standardized from the complete mammograms, and the authors combined all the datasets to create a wide collection of images and used them to fine-tune the CNNs. The precision metric is 98.94%. In Jiao, Gao, Wang, and Li (2018), the researchers classified the various tumors in breast cancer tissue using deep convolutional networks to distinguish between malignant and mild cases and proposed a specific deep metric learning neural network to classify a breast mass. The authors proposed a system in Wichakam and Vateekul (2016) that integrates deep CNN and SVM to detect a mass. A CNN model was built on the mammography spots and the data from the last completely connected layer has been used as a high-level characteristic representation of an image to form SVM of classification.

A deep learning method was proposed to predict mammography breast density on 2174 image in Dontchos, Yala, Barzilay, Xiang, and Lehman (2020) using a deep CNN and ResNet-18.

Another research in Li, Zhuang, Li, Zhao, and Ma (2019) proposes an enhanced DenseNet neural network model, also known as the neural network model DenseNet II, for the effective and reliable classification of benign and malignant mammography. First, the authors preprocessed the mammogram images. Then the neural network model of DenseNet is improved and a new neural network model of DenseNet-II is developed to replace the first convolutionary layer of the neural network model of DenseNet with the startup structure. Finally, the preprocessed datasets for mammography joined the neural network model AlexNet, VGGNet, GoogLeNet, DenseNet, and DenseNet II. The model's mean accuracy is 94.55%. Ting, Tan, and Sim (2019) propose a method named Improving the Convolutional Neural Network for Breast Cancer Classification (CNNI-BCC) improves breast cancer lesion classification. Incoming mammographic diagnostic images of breast cancer may be classified into malignant, benign, and stable patients by CNNI-BCC. In Hai et al. (2019), the authors proposed differentiating the pathological degrees in digital mammograms explicitly. It proposed an end-to-end learning algorithm based on multilevel functions combined. Low-level properties are extracted and selected by guided logistic regression at LASSO. CNN was developed to obtain high-level characteristics. Multilevel derived functions are combined to automate the current end-to-end functions of CNN such that different parts of the network have to pay attention to various levels of functionality.

In Oliver et al. (2010), a quantitative analysis of different traditional mass detection and evaluated qualitatively the advantages and disadvantages of the approaches used are presented, and used deep learning techniques to detect, segment, and classify breast masses from the mammogram. In studies Arevalo et al. (2016), Dhungel, Carneiro, and Bradley (2017) and Kooi et al. (2017), authors proposed an optimization techniques for mass classification. They use deep learning techniques in the extraction process of features to automatically extract distinguishing features. During the classification process, all the characteristics are incorporated into the classifications to make a final decision. Another research in Ribli, Horváth, Unger, Pollner, and Csabai (2018) presented a mass-detection CAD method building on the Faster R-CNN (Faster, 2015). A deep learning system is suited for the simultaneous recognition, location, and classification of large objects in high-resolution, high-contrast natural images. This model was evaluated on INbreast dataset.

Moreover, two publications in Al-Masni et al. (2018) and Al-antari, Al-masni, Choi, Han, and Kim (2018) proposed a CAD system for detecting the mass based on You Only Look Once (YOLO). Also, in Al-antari and Kim (2020), the authors proposed a system to detect and classify breast lesions. Two different datasets evaluate this method named DDSM, and INbreast. The authors used the YOLO detector to detect breast lesions, with F1 scores of 99.2% for DDSM and 98.02% for INbreast. Then the classification was done through three deep learning classifiers, namely regular feedforward CNN, ResNet-50, and InceptionResNet-V2. The classification models of CNN, ResNet-50, and Inception ResNet-V2 achieve average accuracies of 94.5%, 95.8%, and 97.5%, respectively, for the DDSM dataset and 88.7%, 92.5%, and 95.3%, respectively, for the INbreast dataset.

The authors proposed an automated Superimposed Convolutional Auto Encoder (SCAE) in Kallenberg et al. (2016) to learn how to reflect the characteristics of mammographic images on several scales. In this model, to improve the model's robustness, a low-density regularizer was implemented into the model. The researchers are proposing a learning system for mass recognition in Shen et al. (2019) to reduce the annotation effort. These include the Deep Active Learning (DAL) and Autonomous Learning (SPL) paradigm, which can eliminate data uncertainty and retain a stable model with the ability to generalize across different scenarios. This process used 2223 mammograms.

