



# Machine learning techniques for breast cancer computer aided diagnosis using different image modalities: A systematic review

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## ABSTRACT

**Background and objective:** The high incidence of breast cancer in women has increased significantly in the recent years. Physician experience of diagnosing and detecting breast cancer can be assisted by using some computerized features extraction and classification algorithms. This paper presents the conduction and results of a systematic review (SR) that aims to investigate the state of the art regarding the computer aided diagnosis/detection (CAD) systems for breast cancer.

**Methods:** The SR was conducted using a comprehensive selection of scientific databases as reference sources, allowing access to diverse publications in the field. The scientific databases used are Springer Link (SL), Science Direct (SD), IEEE Xplore Digital Library, and PubMed. Inclusion and exclusion criteria were defined and applied to each retrieved work to select those of interest. From 320 studies retrieved, 154 studies were included. However, the scope of this research is limited to scientific and academic works and excludes commercial interests.

**Results:** This survey provides a general analysis of the current status of CAD systems according to the used image modalities and the machine learning based classifiers. Potential research studies have been discussed to create a more objective and efficient CAD systems.

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## 1. Introduction

Breast cancer is one of the most common cancers diagnosed in women around the world and it is a main cause of fatality among women. In low-income and middle-income countries the mortality rates are relatively high compared to developed countries. According to the World Health Organization's International Agency for Research on Cancer (IARC) 2013 report, more than 1.7 million women in 2012 were diagnosed with breast cancer worldwide. This is considered around 11.9% of all cancers diagnosed in the same year with 522,000 death cases reported. It is also expected that by 2025 there will be 19.3 million new cancer cases [1,2]. Moreover, in developing countries like Egypt, the dense population and the patients' ignorance to the disease symptoms and seeking medical consultation either when it's too late or extremely critical leads to higher mortality. Also, shortage of medical specialists and experts in rural areas adds up to the problem of early and accurate diagnosis of breast cancer causing higher mortality rate.

Using information technology and medical data to build medical support systems which can mimic the doctor's reasoning and conclude the symptoms is one solution to breast cancer early detection and hence increase the treatment chances and decrease mortality rate.

Medical image examination is the most effective method for diagnosis of breast cancer. Different medical imaging modalities are used for diagnosis such as: digital mammogram (DM), ultrasound (US), magnetic resonance imaging (MRI), microscopic (histological) images, and Infrared thermography (IRT). As a means to assist radiologists and physicians in identifying abnormalities, these modalities produce images which have reduced mortality rates by 30–70% [3]. Images interpretation is operator-dependent which requires expertise, thus using information technology is a necessity to accelerate and enhance the accuracy of the diagnosis providing a second opinion to the expertise [4]. Using some computerized features extraction and classification algorithms formulated as computer-aided diagnosis/detection (CAD) can be a great helpful tool for physicians and experts in detecting abnormalities.

Many efforts were made to develop CAD systems which are based on the advances of digital image processing, pattern recognition and artificial intelligence. The CAD systems are expected to overcome the operator dependency, increase diagnosis rate, and re-

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duce the expense of medical complementary modalities [5–7]. And thus it may help to reduce false positive reactions that may lead to futile treatment and psychological, physical, and economic costs that come with a false positive. And it also may reduce false negative readings that may cause omission of treatment that could result in remissions. It is reported that the detection sensitivity without CAD is around 80% and with it sensitivity reaches 90% [8]. In 2011, Sadaf et al. [9] studied the performance of full-field digital mammography (FFDM) augmented with CAD tools. The study showed that CAD combined with mammography presented 100% sensitivity in identifying cancers manifesting as microcalcifications and 86% sensitivity for other mammographic appearances of cancer. Accordingly, CAD has become the most active field of research in medical imaging to improve the precision of a diagnosis [10–12].

Computer aided detection is concerned with using a computer output to determine the location of suspect lesions. Afterwards, the radiologists are the one who is in charge of the characterization and diagnosis of the abnormalities as well as the patient management. Computer aided diagnosis on the other hand takes the detection done by a human or a computer and gives an output that determines the characterization of the lesion and gives the probability of malignancy and any abnormalities [13].

In general, a complete CAD system involved segmented structures, the detection of abnormalities and the extraction of their characteristics for a subsequent classification of the problem. Thus, the CAD systems can be categorized into four major stages. The first stage is preprocessing to prepare the images for the subsequent stages such as cleaning the medical image and removing noise from it through a set of image preprocessing operations. The second stage is the segmentation of the region of interest (ROI) in the image, which is a procedure of dividing the input image into several regions according to the visual characteristics. The third stage is the features extraction and selection where features are extracted from the cleaned images then the most discriminative features are selected. The selected features are capable of differentiating between normal and cancerous regions in order to minimize the classification error. Despite large effort, there is still no agreement on the features that are most suitable for this task. Many kind of features such as dynamic features, textural features, and morphological features have been traditionally used in tumor classification [14]. These selected features are organized in a database as an input to the classification stage. The final stage in the CAD system is the classification that is regarded as the heart of the CAD. It is a data mining process that assigns labels or classes to different groups, whose aim is to discover and extract hidden patterns from large datasets using different Machine Learning Technique (MLT) [15,16]. The generated model or patterns are used to predict the future unknown cases. Many MLTs have been used in the medical domain such as: K-nearest neighbors (K-NN) [17], Artificial Neural Network (ANN) [18,19], Decision Tree (DT) [20, 21], and Support Vector Machine (SVM) [22,23]. The selection of an appropriate MLT to build a classifier responsible for separating different kind of breast lesions is the key component of the development of CAD systems [14].

The contribution of this systematic review is to present the state of the art proposed in the literature that focuses on different machine learning techniques used for the classification of breast tumor lesions. Different statistical analysis of different aspects of the CAD systems presented in the selected papers are conducted using charts, rather than just presenting a short summary of all studies. The paper is organized as follows: the “Methodology” in Section 2 presents the process of conducting the review. The “Results” are presented in Section 3. The “Discussion” is presented in Section 4. And finally the paper is concluded in Section 5, and some points of future work are recommended.

## 2. Methodology

### 2.1. Search criteria

This systematic review aims to identify various studies related to breast cancer CAD systems based on medical images and MLT classifiers. The primary aim of this review is to find the answer of the following research questions:

- What are the MLT classifiers currently applied for breast cancer CAD systems based on medical imaging?
- What are the modalities of medical imaging used for the development of breast cancer CAD systems?
- What are the evaluation criteria used for the assessment of breast cancer CAD systems?
- What are the data sets used for the development of breast cancer CAD systems?

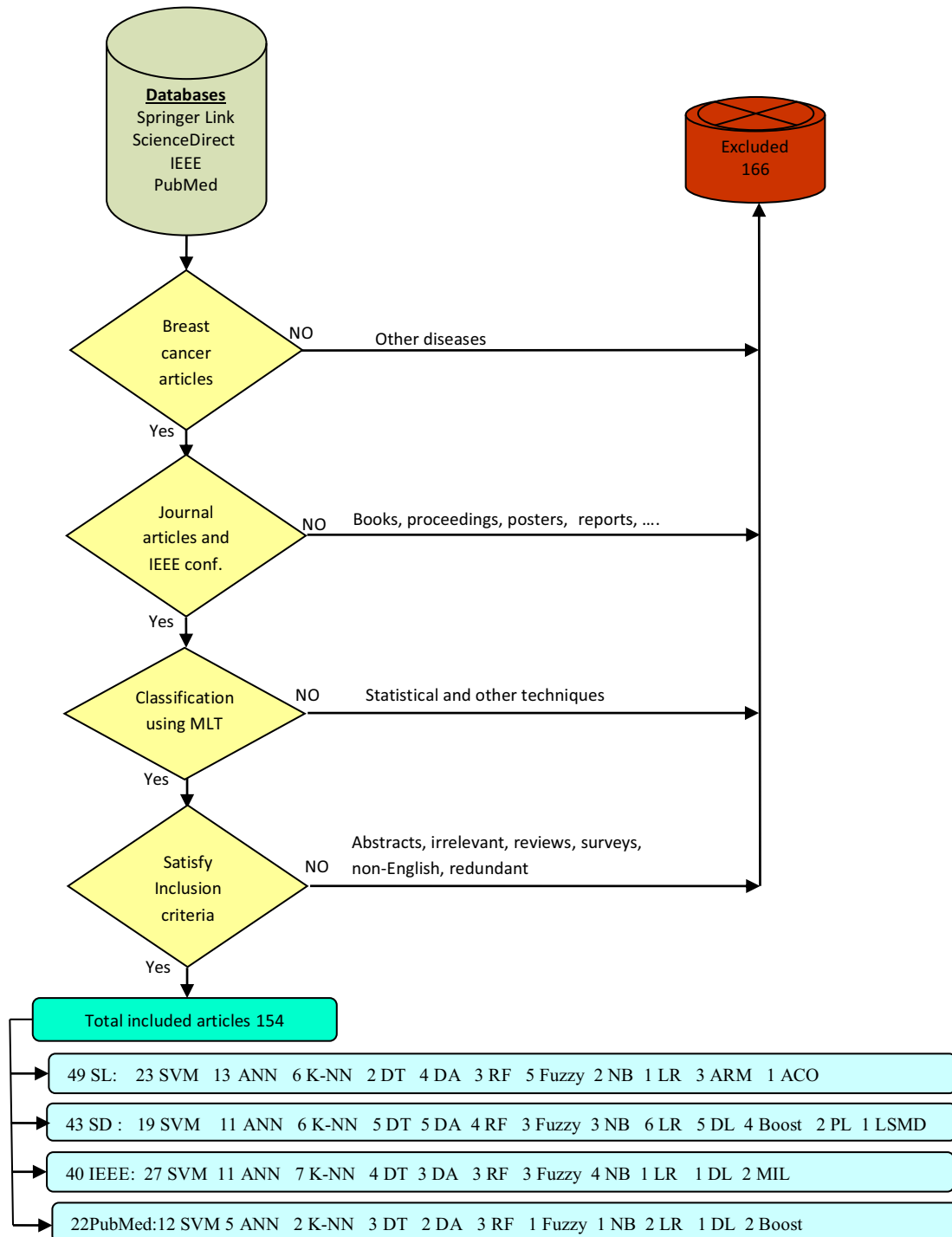
Several electronic databases were searched, Springer Link (<http://www.springerlink.com>), Science Direct (Elsevier) (<http://www.sciencedirect.com>), IEEE Xplore (<http://www.ieeexplore.ieee.org>), and (<https://www.ncbi.nlm.nih.gov/pubmed/>). The following search keywords were used: “breast cancer”, “image”, “learning”, “classification”, “classifier”, “classify”, “computer-aided diagnosis”, “computer-aided detection”, “computer-assisted diagnosis”, and “CAD”. Maximum possible number of publications was investigated through the years from 2012 to January 2017. However, some relevant studies may have been skipped unintentionally. The searching strategy is designed according to different databases searching standards. Table 1 presents the compositions of terms used according to the search engine of each database aiming to obtain all possible existing literature work.

All relevant studies were investigated, but only studies that satisfied the following inclusion criteria are included: (1) breast cancer is the only disease considered (other diseases are excluded); (2) at least one MLT is used as a classifier; (3) at least one of different medical imaging modalities is used (other diagnosis techniques are excluded); (4) the most common performance measures of the applied classifiers are reported (5) all paper articles must be a full complete paper (abstracts only are excluded); (6) work published in between 2012 to January 2017. Some other relevant studies are excluded such as surveys, books, letters, and non English articles. The search was carried out between December 2016 and January 2017. Initially, large amount of research articles was collected due the broadness of the subject under study “computer aided diagnosis/detection”. Totally, 320 studies were retrieved. In the second step, articles irrelevant to the inclusion search criteria are removed. So, only 154 studies (48.125%) are included while the rest 166 studies are not fitted well with the predefined search criteria and these articles are excluded from the retrieved list. In this SR, the information extracted from each study included the used imaging modality, machine learning techniques which are used as classifier, scope of the included study, results using the performance criteria, data sets and number of images/cases used if available. Fig. 1 shows a flow diagram which summarizes the selection of the retrieved studies. It should be noted that many articles include more than one MLT, and they were all counted when constructing the corresponding diagrams.

During the search, a significant variety of medical publications, computational intelligence, image processing and pattern recognition were observed. All retrieved articles have been published in journals of Springer Link, Science Direct, and PubMed. According to IEEE search, most IEEE studies are conference proceedings and are included in this SR. Table 2 shows the details of journals name, publishers and number of articles being published in each journal. From this table, it is shown that: (1) 17 journals published in Springer Link are considered; (2) 15 journals are published in

**Table 1**  
Composition of search terms.

Literature sources	Search in	Search terms
Springer Link	Search Command	("breast cancer") AND ("image") AND ("classification" OR "machine learning" OR "classifier" OR "learning") AND ("computer-aided diagnosis" OR "computer aided detection" OR "computer assisted diagnosis" OR "CAD")
Science Direct	Title, Abstract, Keywords	((("Breast cancer" AND "image") AND ("learning" OR "classification" OR "classifier" OR "classify")) AND ("computer aided diagnosis" OR "computer aided detection" OR "computer assisted diagnosis" OR "CAD"))
IEEE	Title, Abstract, Keywords, "Metadata"	"Breast cancer" AND "image" AND ("learning" OR "classification" OR "classifier" OR "classify") AND ("computer aided diagnosis" OR "computer aided detection" OR "computer assisted diagnosis" OR "CAD")
PubMed	All Fields	("Breast cancer" AND "image") AND ("learning" OR "classification" OR "classifier" OR "classify") AND ("computer aided diagnosis" OR "computer aided detection" OR "computer assisted diagnosis" OR "CAD")



**Fig. 1.** Flow diagram summarizes the selection of the retrieved studies.

**Table 2**  
List of used journals and the corresponding number of papers.

Springer journals	Science Direct journals	PubMed journals	IEEE journals
Journal of Digital Imaging (9)	Computer Methods and Programs in Biomedicine (9)	Medical Physics (6)	Transactions on Medical Imaging (1)
Journal of Medical Systems (8)	Computers in Biology and Medicine (7)	Computational and Mathematical Methods in Medicine (3)	Systems Journal (1)
Neural Computing and Applications (8)	Expert Systems with Applications (5)	Radiology (2)	Transactions on Fuzzy Systems (1)
International Journal of Computer Assisted Radiology and Surgery (4)	Ultrasound in Medicine and Biology (5)	Technology and Health Care (1)	Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans (1)
Multimedia Tools and Applications (3)	Neurocomputing (4)	Journal of Medical Imaging (1)	IEEE Transactions on Biomedical Engineering (1)
BioMedical Engineering OnLine (3)	Medical Image Analysis (2)	Studies in Health Technology and Informatics (1)	
EURASIP Journal on Advances in Signal Processing (3)	Ultrasonics (2)	Physics in Medicine and Biology (1)	
European Radiology (2)	Computerized Medical Imaging and Graphics (2)	Bio-Medical Materials and Engineering (1)	
Sādhana (1)	Applied Soft Computing (1)	Journal of Medical Engineering and Technology (1)	
Journal of Medical Ultrasonics (1)	Information Sciences (1)	Journal of Magnetic Resonance Imaging (1)	
Biomedical Engineering Letters (1)	Engineering Applications of Artificial Intelligence (1)	Journal of Visualized Experiments (1)	
Evolving Systems (1)	Procedia Computer Science (1)	Journal of Engineering in Medicine (1)	
Human-Centric Computing and Information Sciences (1)	Artificial Intelligence in Medicine (1)	Computer Methods in Biomechanics and Biomedical Engineering (1)	
BMC Cancer (1)	Journal of Applied Logic (1)	Journal of Clinical Ultrasound (1)	
Memetic Computing (1)	Academic radiology (1)		
BMC Medical Imaging (1)			
EURASIP Journal on Image and Video Processing (1)			

Science Direct; (3) 14 journals are published in PubMed in addition to those found in Springer Link, Science Direct, IEEE and are found also in PubMed; (4) only five journals published by IEEE are included, each contains 1 paper. As shown in [Table 3](#), there are many IEEE conference papers included. To be precise, a total of 35 papers are collected from IEEE conference proceedings. Regarding PubMed it was found that its search results contain (18) papers published by Springer Link, (31) papers published by Science Direct, and (6) papers published by IEEE, so these papers are excluded from PubMed as they have already been included in the other three databases. After excluding these papers, it was found that there are 14 journals included in PubMed. These journals have been added as PubMed journals as they are collected through PubMed search.

## 2.2. Data extraction

The data extracted from the selected articles are presented in [Tables 4–7](#) which present the search results for Springer Link, Science Direct, IEEE, and PubMed respectively. In the investigated literature, it is found that the frequent problems in breast cancer are: (1) classification between normal and abnormal tissues, (2) classification of abnormal tissue to benign and malignant, (3) classification of breast tissue into dense and fatty tissue, and (4) positive and negative lymph node classification. To solve these problems, five number of image modalities are used: DM, US, MRI, microscopic (histological) images, and infrared thermography (IRT). A total of 16 MLTs are used in the presented literature which are: SVM, ANN, K-NN, Decision tree (DT), Discriminant Analysis (DA)(Quadratic DA (QDA), and Linear DA (LDA)), Random Forest (RF), Fuzzy classifier, Naïve Bayesian (NB), Logistic Regression (LR), Deep learning (DL), Ensemble learning, Association Rule Mining (ARM), Polynomial classifier (PL), Multiple Instance Learning (MIL),

Ant Colony Optimization (ACO), and Least Square Minimum Distance (LSMD). For evaluation of CADs, the most common used performance measures in the literature are: Accuracy (Acc), Sensitivity (Sn), Specificity (Sp), and Area Under the Curve (AUC).

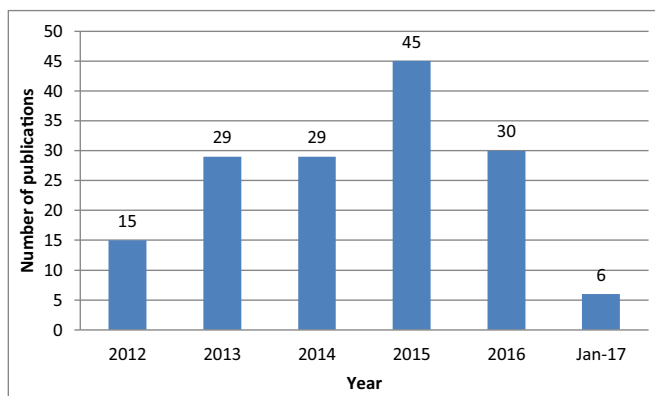
## 3. Results

This SR reviewed the publications of CAD systems from 2012 till January 2017. It was found that a commonly used framework in most of the publications under study includes 4 stages which are preprocessing, segmentation, features extraction and selection, and finally the classification stage that is regarded as the heart of the CAD. In this SR our interest was the usage of different MLTs as classifiers for CADs system of breast cancer.

This section presents the analysis of the results shown in [Tables 4–7](#). In this section, the used modalities, MLTs, performance criteria, and datasets are shortly declared. The proposed work covered the period from 2012 to January 2017. [Fig. 2](#) indicates the rate of publication in this time period. Although breast cancer CAD system is not a new topic, it is clear that the number of its publications is varying slowly over time and it can still be increased in the next time stage. From the bar chart it is shown that the trend is an increased interest in the CAD systems research. The year 2015 has the largest number of publications. Even though a decrease in number of publications is observed in 2016 compared to 2015, still the number of publications in 2016 is stable or a little bit more than the years 2012–2014. Also it is shown that only for the month January 2017 the number of publications is 6 papers, so it is expected to have an increase in number of publications in 2017. Also it is noted from [Tables 4–7](#) that the new trend of deep learning started to be used in 2016 and 2017 which shows an increased interest recently in applying deep learning in CAD systems.