Furthermore, other methods presented in Tables 10 and 11 used the CNN architecture for mass classification. In Suzuki et al. (2016), the authors developed a transfer-learning approach for the training of CNN to detect a mass. The authors in Swiderski et al. (2017) proposed a way to resolve the overfitting of CNN models when there was minimal training data. The authors introduced a structured SVM in Dhungel et al. (2015b) to construct a model that incorporates various types of potential functions, including location a priori, the Gaussian mixture model, and a network of deep beliefs for mass segmentation (Hu et al., 2018). In another publication, the authors proposed a different algorithm for mass detection (Dhungel et al., 2015a). A cascade of deep learning and random forest classifiers were used in the proposed technique.

4.2. Deep learning techniques for ultrasound images

There are several studies which used DL for detecting and classifying Ultrasound breast cancer. Authors in Qi et al. (2019) developed a model that uses deep convolutional neural networks with multiscale nuclei and skip connections. The model depends on two elements: the first element is to determine whether the image contains malignant tumors, and the second element is to detect large nodules in the image.

The authors in Byra, Piotrzkowska-Wróblewska, Dobruch-Sobczak, and Nowicki (2017) presented a neural network for breast classification, with three convolution layers and two completely connected layers. The data collection used included 166 tumors with malignancies and 292 benign masses. The mean AUC was 0.912 with 83.0% precision and 82.4% sensitivity.

The authors proposed CNN in Xu et al. (2019) used to segment breast ultrasound images into four main tissues: skin, fibroglandular tissue, three-dimensional (3D) mass, and adipose tissue. Quantitative measures to evaluate the effects of segmentation, including precision, recall, and F1 calculation, have all reached more than 80%, indicating that the proposed method is capable of differentiating functional tissue in the breast ultrasound image.

In Wang et al. (2020), the authors propose a CAD system based on CNN that classifies breast lesions as benign and malignant. The proposed CNN embraces a modified Inception-v3 architecture to provides efficient feature extraction to extract multiview features from both views. The proposed CNN has been trained on 316 breast lesions. The AUC value was 0.9468, while the sensitivity and specificity were 0.886 and 0.876, respectively.

In addition, Table 12 summaries and provides several studies. In Yap et al. (2017), the authors use deep learning approaches to detect ultrasound lesions and study three different methods: a patch-based LeNet, a U-Net, and a transfer learning approach using an FCN (Fully Convolutional Network). AlexNet pre-formed using complete folding networks. Byra et al. (2019) introduced a CNN system focused on the transfer learning to distinguish benign or malignant breast lesions and obtained a 93.6% AUC on a test collection of 150 cases. They used the CNN VGG19 model previously trained in the ImageNet dataset and configured it for 882 ultrasonic breast mass images. In Han et al. (2017), the authors trained a GoogleNet (Szegedy et al., 2015) on 7408 ultrasounds and tested it on 829-images. This model is an ingredients algorithm of S-Detect application which is implemented in RS80A and achieved 90% accuracy, 86% sensitivity, and 96% specificity in the test dataset. The authors in Cheng et al. (2016) used a Stacked Self-Encoding model (Vincent et al., 2010) to classify breast lesions and obtain an AUC of 89.6% or breast lesion classification, which exceeds conventional methods based on ML. The authors in Zhang et al. (2016)

Table 10
Overview of papers for Mammogram images of breast cancer detection.

Reference	Contribution	Architecture of DL	Method for training	Used datasets
Dhungel, Carneiro, and Bradley (2015b)	– Segmentation of mass	– DBN	– End to end	– DDSM – INBreast
Dhungel, Carneiro, and Bradley (2015a)	– Detection of mass	– Hybrid: – DBN – CNN	– End to end	– DDSM – INBreast
Suzuki et al. (2016)	– Detecting mass	– CNN	– Transfer learning	– DDSM
Swiderski, Kurek, Osowski, Kruk, and Barhoumi (2017)	– Recognition of a lesion	– CNN	– End to end	– DDSM

Table 11
Summary of Mammogram papers using deep learning techniques; ADN: Adaptive De-convolution Network.