**Table 3**  
List of IEEE conferences.

Name of used IEEE conferences
Society of Instrument and Control Engineers of Japan (SICE), 2016 55th Annual Conference of the Information Science and Technology (CiSt), 2016 4th IEEE International Colloquium on Advanced Robotics and Mechatronics (ICARM), International Conference on Evolutionary Computation (CEC), 2016 IEEE Congress on Programming and Systems (ISPS), 2015 12th International Symposium on Intelligent Systems and Control (ISCO), 2015 IEEE 9th International Conference on 2015 IEEE Congress on Evolutionary Computation (CEC)
2015 IEEE 28th International Symposium on Computer-Based Medical Systems
2015 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON)
Computer, Communications, and Control Technology (I4CT), 2015 International Conference on Image Processing (ICIP), 2015 IEEE International Conference on
2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI)
Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2015 38th International Convention on Computing, Control, Networking, Electronics and Embedded Systems Engineering (ICCNEEE), 2015 International Conference on
2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (1)
2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (2)
2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI)
2015 International Conference on Advances in Biomedical Engineering (ICABME)
2015 27th International Conference on Microelectronics (ICM)
Computational Intelligence in Healthcare and e-health (CICARE), 2014 IEEE Symposium on
2014 22nd Iranian Conference on Electrical Engineering (ICEE)
Intelligent Systems: Theories and Applications (SITA-14), 2014 9th International Conference on IWSSIP 2014 Proceedings
2014 International Conference on Computer, Control, Informatics and Its Applications
Information Technology and Electrical Engineering (ICITEE), 2014 6th International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), 2014 International Conference on Soft Computing and Pattern Recognition (SoCPaR), 2014 6th International Conference of Multimedia Computing and Systems (ICMCS), 2014 International Conference on
2013 IEEE International Conference on Image Processing
Bioinformatics and Bioengineering (BIBE), 2013 IEEE 13th International Conference on Visual Communications and Image Processing (VCIP), 2013
Systems, Signal Processing and their Applications (WoSSPA), 2013 8th International Workshop on Image Analysis and Interpretation (SSIAI), 2012 IEEE Southwest Symposium on
Multimedia Computing and Systems (ICMCS), 2012 International Conference on

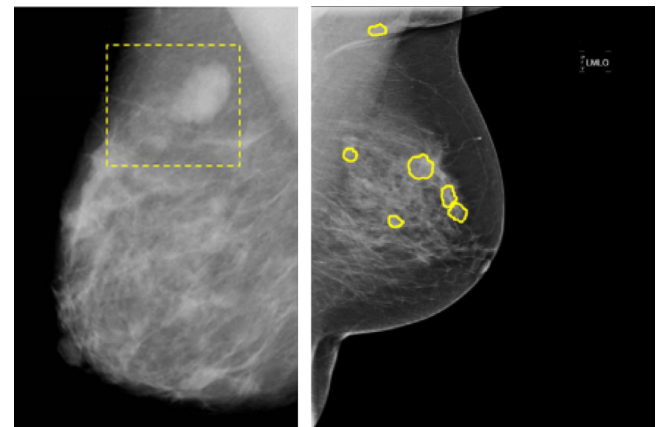


**Fig. 2.** Number of papers published on CADs from 2012 to January 2017 using specified criteria.

### 3.1. Image modalities

Different image modalities are used to examine the presence of breast cancer nowadays. The image modalities investigated in this SR are:

DM is the most commonly and important used screening technique in clinical practice. It has the capability of detecting tumors before they develop further and become easily detected and felt by the physician. Although the DM has drawbacks as being an inappropriate screening technique for ladies with dense breasts because it uses ionizing radiations, still X-ray mammography is the standard breast cancer screening method that offers high 2D resolution. Thus DM is able to detect very small variations in composition of the tissues as micro-calcifications [177]. DM is used ex-



**Fig. 3.** Samples of DM images used in publications of the proposed SR (adapted with permission from Springer Publisher from Ref. [24] and with permission from Elsevier Publisher from Ref. [73]) [24,73].

tensively in the proposed SR where out of 154 used papers there are 98 papers that depend on DM to classify breast cancer tissues. Fig. 3 shows samples of DM images used in different publications of the proposed SR.

US is a convenient modality for cancer detection for ladies having dense breasts. Moreover, it is useful for tumor detection when getting negative mammography. US evaluates the size of tumor and it can characterize abnormalities discovered by DM. On the other hand, its capability of discovering contra-lateral malignant lesions is limited [178]. Elastography and shear wave elastography are a developing form of US. Number of papers included in the presented SR that adopt US images for detecting and diagnosing of



**Table 4**  
Springer Link search results.

Reference	Imaging modality	Machine learning technique	Scope	Evaluation results	Image data sets
[24]	DM	KNN	classifying ROI as normal or abnormal	Acc = 92.81% $\pm$ 0.0093, Sn = 92.85% $\pm$ 0.0099, AUC = 0.9713	IRMA MIAS
[25]	DM	SVM	classifying normal and masses	average Acc from 68 to 100%	MIAS
[26]	DM	Associative classifier with fuzzy-ANN	classification of breast tissues and masses	Acc = 95.11%, Sn = 92.22%, Sp = 96.39	109 cases DDSM
[27]	DM	Fuzzy Gaussian Mixture Model (FGMM)	classify into malignant or benign	Acc = 93%, Sn = 90%, Sp = 96%	170 benign 130 malignant DDSM
[28]	DM	SVM RF NB	predicting benign/malignant lesions, dense/fatty tissue classification, finding identification (mass / microcalcification distinction)	benign/malignant: ACC = 89.3% to 64.7% dense/fatty tissue: ACC = 75.8% to 78.3% finding identification: ACC = 71.0% to 83.1%	INbreast BCDR
[29]	DM	SVM	classify abnormalities using fusion features	Acc = 93.17%, Sn = 92.71%, Sp = 93.46%	MIAS
[30]	US	KNN	diagnose non-mass lesions appearing as hypoechoic areas	Sn = 87.8%, Sp = 89.5%, AUC = 0.93	Private 97 cases
[31]	DM	Adaptive Differential Evolution Wavelet-ANN (Ada-DEWNN)	classification of benign/malignant breast tissues.	MIAS: Acc = 89.38%, Sn = 83.58%, Sp = 93.43%, AUC = 0.935 DDSM: Acc = 87.27%, Sn = 82.5%, Sp = 90.33%, AUC = 0.920 Acc = 74.7%, AUC = 0.816	MIAS DDSM
[32]	MRI	KNN	non-invasive lesion subtypeclassification	Acc = 86.96%, Sn = 86.96%, Sp = 86.96%, AUC = 0.894	Private 200 patients
[33]	US	SVM	discriminate benign and malignant tumors	SVM: AUC = 0.932 ANN: AUC = 0.925	Private 138 cases
[34]	DM	SVM	multiple classifier system for masses classification	Acc = 83.53%, Sn = 92.31%, Sp = 82.2%, AUC = 0.8033	DDSM 303 images
[35]	DM	SVM	detection of masses	Acc = 97.73%, Sn = 92.5% Sp = 98%, AUC = 0.9505	DDSM MIAS
[36]	DM	RF	automated segmentation and classification method	Acc = 87%, Sn = 90 to 47%, Sp = 84 to 84%	DDM
[37]	DM	Fuzzy C-Means (FCM)	ROI classification into benign, malignant, or normal tissue.	Sn = 92%, AUC = 0.8676	Inbreast 410 images
[38]	DM	SVM	detection of microcalcifications (MC)	Acc = 95.85%, Sn = 96%, Sp = 91.46%, AUC = 0.9444	Private 120 images
[39]	US	SVM	detection and diagnosis of breast masses	IRMA: Sn = 99%, Sp = 99% DDSM: Sn = 97%, Sp = 96% Acc = 96.67%, Sn = 96.67%, Sp = 96.67%, AUC = 0.9827	70 benign 50 malignant IRMA DDSM
[40]	DM	SVM	classify feature vector as malignant or nonmalignant	Acc = 97.14%, Sn = 98.24%, Sp = 95.08%, AUC = 0.9938	Private 210 images 120 benign 90 malignant WBC
[41]	US	SVM	evaluating breast tumors.	Acc = 99%, AUC = 0.90	699 cases 458 benign 241 malignant MIAS
[42]	DM	SVM	Classification of breast cancer	SVM: Acc = 82.8%, Sn = 94%, Sp = 77.8%, AUC = 0.809 Detection rate = 100%	Private 234 training 93 test Private
[43]	DM	SVM	classification as malignant masses and benign tumors	Acc = 79.52%	61 biopsy-lesions Private
[44]	MRI	SVM KNN RF	discriminating malignant and benign breast lesions.	Private: Acc = 95%, Sn = 93% MIAS: Acc = 94%, Sn = 82%	146 images 29 malignant 117 benign private MIAS
[45]	MRI	Fuzzy C-Means (FCM)	detecting breast masses		
[46]	IRT	ACO	classifying breast into benign and malignant cases		
[47]	DM	Fuzzy C-Means (FCM)	microcalcifications cluster enhancement method		

(continued on next page)

Table 4 (continued)

Reference	Imaging modality	Machine learning technique	Scope	Evaluation results	Image data sets
[48]	DM	SVM	breast mass classification	AUC = 0.805 ± 0.012	DDSM 600 benign and 600 malignant
[49]	DM	DT	detection of breast cancer based on three types of decision tree classifiers	Acc = 97.51%, AUC = 0.99382	WBC 699 cases 458 benign 241 malignant
[50]	DM	ANN	detection and classification of breast cancer.	Acc = 97.66%, Sn = 98.65%, Sp = 95.82%, AUC = 0.993	WBC
[51]	US	LDA	distinguishing positive and negative lymph nodes.	AUC = 0.85	Private 90 patients
[52]	DM	SVM ANN	detect and classify masses	SVM: AUC = 0.937 ANN: AUC = 0.925	DDSM
[53]	US	Multiple-DA	classification of breast mass	invasive carcinomas: Acc = 88.4% noninvasive carcinomas: Acc = 80.6% Fibroadenomas: Acc = 86.0% Cysts: Acc = 84.1% AUC figures	Private 363 images 65 training set 298 test set
[54]	MRI	SVM	diagnosis of non-mass-enhancing lesions.		Private 84 images 61 malignant 23 benign
[55]	DM	ANN KNN	detection of malignant masses and architectural distortions	true-positive fraction (TPF) = 0.620	Private 200 cases
[56]	DM	ANN	tissue density classification using local binary pattern	AUC = 0.79	Private 400 image
[57]	DM	Association rule mining (ARM)	benign–malignant classification	Acc = 98%, Sn = 97.4%, Sp = 98.6%	DDSM
[6]	DM	ARM	classify between normal and cancerous tissues	Sn = 96.5% Sp = 96.88%	DDSM
[58]	US	Binary-LR	classification of BI-RADS category 3 breast masses	Sn = 95%, Sp = 73%, AUC = 0.95	Private 69 masses 21 malignant 48 benign
[59]	MRI	NB-QDA (NQDA) SVM	classification of the challenging lesions	NQDA: AUC = 0.87	Private 63 patients
[60]	DM	Fisher's LDA local linear wavelet-ANN based firefly	classifying breast cancer tumor	Acc = 98.14%	WBC
[61]	DM	LLWNN based recursive least square (RLS)	breast cancer recognition	Acc = 97.2%	WBC
[62]	US	Probabilistic-ANN	discriminate between benign and malignant	Acc = 93.5%	
[63]	DM IRT	SVM	detecting breast cancer.	Acc = 88.10%, Sn = 85.71%, Sp = 90.48%	Private 50 images 25 normal 25 cancerous
[64]	DM	Swarm Optimization-ANN	detects the presence of microcalcification clusters.	MIAS: Sn = 95%, Sp = 92.3%, AUC = 0.9761 Private: Sn = 91%, Sp = 86.1%, AUC = 0.9138 Sn = 96.9%, Sp = 92.9%, AUC = 0.97843	MIAS Private
[65]	DM	Differential Evolution Optimized Wavelet-ANN	detection of tumor masses		MIAS
[66]	US	SVM	classify tumors into benign and malignant	Acc = 91.07%, AUC = 0.96	Private 168 cases 72 malignant 96 benign
[67]	DM	SVM	classify potential micro-calcifications	Acc = 100%	MIAS Private
[68]	DM	Kernel Self-optimization Fisher-DA	breast tissue density classification	Acc = 94.46%	MIAS
[69]	DM	SVM ANN	characterize breast lesions according to BI-RADS classes	SVM: Acc = 96.91%, AUC = 0.924 ANN: Acc = 97.14%, AUC = 0.933	Private 286 cases

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Table 4 (continued)

Reference	Imaging modality	Machine learning technique	Scope	Evaluation results	Image data sets
[70]	US	SVM	categorize the breast masses to benign or malignant classes.	Acc = 95%, Sn = 90.91% Sp = 97.87%	Private 80 cases 33 malignant 47 benign DDSM
[71]	DM	Ensemble learning system consisting of (DT, SVM, and KNN)	classification of a suspicious mass as malignant or benign	Acc = 72%	

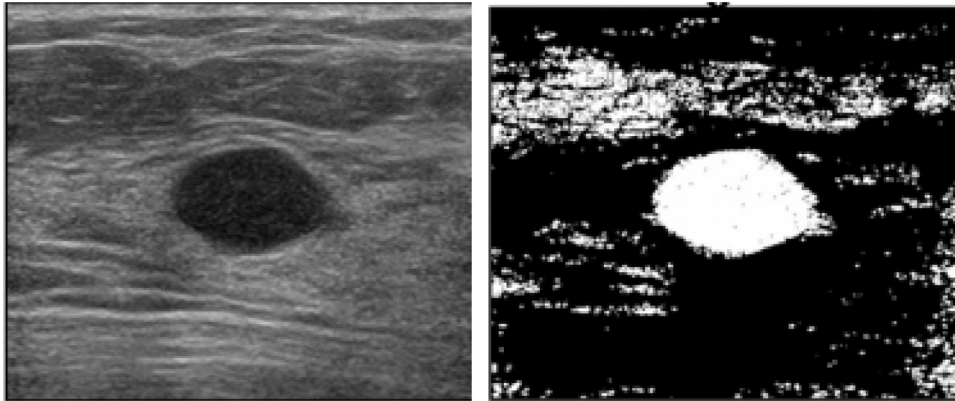


Fig. 4. Samples of US images used in publications of the proposed SR (adapted with permission from Elsevier Publisher from Ref. [72]) [72].

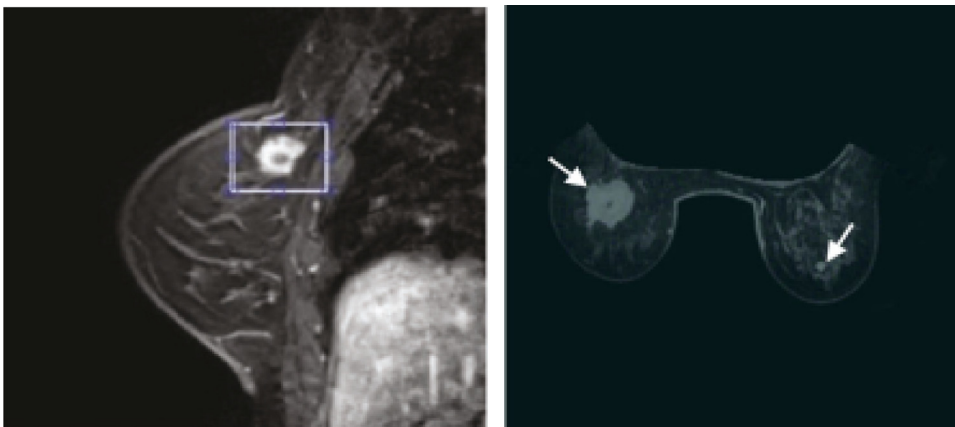


Fig. 5. Samples of MRI images used in publications of the proposed SR (adapted with permission from Springer Publisher from Refs. [44,45]) [44,45].

breast cancer are 30 papers. Fig. 4 presents samples of US images used in publications of the proposed SR.

MRI images the whole breast and presents it as thin slices that cover the entire breast volume; moreover, it provides information about the vascularity of the breast tissue. It shows high potential for screening of high-risk women, and evaluating therapy effects [179]. Only 14 papers mentioned in this SR use this type of modality. Fig. 5 presents samples of MRI images used in different publications of the proposed SR.

Microscopic images are using histological images which are *microscopic examinations* of tissues to detect tumors. Only 8 papers in this SR use microscopic images. Fig. 6 presents samples of microscopic images used in publications of the proposed SR.

IRT can be used in observing pre-cancerous and early signs of breast cancer using the temperature spectrum; tumorous cells have high temperature than healthy ones. Five papers included in this SR are using IRT. Fig. 7 presents samples of IRT images used in publications of the proposed SR. One of the considered papers

used both of US and DM, so the total number of modalities in the chart is 155.

From data extraction process, Fig. 8 shows a pie chart of the used image modalities in the proposed literature papers. Each sector of the pie shows the extent of utilizing each of these different modalities. It is shown that the most used medical images for detection of breast cancer using CADs is the DM.

### 3.2. Selected features

The selected features are capable of differentiating between normal and cancerous regions in order to minimize the classification error. Different publications use different set of features which they found most suitable for this task. A huge number of features are assembled in this SR but only samples of the most used and selected features are presented in this section.

The most used features types which have been found in publications of this SR for breast cancer classification are histogram, morphological, textural, speculation, geometric, kinetic, and binary



**Table 5**  
Science Direct (Elsevier) results.

Reference	Imaging modality	MLT	Scope	Evaluation results	Used data set
[72]	US	LR	classify breast tumors based on tumor size.	In data subset of tumors < 1 cm: Acc = 81.4%, Sn = 83.3%, Sp = 79.5%, AUC = 0.852 In data subset of tumors ≥ 1 cm: Acc = 81.8%, Sn = 85.4%, Sp = 77.8%, AUC = 0.855 AUC = 92.2%	Private 156 tumors 78 benign 78 malignant
[73]	DM	DL	detection of malignant lesions and benign abnormalities		Private 45,000 images
[74]	DM	QDA	automatic localization of malignant sites of asymmetry	Acc = 79%, Sn = 83%, Sp = 75%	MIAS DDSM 94 images
[75]	US	RF	Benign/malignant tumor classification	AUC = 99%	Private 31 malignant 28 benign
[76]	shear-wave elastography	DL	differentiation between benign and malignant breast tumors.	Acc = 93.4%, Sn = 88.6%, Sp = 97.1%, AUC = 0.947	Private 227 images 135 benign 92 malignant
[77]	DM	Extreme Learning Machine (ELM-ANN)	distinguishing malignant masses from benign ones	DDSM: Acc = 95.73, Sn = 94.88 Sp = 97.16, AUC = 0.9742 MIAS: Acc = 96.02%, Sn = 96.29% Sp = 94.32%, AUC = 0.9659	DDSM MIAS
[78]	DM	DL	diagnosis of breast cancer	Acc = 82.43%, Sn = 81% Sp = 72.26%, AUC = 0.8818	Private 1874 pairs of images
[79]	US	DT ANN RF SVM	distinguish benign from worrisome lesions	SVM: Acc = 77.7%, AUC = 0.84 RF: Acc = 78.5%, AUC = 0.83	Private 283 lesions
[80]	DM	ANN	classify tumors as benign or malignant	Acc = 90.94%, Sn = 100% Sp = 97.30%, AUC = 96.89%	MIAS 57 images 37 benign 20 malignant
[81]	DM	DT, DA KNN, NB Probabilistic-ANN SVM, AdaBoost Fuzzy Sugeno (FSC)	classification of normal, benign and malignant	KNN: Mean Acc = 98.69% Sn = 99.34%, Sp = 98.26%	DDSM 690 images
[82]	DM	ANN	online classification as normal benign/malignant tumor.	Acc = 96% Sn = 98.6% Sp = 89.3%	MIAS BancoWeb 100 images
[83]	DM	ANN Neuro-fuzzy	mass detection process	BRBP-ANN: Average Recognition rate = 97.08% Neuro-fuzzy: average recognition rate = 95.42% Acc = 96.7%	MIAS
[84]	DM	DL	breast mass classification		DDSM
[85]	DM	DL	classification of mass lesions	AUC = 0.826	Private 344 patients
[86]	DM	DT RF SVM PL	differentiating normal, benign and malignant in breast tissue	PL: Acc = 100% AUC = 1.00	DDSM BCDR
[87]	DM	ANN SVM	computer aided detection (CAD) systems	ANN: Acc = 79.1%, Sn = 81.6%, Sp = 71.1%	Private 400 cases
[88]	cytological images (microscopic Images)	ANN SVM	classification system for cancer malignancy grading	ANN: Acc = 87.1%, Sn = 100%, Sp = 86.4% SVM: Acc = 77.23%, Sn = 96.49%, Sp = 77.27%	Private 202 images in the database, 101 cases. Pair of images describes a single case
[89]	US	Binary-LR	computer-aided tumor detection	mapping rate of 80.39%	Private 18 cases
[90]	DM	SVM	classification as mass or normal and breast density classification	Mini-MIAS: Acc = 99%, AUC = 0.9325 Inbreast: Acc = 92.37%, AUC = 0.99	Mini-MIAS Inbreast
[91]	shear-wave elastography	LR	distinguish malignant from benign breast tumor	Acc = 88%, Sn = 81% Sp = 91% AUC = 0.89	Private 57 benign 31 malignant

(continued on next page)

Table 5 (continued)