Reference	Technique	Contribution
Jamieson, Drukker, and Giger (2012)	– ADN	Mass classification using 4 layers ADN.
Fonseca et al. (2015)	– CNN	Estimation of breast density by Pre-trained network extracting features classified with SVM.
Akselrod-Ballin et al. (2016)	– CNN	Using R-CNN for the mass localization and classification.
Dubrovina, Kisilev, Ginsburg, Hashoul, and Kimmel (2018)	– CNN	Classifying tissues using normal CNNs.
Dhungel, Carneiro, and Bradley (2016)	– CNN	Combining different CNNs with hand-crafted apps.
Hwang and Kim (2016)	– CNN	Mass localization by weakly CNN.
Huynh, Li, and Giger (2016)	– CNN	Pre-trained CNN applied to the classification of mass.
Kisilev, Sason, Barkan, and Hashoul (2016)	– CNN	RCNN in conjunction with multi-class losses trained.
Qiu et al. (2016)	– CNN	CNN for directly classifying potential cancer risk based on negative mammograms.

Table 12
Summary of papers that use deep learning methods for ultrasound images.

Reference	Application	Deep learning architecture	No. of dataset images	Test-set no.	Performance metrics
Cheng et al. (2016)	Classification	Stacked denoising autoencoder Vincent, Larochelle, Lajoie, Bengio, and Manzagol (2010)	520	Cross-validation of ten fold	– Acc value: 82.4% – TP value: 78.7% – TN value: 85.7% – AUC value: 89.6%
Zhang et al. (2016)	Mass classification	Proprietary	227	Cross-validation of five fold	– Acc value: 93.4% – TP value: 88.6% – TN value: 97.1%
Han et al. (2017)	Classification	CNN based on VGG19	7408	829	– Acc value: 91.23% – TP value: 84.29% – TN value: 96.07% – AUC value: 96.01%
Byra et al. (2019)	Breast classification	CNN based on VGG19	882	150	– Acc value: 88.7% – TP value: 84.8% – TN value: 89.7% – AUC value: 93.6%
Yap et al. (2017)	Detection	FCN-AlexNet	306	Cross-validation of ten fold	– TP value: 98%
Kumar et al. (2018)	Mass segmentation	U-Net	433	61	– TP value: 84%

used a two-layer DL model, which includes a fully integrated neural net as the first layer for extracting characteristics and a constrained Boltzmann system as the second layer for better display of characteristics, obtained better output with their two-layer DL model in the classification of breast lesions from SWE images. Also Kumar et al. (2018) use the U-net to detect the mass.

4.3. Deep learning techniques for magnetic resonance imaging

In Fang et al. (2019), the authors propose a classification method based on CNN and Image Quality Assessment (IQA) algorithms. First, they used the CNN architecture to calculate the number of pixels in lesions where maximum grouping layers are used. Next, a high density of pixel areas is assigned with high-quality values which represent more characteristics of texture and grayscale. Lastly, they created a multi-SVM image core using the quality values obtained for a breast cancer classification. While in Gibson et al. (2018), the authors present the NiftyNet open-source framework for deep learning medical imaging. The NiftyNet framework offers a scalable deep learning pipeline for a variety of applications in medical imaging, including applications for segmentation, regression, and imagery. NiftyNet is based on the TensorFlow system and supports standard functions such as TensorBoard 2D and 3D image visualization, as well as calculation graphs.

In Feng et al. (2020), a Knowledge-driven Feature Learning and integration method to distinguish between benign and malignant breast lesions was proposed. This method used 100 MRI and achieved a sensitivity of 84.6%, specificity of 85.7%, and an accuracy of 85.0%.

4.4. Deep learning techniques for histological images

The authors in Chen, Dou, Wang, Qin, and Heng (2016) proposed a deep cascade network for the detection of mitosis. They first formed an FCN model to extract a mitotic candidate from all histology slides, then they optimized a pre-formed caffeNet model (Jia et al., 2014) on large format images of ImageNet to classify mitosis. In Albayrak and Bilgin (2016), the authors have developed a deep learning algorithm for the extraction of characteristics allowing them to detect mitoses. The CNN model was used in the proposed algorithm to extract the characteristics that have been used to form an SVM for mitosis detection. In Spanhol et al. (2016) AlexNet is used to construct a CNN model for the classification of benign or malignant tumors in Krizhevsky et al. (2012), and worked on a BreaKHis dataset. In Yang, Ran, Zhang, Xia, and Zhang (2019), the researchers propose an Ensemble of MultiScale Convolutional Neural Networks (EMS-Net) to classify histopathological breast stained with hematoxylin–eosin into four categories, including normal tissue, benign lesions, carcinoma in situ and invasive carcinoma. They, firstly converted each image into several scales, then they used the expanded and extended training fields on each scale to optimize the pre-trained DenseNet-161, ResNet-152, or ResNet-101. This algorithm

Table 13
Summary of thermography papers using deep learning techniques; DWNN: Deep wavelet Neural Network.