Reference	Imaging modality	MLT	Scope	Evaluation results	Used data set
[92]	DM	SVM	automatic mass detection for diagnosis of suspicious regions	Sn = 82.4%	DDSM
[93]	DCE-MRI	LDA KNN Gentleboost (GB) SVM RF	detection of breast	RF: Sn = 95%	Private 209 images
[94]	US	SVM	automatically detect the tumor regions	Acc = 0.983 ± 0.013 Sn = 0.974 ± 0.035 Sp = 0.985 ± 0.019 AUC = 0.997 ± 0.003	Private 46 images
[95]	DM	AdaBoost	detection and classification as benign /malign	Mean Acc = 91.43% Sn = 87.15%, Sp = 93.58% AUC = 0.9036	MIAS
[96]	DM	KNN	distinguish between normal and abnormal breast tissues and tumors as malignant or benign	Mini-MIAS abnormality detection: Acc = 91.27, AUC = 0.989 malignancy detection: Acc = 81.35, AUC = 0.841	Mini-MIAS 252 images DDSM 11,553 ROI
[97]	DM	SVM	classification of regions extracted as mass /non-mass.	Acc = 98.88% Sn = 98.60% Sp = 98.85%	DDSM 3404 ROI
[98]	Elastography	Fuzzy C-means	distinguishing malignant from benign tumors	Acc = 80%, Sn = 80% Sp = 80%, AUC = 0.84	Private 45 malignant 45 benign
[99]	DM	SVM	distinguishing between abnormality (mass/ microcalcifications) &(benign/malignant)	Acc = 99% ± 0.50 AUC = 0.9900 ± 0.0050	MIAS Inbreast
[100]	DM	ANN	classification as(normal/abnormal) then the abnormal as (benign/malignant)	RBFNN(normal/abnormal): Acc = 93.98, Sn = 97.22% Sp = 91.49% RBFNN(benign/malignant): Acc = 94.29%, Sn = 100% Sp = 89.47%	MIAS
[101]	US	NB LR AdaBoost	differentiating benign and malignant masses	Sn = 90% sp = 97.5% AUC = 0.98	private 246 patients
[102]	US	SVM	lymph node classification	Sn = 95%, Sp = 90%, AUC = 95%	Private 105 images
[103]	US	Binary LR	second viewer to avoid misclassification of carcinomas.	Acc = 83%, Sn = 76%, Sp = 88%	Private 69
[104]	DM	SVM	predict the near-term risk of developing detectable high risk breast cancer in the next sequential screening mammography examination	AUC = 0.754 ± 0.024	Private 90 cases
[105]	DM	LDA	breast density classification	MIAS: Acc = 99.75 FFDM: Acc = 91.58%	MIAS 322 images Private full-field digital mammogram (FFDM) 1459 images
[106]	DM	SVM KNN DT Fisher LDA	classify as normal, benign, and malignant	SVM: Acc = 90.60%	DDSM IRMA MIAS
[107]	DM	Extreme Learning Machine (ELM-ANN)	breast tumor detection	Acc = 82.6% Sn = 86%, Sp = 78.9%	Private 482 images
[108]	DM	MLP-ANN KNN SVM	classify as normal/abnormal & benign/malignant	MLP-ANN: Acc = 71% Sn = 66% Sp = 77% AUC = 0.98 ± 0.03	MIAS 181 images
[109]	DM	PL	define the mammogram images as normal or abnormal		DDSM 360 images
[110]	microscopic images	KNN NB DT	classify as benign/malignant	All classifiers: Acc = 96 to100%	Private 500 images 25 benign 25 malignant
[111]	DM	SVM	classification as mass or non-mass	Acc = 96.38%, Sn = 100% Sp = 95.34% AUC = 0.93	DDSM

(continued on next page)

Table 5 (continued)

Reference	Imaging modality	MLT	Scope	Evaluation results	Used data set
[112]	DCE-MRI	LSMD LR SVM	differentiation between malignant and benign lesions	SVM: Sn = 95% Sp = 78.19% AUC = 0.9651–0.9755	Private 115 images 78 malignant 37benign
[113]	DM	SVM	predict the risk or likelihood of breast cancer development	AUC = 0.725 ± 0.018	Private 994 cases
[114]	MRI	SVM	classify into normal or non-normal	Acc = 98%	Private 120 images 70 normal 50 abnormal

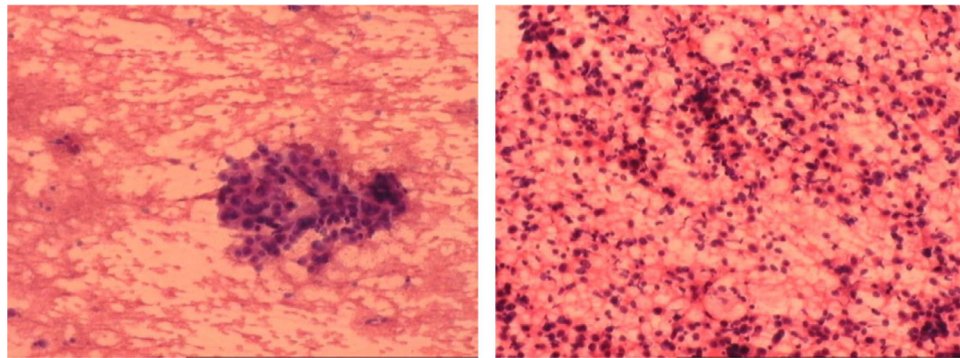


Fig. 6. Samples of histological images used in publications of the proposed SR (adapted with permission from Elsevier Publisher from Ref. [88]) [88].

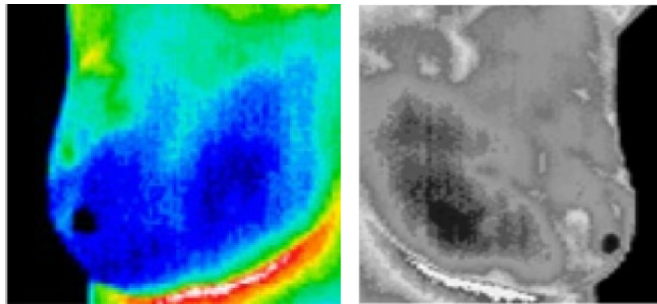


Fig. 7. Samples of IRT images used in publications of the proposed SR (adapted with permission from Springer Publisher from Ref. [63]) [63].

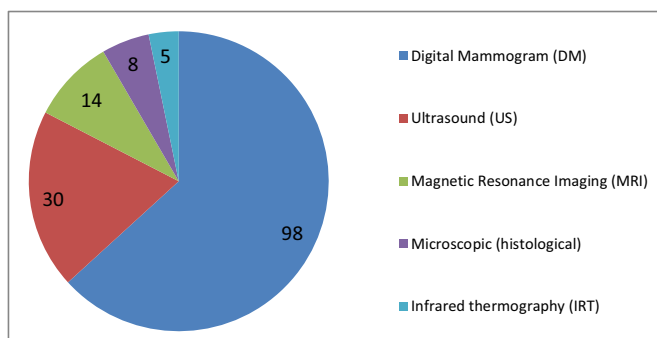


Fig. 8. Pie chart of different modalities used in different CAD systems.

object features. Samples of observed features for each of these different types are:

**Histogram Features** like Mean, Standard Deviation, Skew, Energy and Entropy.

**Morphology** like Area overlap ratio, normalized average radial distance ratio, standard deviation of normalized distance ratio,

variance of distance ratio, compactness, smoothness, margin sharpness, variance in margin sharpness.

**Textural** like Contrast, Correlation, Difference in entropy, Difference in variance, Energy, Entropy, Homogeneity, Information measure of correlation, Maximum correlation coefficient, Sum average, Sum entropy, Sum variance, Variance, Inertia, Inverse difference

**Spiculation** like Margin sharpness, Full Width Half Maximum (FWHM) border, Variance in margin sharpness, FWHM grown, Radial gradient index, Radial gradient grown, Radial gradient border, FWHM ROI, Radial gradient ROI, FWHM margin, Radial gradient margin.

**Geometric:** Size, Circularity, Sphericity, Irregularity.

**Kinetics:** Maximum enhancement, Time to peak, Uptake rate, Washout rate, Curve shape index, Enhancement at first post contrast time point, Signal enhancement ratio.

**Binary Object Features** like Area, Centroid, Orientation (Axis of least second moment), Perimeter, Euler number, Projection, Thinness and Aspect ratio [166,167,169].

The selected features are always organized in a database and provided as an input to the MLT classifier.

### 3.3. Machine learning techniques

Several MLTs are used for breast cancer detection, prediction, and diagnosis. For the classification algorithms, the dataset is divided into training and test sets. Developing the model is done using the training dataset; afterwards the validation of the training model is accomplished using the test dataset. From data extraction process, many MLTs are used for the classification of breast tissues based on the features extracted from images.

In Tables 4–7, only the results obtained due to the test set examination are extracted. Some studies use more than one MLT classifier to find the best method in classification of different breast cancer problems, in this case only the best Acc values achieved for each problem are recorded such as in [28]. In papers that adopt one or more classifiers and use others for the purpose of comparison, only the adopted classifiers are mentioned. In

**Table 6**  
IEEE search results.

Reference	Imaging modality	Machine learning technique	Scope	Evaluation results	Used data set
[115]	DM	DL	classification to mass and normal	Sn = 89.9%	Private 198 images (99 mass and 99 normal)
[116]	DM	SVM	classification as normal or abnormal	MIL: AUC = 94.4%	DDSM
[117]	DM	SVM	Classification of breast cancer	Acc = 91.25%	(DDSM)
[118]	US	Back Propagation –ANN	Classification of breast cancer	Acc = 94.0% Sn = 94.4% Sp = 93.6%	Private 200 images 102 benign 98 malignant
[119]	DM	NB DT KNN SVM	classification of breast tumors	SVM: Acc = 74.92%	MIAS Inbreast
[120]	histopathology images (microscopic Images)	KNN SVM RF Quadratic Linear Analysis (QDA-LDA)	classification into two classes	QDA: Acc = 100%	Private 7909 images 82 patients
[121]	DM	Transductive Semi Supervised - SVM	classification of the tumors in terms of benignity or malignancy	Acc = 93.1% Sn = 83.0% Sp = 89%	DDSM 200 images
[122]	DM	SVM KNN	classification of tissue density	SVM: Acc = 91.51%, Sn = 87.33% Sp = 93.63%	MIAS
[123]	IRT	DT	classification of breast cancer	Acc = 90.10% Sn = 81.02% Sp = 92.35%	Private 150 images
[124]	DM	Optimum-Path RF	classification to identify the presence of breast masses	Recognition rate = 99.9%	Private 120 images
[125]	DM	SVM	classification of breast cancer	Acc = 96.3%, Sn = 98.7% Sp = 90.1%	MIAS
[126]	DM	ANN	classification of breast tissues into groups of normal and abnormal	Classification rate = 91.64%	MIAS
[127]	DM	SVM	classification of breast cancer	MIAS: Acc = 95.80%, Sn = 98.43% Sp = 93.34% DDSM: Acc = 95.78%, Sn = 96.74% Sp = 94.87%	MIAS DDSM
[128]	DM	SVM	classification of breast cancer	Acc = 94.44%, Sn = 95.88% Sp = 93.10%	DDSM
[129]	DM	Fisher's Linear-DA SVM, DT KNN	classification of breast cancer	SVM: Acc = 94.67%	IRMA
[130]	DM	SVM KNN DA	classification between masses and normal breast tissue	KNN: Sn = 94% Sp = 98%	DDSM
[131]	DM	Multiple-Instance Learning (MIL)	Classification to recognize benign versus cancer discrimination	Acc = 91.1%	DDSM 720 images
[132]	IRT	Fuzzy Classifier	classification between cancerous and healthy breasts	Sn = 82.35% Sp = 92.15%	Private
[133]	DM	ANN	classification of masses on a risk rate scale	Acc = 98%	Private 100 patients
[134]	DM	SVM	classification of breast cancer	Acc = 98.33%	Private
[135]	pathological images microscopic images	SVM	differentiating stage I breast cancer from other stages	Classification accuracy improved by 3%. Classification performance is 12%.	Publicly available database TCGA (The Cancer Genome Atlas). 86 patients
[136]	DM	Echo State Network (ESN-ANN) SVM	classification as malignant and benign cases	ESN-ANN: Acc = 98%	MIAS
[137]	Microscopic	SVM	classification of breast cancer	Classification efficiency = 82%.	Private
[138]	MRI	SVM	classification of suspicious malignancy	Acc = 94%	Private 70 clinical cases
[139]	DM	SVM	classify normal from abnormal cases	Acc = 96%	DDSM

(continued on next page)

Table 6 (continued)

Reference	Imaging modality	Machine learning technique	Scope	Evaluation results	Used data set
[140]	IRT	Sequential Minimum Optimization-SVM NB	classification for detection of malignant breast conditions	SMO-SVM: Acc = 61.8%, Sn = 61.72% Sp = 62.9%	Private 102 images 54 normal 48 finding
[141]	DM	Multi-Layer Perceptron (MLP-ANN)	classification between normal, benign, and malignant.	MLP-ANN: Acc = 96.66% Sn = 96.73% Sp = 97.35% AUC = 96.6%	Private 40 images 14 benign 6 malignant 20 normal
[142]	DM	(MLP-ANN)	classification into malignant, benign and normal cases.	Acc = 91.66%, Sn = 88.88% Sp = 93.72% AUC = 96.7%	private 40 images
[143]	US	Fuzzy-ANN	Classification of breast nodules as either benign or malignant	Acc = 90% to 92%	Private 65 images 31 benign 34 malignant
[144]	DM	Radial Basis Function-ANN (MLP-ANN)	classification into benign and malignant masses	Acc = 89%, Sn = 89.5% Sp = 11.54%	Mini MIAS 148 images
[145]	DM	SVM KNN	classification of breast cancer	AUC Figures	MIAS 80% training 20% testing.
[146]	DM	SVM	classification of breast cancer	SVM: Recognition rate = 89% Acc = 89.0 ± 3.6%, Sn = 91.0 ± 5.2%, Sp = 91.0 ± 6.6%	DDSM
[147]	US	SVM	classification of breast masses	Reduced FPs by 30% with the true detection rate at 85%.	Private 200 images
[148]	DM	SVM	classification of breast cancer	SVM: Acc = 74% MLP: Acc = 76%	Private 200 images MIAS
[149]	DM	SVM, NB KNN, LR DT, RF (MLP-ANN)	classification of breast cancer	Acc = 88.18%, Sn = 88.33% Sp = 88.00%	Private 105 cases
[150]	US	SVM	classification of breast cancer	Acc = 89.09%	DDSM 600 training 200 test
[151]	DM	SVM	classification of breast masses	Sn = 87%	Private 66 cases
[152]	DM	Adaptive Kernel Learning – NB	classification of breast cancer	SVM: Sn = 98% at 0.85 FP/image	MIAS
[153]	DM	ANN SVM	classification of breast cancer	ANN: Sn = 98% at 0.6 FP/image	
[154]	DM	Fuzzy Inference Systems (FIS) SVM	classification to detect micro calcifications	SVM: Sn = 99.60% Sp = 99.11%	MIAS 16 images

the papers that try many MLTs to classify breast cancer problems, all of them are mentioned and only the best achieved results are recorded in the data tables. In case of using combined MLTs, all of them are mentioned and Acc of the combined techniques are recorded.

A brief description of each technique used in the SR is given below:

*SVM classifier* is the widely used MLT in the papers investigated in our SR. It is a supervised classifier. It builds a model that uses a hyperplane as a boundary that distinguishes various points in 2 different classes and separates them. This plane is used to classify a test sample [180]. In the presented study, the number of publications which adopts SVM as a classifier is 81 which represents 52.6% of the total considered studies. The maximum accuracy achieved using SVM is 100% as stated by [67]. Also, in [90] the Acc. value achieved by SVM is 99%. As can be seen, classifying breast cancer tissues using SVM can accomplish an excellent Acc values.

*ANN classifier* is a network that connects all nodes together imitating the human brain neurons. The input to one of the nodes is the sum of the output of all the nodes to which it is connected multiplied by a certain determined weight. A “transfer function” processes the output value from a certain node. The NN is formed

of consecutive layers. An input layer receives data and transfers it to nodes in the first hidden layer after assigning them weights. The result is transformed to the nodes in the next layer and so on. The last layer provides the network's output. Number of ANN publications considered in the presented SR are 40 which is considered 25.97% from the total publications number. ANN has been combined with many other classification techniques such as: in [26], it is combined with associative classification technique which is called (ACNN) and with adding fuzzy it is called (ACFNN), this combination is created and evaluated. A fuzzy neural network is a single architecture combining the elements of fuzzy and neural network. It is a learning machine that uses the parameters as fuzzy sets. By using these techniques in combination with ANN, the authors indicate that the performance of ACFNN is better than ACNN with Acc equal to 95.1%. Also, the fuzzy inference system (FIS) is used with ANN as a neuro-fuzzy system in [83] with Acc 95.42%. Four considered papers are using wavelet neural networks (WNN) classifiers which is a kind of feed-forward network whose activation functions are drawn from wavelet basis such as [60] that has Acc of 98.14%. Five papers are using a multilayer perceptron (MLP) which is a feed-forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. The Acc



**Table 7**  
PubMed search results.

Reference	Imaging modality	Machine learning technique	Scope	Evaluation results	Used dataset
[155]	US	SVM	classification to tumor class	Acc = 98.2%, Sn = 98.4%, Sp = 97.8%	Private 110 cases
[156]	Histopathology (microscopic images)	DL	breast cancer detection	Breast results (mean $\pm$ std): Acc = $0.86 \pm 0.03$ , Sn = 1, Sp = $0.72 \pm 0.10$	Private 58 H&E-stained histopathology images of breast tissue
[157]	DM	GentleBoost	Classify microcalcification groups	Sn = 76%, Sp = 98%	Private 1088 cases
[158]	DM	SVM NB KNN LR DT RF MLP – ANN	detection of mass	RF: Acc = 91.4%, Sn = 67.9%, Sp = 93%, AUC = 90.1%	mini-MIAS322 digitized mammograms
[159]	MRI	RF	differentiate among mass and non mass	Sn = 100%, Sp = 77%, AUC = 92%	Private 240 patients
[160]	US	SVM	distinguishing between TNBC and benign	Acc = 94.81%, Sn = 94.12%, Sp = 96.72%	Private 169 images
[161]	microscopic images	RF SVM	diagnosis of breast cancer	Acc = 90%, Sn = 94.59%, Sp = 96.72%	Private 228
[162]	DM	ANN	detection of breast cancer	Sn = 68.8%, Sp = 95%, AUC = $0.851 \pm 0.046$	Private 1896
[163]	US	SVM	discriminate the grades of breast cancer tumor	Acc = 85.14%, Sn = 79.31%, Sp = 86.55%	Private 148 images
[164]	DCE-MRI	SVM	classifying as malignant and benign	Sn = 80.0%, Sp = 90%, AUC = $0.919 \pm 0.029$	Private 115 images
[165]	DM	AdaBoost-SVM	diagnosis of breast cancer	AUC = 0.89	DDSM
[166]	DM	Fully Complex-Valued Relaxation Neural Networks (FCRN) ANN	classification as normal, benign and malignant	Acc = 98, Sn = 97, Sp = 100, AUC = 0.947	MIAS
[167]	DCE-MRI	SVM	discriminate between lesion classes	AUC = 0.77	Private 585 cases
[168]	MRI	fuzzy c-means	distinguishing malignant and benign lesions	AUC = 0.88	Private 15 malignant and 8 benign
[169]	MRI	Bayesian ANN	classification of breast cancer using HiSS MRI and clinical DCE-MRI	For HiSS AUC = $0.92 \pm 0.06$ For DCE-MRI AUC = $0.90 \pm 0.05$	Private 40 cases with 34 malignant, 7 benign lesions
[170]	microscopic images	KNN ANN SVM	classification into different grades of malignancy (grades I–III)	SVM ACC = 96.9	Private 65 ROIs: 20 grade I, 20 grade II, and 25 grade III.
[171]	DM	QDA	detection of breast diseases at their early stages	SN = 80% AUC = 0.70.	Private 158 images
[172]	DM	DT LDA SVM	classify breast cancer as normal, benign, and malignant	DT: private DB Acc = 96.3% DDSM Acc = 91.6%	Private 300 images DDSM 300 images
[173]	US	DT	classify breast cancer	AUC = $0.90 \pm 0.03$	Private 250 patients 96 malignant 154 benign
[174]	DM	SVM	detection of suspicious lesions in mammogram	Sn = 94.5%	MIAS 164 images
[175]	DM	LR	classify breast cancer	AUC = 0.7838	DDSM Private (1006 cases (646 benign and 360 malignant))
[176]	US	SVM	classifying solid breast masses	ACC = 75.5, Sn = 78.9%, Sp = 73.6%, AUC = 0.82	private 110 images

achieved using MLP in [141] is 96.66%. Many other types of ANN have been used in the literature such as probabilistic ANN, radial basis function (RBF), extreme learning machine (ELM), and convolutional ANN or CNN which is used in deep learning.