Reference	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, de Santana, Andrade, de Lima, and dos Santos (2020)	– DWNN	– Detecting the breast masses.	– Sn value: 0.95
Cabıoğlu and Oğul (2020)	– CNN	– CAD system that uses transfer learning to classify breast cancer.	– Accuracy: 94.3%

achieves an accuracy of 91.75 ± 2.32% in a five-fold cross-validation with 400 training images.

In Cruz-Roa et al. (2014), a CNN model is provided to automatically classify invasive ductal cancer in Whole Slide Images (WSI) and thus to distinguish between invasive and non-invasive images. Moreover, in Gecer et al. (2018), the authors proposed a system that divides the WSI into five diagnostic categories. First, a detector that uses four fully folded arrays that have been formed with screening samples from pathology screenings performs multi-scale localization of regions of diagnostic interest relevant to WSI. Subsequently, a convolutional network formed from consensus-based reference samples classified the image fields as non-proliferative or proliferative changes, atypical ductal hyperplasia, in situ ductal carcinoma, and invasive carcinoma. Finally, the features and classification maps for pixel-by-pixel labeling and categorization are grouped at the slide level. Experiments with 240 WSI have shown that salience detector and classifier networks work better than competing techniques, and the accuracy of 55% on five slides was not statistically different from the forecasts of 45 pathologists.

The authors applied the preformed Inception-V3 model in Vang, Chen, and Xie (2018) for the classification into 4 groups with some post-treatment. The software Inception V3 is a preformed algorithm that was developed to classify the images in the ImageNet database into 1000 different classes of image. Furthermore, the authors in Gao, Rong, Shen, and Xiong (2016) constructed a simulation algorithm that selected weakly CNN from a range of CNNs to build a Strong leaner for video recognition. The studies in Han, Meng, Khan, and Tong (2016) and Wang, Zhang, Han, Shen, and Qian (2016) implemented an improving technique to regulate CNN Loss function. Moreover, the authors proposed a CNN model in Wahab, Khan, and Lee (2017) to distinguish the mitotic and non-mitotic nuclei.

A multi-scale architecture of the CNN was built in Albarqouni et al. (2016). After the Softmax layer, an aggregation layer was added to combine a CNN with overcrowded annotations to merge the predictive results with the annotation results of many participants.

In Xu, Xiang, Hang, and Wu (2014), the authors presented a Stacked Sparse Auto Encoder (SSAE) method for the classification of nuclei into breast cancer histopathology. During the training process, the SSAE was optimized using a greedy technique in which one hidden layer was generated at a time, and used output from the previous layers to mask the next hidden layer.

In Roy, Banik, Bhattacharjee, and Nasipuri (2019), the authors presented a patch-based classifier (PBC), using CNN for classification. The classification system proposed working in two separate forms: a One Patch in One Decision (OPOD) and All Patches in One Decision (APOD). This model uses the ICIAR 2018 breast histology image data set, which consists of 4 different classes, namely normal, benign, in situ and invasive carcinoma. Experimental results indicate the OPOD achieved classification accuracy per patch of 77% for 4 histopathological classes and 84.71% for 2 histopathological classes on the test set. Furthermore, APOD technique achieved an image classification accuracy of 90.0% for class 4 and 92.51% for classification 2 classes on the divided test set. The proposed model also achieved an accuracy of 87% for the hidden test recording of ICIAR-2018.

In Wang et al. (2020), the authors propose a hybrid structure that includes Double Deep Transfer Learning (D2TL) and an Interactive Cross-task Extreme Learning Machine (ICELM) based on the extraction of the features and representability of CNN. This method was tested on 134 histopathological images of breast cancer.

In Vo, Nguyen, and Lee (2019), the authors provided a method using DL techniques to extract the most useful visual characteristics for the classification of breast cancer, and suggested a stimulus strategy to achieve the main goal of effectively enriching the system by gradually merging deep learning techniques (weakly classifiers) into a strong classification.

The authors in Song, Zou, Chang, and Cai (2017) merged a neural convolutional network with a characteristic Fisher layer to encode the local characteristics of breast cancer tumors in a more segregated space where breast cancer types were effectively differentiated from one another. In Yan et al. (2020), the authors propose a combined Convolutional Network and a Recurrent Deep Neural Network for the classification of breast cancer.