*KNN classifier* is a supervised classification method. It classifies an unknown sample by initially calculating the distance of that sample to all the training samples. It determines  $k$  smallest distances. The output class label of the unknown sample is assigned by the most represented class in these  $k$  classes. The number of KNN publications considered in the presented SR is 21 which is considered 13.63% from the total publication number. Many MLTs were used in [81], KNN is the classifier which achieved the highest recorded mean Acc, that is 98.69%.

*DT* sets a series of carefully composed questions about the attributes of the test record in a tree structure. Every time an answer is received, a follow-up question is asked till a conclusion is driven about labeling the class of the record. A decision tree classifier is composed of one root node, several internal nodes, and several terminal nodes. The root and internal nodes include the test conditions for the attributes to distinguish between records that have different qualities. All terminal nodes are assigned a class label. For building decision trees the core algorithm uses entropy to evaluate how homogenous the sample is. If homogeneity is fully satisfied the entropy is zero and if the sample is an equally divided it has entropy of one. Decision tree construction is about finding an attribute that returns the highest information gain or in other words that returns the most homogeneous branch. The information gain is based on the decrease in entropy after the splitting of a dataset based on a certain attribute. The number of DT publications considered in the presented SR is 14 which is considered 9% from the total publication number. The highest Acc value achieved using DT is 97.51% in [49].

*DA* is a statistical supervised classifier that aims to find decision functions that respond to samples from different classes in a different manner. Three types of DA are collected in the presented SR which are Linear (LDA), Quadratic (QDA), and Kernel. All types of DA are counted together; the number of DA publications considered in the presented SR is 14 which is considered 9% from the total publication number. The highest Acc value achieved using kernel self optimization fisher DA is 94.46% in [68].

*RF* merges several decision trees for prediction, and they are constructed by grabbing several classification trees together. Each one of these trees is an independent one. When data is extremely unbalanced the RF gives suboptimal results. RF can be implemented easily and it performs predictions for large number of input variables with high accuracy. The number of RF publications considered in the presented SR is 13 which is considered 8.4% of the total publication number. Using RF in [124] achieved maximum Acc of 99.9%.

*Fuzzy classifier* specifies partial membership for an object in different classes with different degrees. A classifier is described by fuzzy IF-THEN rules. Fuzzy c-mean (FCM) is the most popular unsupervised classification algorithm based on fuzzy. In this case, the data points have their membership values with the cluster centers, which will be updated iteratively. Twelve papers are using fuzzy classifiers which are considered 7.79%. In [45] the achieved Acc is 100% using fuzzy.

*NB* depends on a probabilistic technique and Bayes theorem. It gives probabilities that a given pattern belongs to a specific class. The probability of a random class variable is measured and computed from observations that are given about the value of another set of random variables. There are 10 NB classifiers found in the collected studies which are considered 6.4%. NB achieved Acc ranges from 96 to 100% as stated in [110] for all used classifiers.

*LR* was developed by statisticians and it is commonly used in learning as other classifiers developed by the ML scientists. LR is

mostly used for binary classification problems. It predicts the probability of an incident based on a set of values used as predictors. In this SR, 10 publications adopt LR as a classifier which is considered 6.4%. The maximum Acc recorded using LR is 88% in [91].

*DL* recent trend in machine learning resulted in new techniques to train deep neural networks, which produce highly successful applications in many pattern recognition tasks such as image and speech recognition [73]. So the most publications found in this SR that uses DL are recent ones. DL is a set of algorithms that try to learn in multiple levels, representing various levels of abstraction. DL typically uses ANN. Distinct levels of concepts are represented by the levels in the learned statistical models. Concepts of higher level are defined from lower-level ones, and at the same time these lower level ones can help to define other higher-level concepts. DL uses the back propagation algorithm to find out complicated structure in huge data sets to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer [181,182]. The maximum Acc recorded using DL is 96.7% in [84].

*Ensemble system* is a combination of optimized classifiers whose output was combined using ensemble combination rules like majority voting, minimum, maximum, average and product. A few number of ensemble systems are found in our SR. One of them consists of (DT, SVM, and KNN) and its achieved Acc was 72% [71]. It is observed that using standalone classifier achieve greater Acc value than when it is used in ensemble system. Also, four boosting learning are found in data extraction. Boosting is an ensemble machine learning method which converts weak learners to strong ones. The used boosting algorithms are Adaptive Boosting (AdaBoost), and Gentleboost. In [95], the achieved mean Acc using AdaBoost is 91.43%. In general, using ensemble algorithms in breast cancer CADs is considerably little which can be a point of research in the future to improve the performance of CAD systems for better cancer diagnosis.

*ARM* is used for discovering the repeated items, correlations, or associations in different datasets and thus generates the association rules between sets of items. Three papers uses ARM with achieved Acc 98% in [57].

*MIL* is a supervised learning that solves learning problems with incomplete information about data labels. In MIL, each instance is described by a feature vector and the class label is associated with a big bunch of instances. The aim of the MIL is to develop learning model for these bunches classification. Two articles have used MIL as a classifier [131] and [116] the first one achieved Acc of 91.1% and the second obtained AUC of 94.4%.

*PL* maps a  $d$ -dimensional feature vector into an  $L$ -dimensional vector. Therefore, the dimensionality of the expanded vector can be expressed in terms of the polynomial order and the dimensionality of the input vector. Finally, the classifier output is obtained after a linear combination of the expanded vector. Two papers are using PL to classify breast cancer tissues. 100% Acc value has been obtained in [86].

Each of the following MLTs have been used in one article:

*ACO* is used for classification using an Ant-Miner algorithm. It is built on performing classification using a rule base that is to be optimized using ant colony optimization. [46] uses ACO and obtains a little Acc value of 79.52%.

*LSMD* uses a classification rule that calculates the minimum Euclidean distance between the unknown item and the mean values of each of the other classes, using a linear equation that minimizes the least square errors [112].

The obtained MLTs data have been analyzed using pie chart to find the most prominent technique used in CAD of breast cancer as declared in Fig. 9. It is noticed that SVM is the most used classification techniques for breast cancer CADs, and then ANN and K-NN

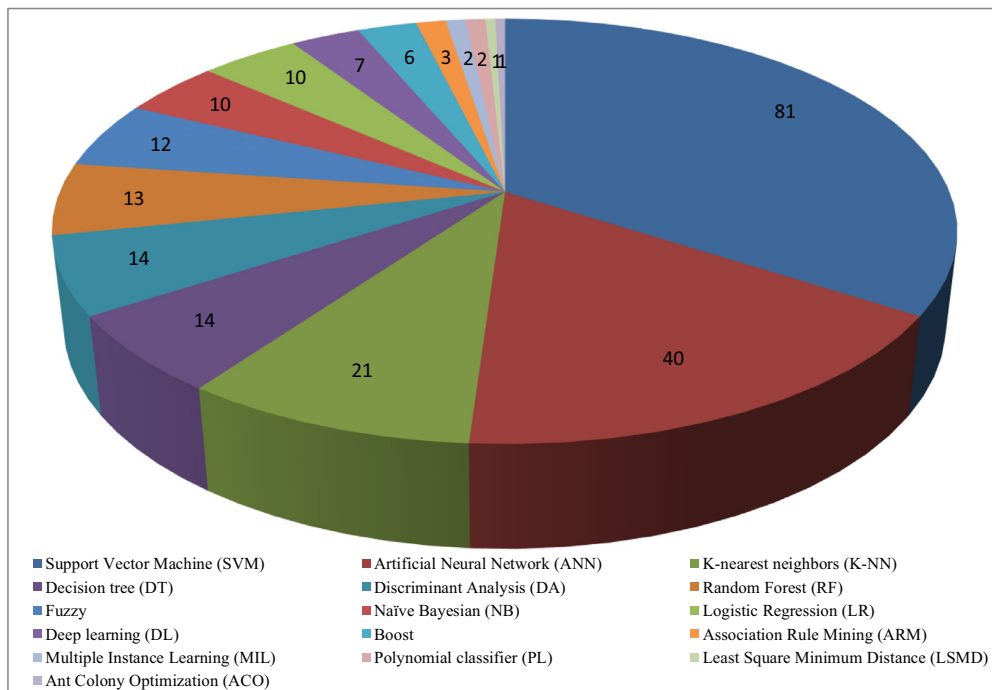


Fig. 9. Pie chart of the various MLTs used in CAD of breast cancer.

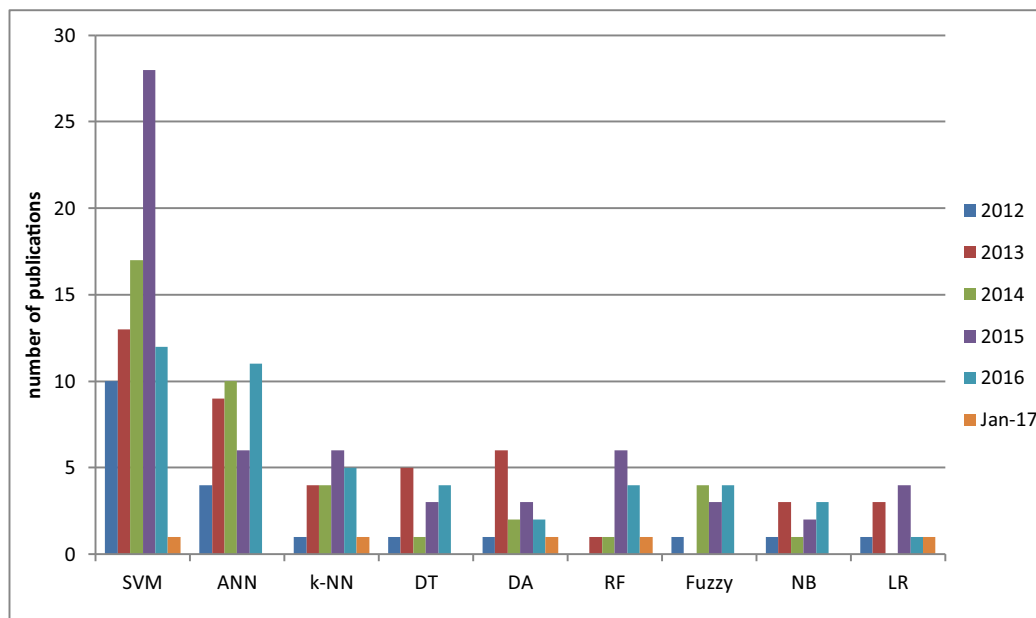


Fig. 10. Bar chart of the most commonly used MLTs in CAD of breast cancer per year.

come afterwards. Other techniques have been explored but have not been widely adopted.