In Mehra et al. (2018), the researchers performed a classification model and use transfer learning, taking into account three previously developed networks: VGG16, VGG19, and ResNet50. A pre-trained VGG16 with a logistical regression classifier provided 92.60% accuracy, an area below the ROC curve (AUC) is 95.65% , and a 95% Accuracy–Precision Score (APS).

In Reddy, Soni, and Reddy (2020), the authors proposed a DNN with support value for detecting breast cancer that improved the traditional classification of machine learning. This method presented pseudocodes together with mathematical equations for assessing results. The dataset used contains 8009 images of the histopathology of over 683 patients with varying magnification levels.

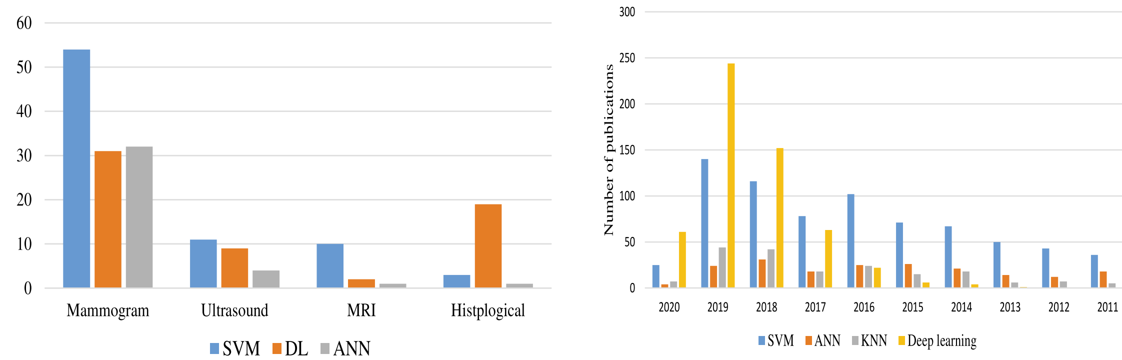
The authors developed a DL model in Toğaçar, Özkurt, Ergen, and Cömert (2020) based upon a CNN called BreastNet. Using BreaksHis dataset, this model achieved 98.80% accuracy.

In Yan et al. (2020) the authors proposed a combination between a convolutional and recurrent deep neural network for the classification of the histopathological images of breast cancer. The average accuracy value was 91.3%.

4.5. Deep learning techniques for thermography images

Detection of breast cancer thermography has significant clinical benefits, such as the ability to classify and detect breast cancer very early, here are some of the deep learning techniques described in Table 13.

To sum up all the aforementioned analysis, the following observation from the experiment are worth mentioning: Fig. 9a illustrates the most commonly used ML techniques and DL with various modalities, and Fig. 9b demonstrates the number of publications from 2010 to 2019 that used the most common classifiers: SVM, ANN, k-NN, and deep learning based on the Scopus database. Moreover, according to the literature studies presented in the current review, Fig. 10 illustrates a Pie chart of the number of image modalities used in the review of the publication suggested in the articles.



(a) The most commonly used ML techniques and DL with various modalities.

(b) The number of publications per year of the most commonly used ML technique and deep learning for breast cancer classification based on Scopus database.

Fig. 9. Deep learning and machine learning techniques for breast cancer classification researches performed in the last decade [2010–2019].

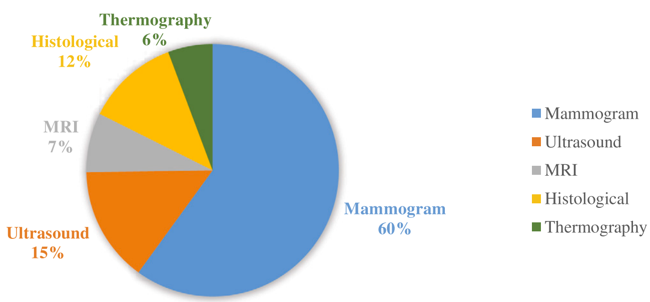


Fig. 10. Overall modalities used in different models for breast cancer detection.

5. Future trends and challenges

This section provides future directions for research that can be used in breast cancer classification and detection, and substantial efforts are required to enhance the efficiency of breast cancer classification. Despite the positive results of the reviewed literature, there are still some limitations and challenges that need to be overcome about ML and DL techniques for breast cancer detection and classification. The review identified several key challenges, as well as the inherent trends, directions for future study, and challenges are discussed as follows:

1. The first challenge we observed in the articles reviewed was that the lack of comprehensive training datasets has been a major challenge in the training of deep learning models for medical imaging. DL requires huge training data because the performance of the DL classifier depends to a large extent on the size and quality of the data set. However, the lack of data is one of the main obstacles to DL's success in medical imaging. Moreover, creating large medical imaging data is difficult because annotating the data requires a great deal of time and effort not only from an individual but from several experts to exclude human error. It is also difficult to construct large medical imaging data because annotating the data requires a great deal of time and effort not only from an individual but from several experts to exclude human error.
2. Most of the studies analyzed used different datasets privately obtained by Clinics or cancer research agencies for evaluating and analyzing these. Chief drawbacks of this argument are that the performance of such models across different studies are difficult to compare with.
3. Another limitation in some publications is the use of data expansion approaches rather than transferring learning to prevent overfitting.
4. The lack of benchmarks was seen as a challenge and a lack of flexibility.
5. Unsupervised grouping methods for the classification of breast cancer. The majority of the selected primary studies used the classification of breast cancer based on the supervised learning method. The use of labeled images for training has led to better results with these approaches. Nonetheless, in real life, it is hard to gather images of breast cancer with correct indications that have been labeled by professional doctors. In most cases, there are a significant number of unidentified medical images available. A great many blank labels are a major source of knowledge and cannot be used for supervised learning. Thus the model of classification for breast cancer is desperately needed and can be trained using a range of grouping techniques without supervision.
6. Reinforcement learning methodology for the classification of breast cancer. Enabling an ML model to be able to learn from its surroundings is a huge challenge at the same time. The key problems are providing enough image samples of breast cancer to represent all forms of breast cancer. The implementation of a learning-based reinforcement model can thus convincingly increase the efficiency and performance of techniques for the classification of breast cancer using medical images.
7. Robustness compared to data collection methods. It is important to tackle the robustness issue of various clinical/technical situations so that more datasets can be introduced slowly. Such differences include different image acquisition scanners, different lighting conditions, different sizes and views in various image modalities, various presentation characteristics of the coloring and enlargement factors.

In future work, in addition to the previous points:

- Generic public image datasets containing various image modalities will be used to support the classification task dependency on more than one modality and incorporate information from several points of view. It will be rich if they have an autumn DNA case series.
- Another exciting development that has emerged in recent years is a deep learning classifier. Over recent years, interest in the applications of computer-aided diagnosis systems have increased. Developing a DL with a hybrid-architecture computer-aided diagnosis systems that Includes different modalities of images.
- Another important point is the development of 3D mammography-based CAD systems, a new trend that can help boost CAD performance. For future production of CAD systems, these issues need to be taken into account.

- Instead of using only such image modalities (mammograms, ultrasound, MRI, and histological), certain types of images of breast cancer as Computed Tomography (CT) images or thermal images that can boost the efficiency of classification models for breast cancer can be used too. The same patient must get MRI or CT images. Images will also be gathered of all types of breast cancer cases. For the classification of multi-class breast cancer, boundary images should be labeled since they allow scholars to assess the effectiveness of the recently developed multiple classes breast cancer classification model.
- There is a critical need to build a robust and computer-efficient CAD system to help clinicians diagnose breast cancer at an early stage.
- Cross-validation is a method for validating the model to test the generalization of the model results in a hidden/invisible set of data. The aim is to classify a dataset to test model in the training process and to solve problems such as underfitting, overfitting and to show how the trained model is generalized into an independent dataset.

6. Conclusion

In this study, we review the latest studies focused on the detection and classification of breast cancer, using various machine learning and deep learning techniques in five image modalities. This review divides machine learning and deep learning applications into five categories according to the medical image types described in Sections 3 and 4. Five different popular machine learning techniques are the strengths of the review, including SVM, DT, Nearest Neighbor, Naive Bayesian Network, and ANN. The review also focused on the Convolutional Neural Network and its Deep Learning architectures used to detect and classify breast cancer from different image modalities. This review provide a description of the medical imaging as well; Mammograms, Ultrasound, MRI, Histological, and Thermography images.

CRediT authorship contribution statement

Essam H. Houssein: Conceptualization, Methodology, Formal analysis, Writing - review & editing. **Marwa M. Emam:** Conceptualization, Methodology, Resources, Writing - original draft, Writing - review & editing. **Abdelmgeid A. Ali:** Supervision, Writing - review & editing. **Ponnuthurai Nagaratnam Suganthan:** Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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