Moreover, Fig. 10 presents the number of publications using a certain MLT for a specified year. The first 9 MLTs most commonly used for breast cancer CAD systems were plotted versus the years considered for this study; 2012 till January 2017.

### 3.4. Evaluation metrics

When a classifier is being trained using training data samples, test data are then fed to the classifier to be classified to assess the performance of the classifier. From data extraction process, it can be stated that there are several ways for assessing classifiers.

In the evaluation process, the positive samples are those which go under the main class of interest. For cancer diagnosis, the positive samples are those of malignant/abnormal class and the negative samples are those of the benign/normal class.

The main and most used evaluation metrics applied to CAD systems include Acc, Sn, Sp, and AUC. These are the most repeated performance measures which are clearly mentioned in the selected articles. The articles which use other performance measures are not omitted to maximize utilization. However, only the popular metrics are defined as follows: (1) Acc represents how near the predicted class is to the actual one. That's to say it indicates percentage of samples that are rightly classified (normal and abnormal) to the total samples. (2) Sn is the true positive rate that de-

termines the percentage of correctly classified abnormal samples. (3) Sp is the true negative rate which determines the percentage of correctly classified normal samples. (4) AUC is a common metric that represents a way to choose optimal models and ignore sub optimal ones. It is the area under the Receiver Operating Characteristic curve (ROC), which is a curve of the true positive rate versus the false positive rate. The AUC takes a value between 0 and 1. A good diagnostic test is obtained when the AUC is close to one. Reasonable tests have AUC greater than or equal to 0.5 and less than 1 [16].

Equations of Acc, Sn, and Sp are given as follows:

$$\text{Acc} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \quad \text{Sn} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad \text{Sp} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

where TP: true positive, TN: true negative, FP: false positive, FN: false negative.

### 3.5. Databases

Some public image databases are widely used for applying breast cancer classification methods. These databases are mostly DM images such as Digital Database for Screening Mammography (DDSM) [183], Mammographic Image Analysis Society (MIAS) [184], Image Retrieval in Medical Applications (IRMA) [185], Wisconsin Breast Cancer (WBC), and BancoWeb [186]. Also, there are two Portuguese's datasets, the first is the INbreast database [187] and the second is Breast Cancer Digital Repository (BCDR) [188].

Moreover, papers using other types of image modalities usually depend on private databases for applying their methods. Private databases are collected by individual groups independent of each other. Private databases present images of patients case studies collected in local hospitals or research centers. This holds back the analysis and comparison of different algorithms developed by one research group with the others and makes it ineffective. It is recommended to have standardized datasets that contain images from multiple sources for different image modalities.

In data extraction process, the used datasets in each article are collected as well as the number of images, patients, and cases as stated in the article. Also, the distribution of the datasets as (training and testing), (benign and malignant), and (normal and abnormal) is gathered. There is no standard neither in the number of cases used nor in the division of cases into benign and malignant or into normal and abnormal. So, there is a variety in the distribution of the data according to the insight of each author.

## 4. Discussion

It is noticed that there is a significant diversity in the usage patterns of MLTs, some of them have been used extensively, some have been used less frequently, and others have been used in low rates. Fig. 11 presents a hierarchy chart of MLTs categorized according to frequency of usage in CAD systems for breast cancer according to the studied articles.

A conclusion can be extracted from the studied articles according to the used image modalities combined with different MLTs as follows:

DM has been used with SVM in 50 papers; the range of achieved Acc is from 64.7% to 100%. Two papers have achieved Acc 100% and 19 papers achieved accuracy in range 90% - 99.5%. US has been used with SVM in 14 papers, the Acc ranges from 75.5% to 98.3%. Also, 9 papers are using MRI combined with SVM with maximum Acc value of 98% and the least achieved Acc was 82.8%. And 6 papers used microscope-SVM and the Acc registered is 96.9%. Only 2 papers are using IRT-SVM and the achieved Acc were 88.1% and 61.8%.

ANN is used with DM, US, MRI and microscopic images; it is used with DM in 34 papers and with US in 4 papers, one of them

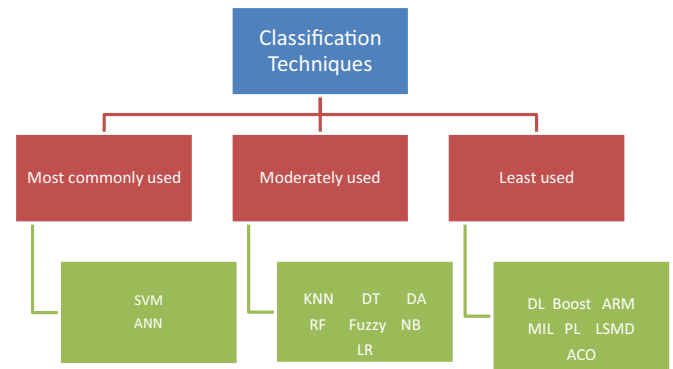


Fig. 11. Classification techniques categorized according to frequency of usage in CAD systems for breast cancer.

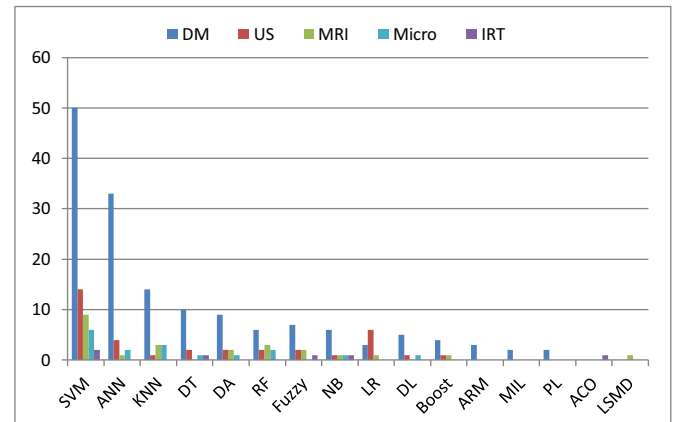


Fig. 12. The number of used MLTs with different modalities.

used both DM and US, only one paper with MRI and 2 papers with microscopic. In 20 papers with DM-ANN the Acc ranges from 90% to 98.14%. In the rest of the papers that stated the Acc values, its value ranges from 71% to 89.38%. The highest achieved Acc with US-ANN is 94%.

KNN has been used in 21 papers, 14 with DM with the highest Acc registered 98.69%. One publication combined KNN with US, 3 combined with MRI, and 3 combined it with microscopic modality. Table 8 shows the number of used MLTs distributed on different modalities and the highest registered Acc of each combination. Fig. 12 shows the number of used MLTs versus different modalities.

## 5. Conclusions and future work

This systematic review aims to help researchers in innovating and developing CAD systems to assist the medical society in detection/diagnosis and early treatment of breast cancer. The state-of-the-art of the MLTs that have been used for CAD to detect breast cancer from different image modalities has been explored. According to the collected data, it is difficult to comprehensively compare methods with each other due to several factors. Some of these factors are: the databases used for assessment, the samples of images selected for assessment, the number of samples used, the assessment approach (validation methodology, training and testing set) used. Moreover, the tuning of parameters involved in different methods varies from one method to the other, thus adding another obstacle for fair comparison between various methods. Generally, among the classifiers mentioned in the literature, SVM classifier has been used extensively for breast tissue classification purposes. The usage of artificial intelligence methods is increasing because

**Table 8**

The number of used MLTs with different modalities and the highest achieved Acc.

Total	SVM	ANN	KNN	DT	DA	RF	fuzzy	NB	LR	DL	boost	ARM	MIL	PL	ACO	LSMD
DM	50	33	14	10	9	6	7	6	3	5	4	3	2	2		
	100%	98.14%	98.69%	97.51%	99.75%	99.9%	95.11%	89.3%	–	96.7%	91.43%	98%	91.1%	100%		
US	14	4	1	2	2	2	2	1	6	1	1					
	98.3%	94%	–	–	88.4%	78.5%	90–92	–	88%	93.4%	–					
MRI	9	1	3		2	3	2	1	1		1					1/–
	98%	–	74.4%		–	–	100%	–	–		–					–
micro	6	2	3	1	1	2		1		1						
	96.9%	87.1%	96–100%	96–100%	100%	90%		96–100%	–	86%						
IRT	2			1			1	1							1	
	88.1%			90.1%			–	–							79.52%	

of the effectiveness in classification and detection schemes assisting experts in the medical field.

Clinically, in countries that are routinely using CAD, there is disagreement over the feasibility of using it as a result of some problems such as time and cost increase due to false positive and lack of training that lead to ignore suspicious lesions. Otherwise, in other countries, it is truly challenging to bring CADs into clinics by persuading the physicians with the effect of CADs as a supporting tool to improve physicians' performance. If some requirements are fulfilled then the CAD system may become widely applied in clinical practices without quarrel. These requirements are that the CAD should save the radiologists and physicians time and effort, and it should be affordable. Advances in CADs systems are to be obtained by their application and trial in clinics. Observing the pitfalls during the CADs clinical application will lead to improving their performance, thus reducing false positive that may lead to psychological, physical, and economic costs, and reducing false negative readings that may cause neglecting of treatment.

In the future work, it is recommended to have standardized public image databases that contain images from different image modalities for the same case to support the dependency of more than one image modality in classification task and combine information from multiple views. It will be wealthy if they contain DNA sequence of cases. This will enable CADs to provide results that depend on different perspectives concerning different modalities and even sequences.

Moreover, deep learning classifier is a promising trend that appeared in the recent years. There is an increased interest in applying it in CADs systems in the last couple of years. Also swarm intelligence is worth studying as it was rarely applied in the investigated publication in CADs systems. Developing MLT-CAD system that combines more than one image modality is a necessity. Also developing CAD systems using 3D mammography which is a new trend that may help to improve CAD efficiency is an important issue. These points should be considered to develop CAD systems in the future.

### Conflict of interest

The authors have no conflict of interests to declare.

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### References

- [1] WHO, in: Latest World Cancer Statistics Global Cancer Burden Rises to 14.1 million New Cases in 2012: Marked Increase in Breast Cancers Must Be Addressed, World Health Organization, 2013, p. 12.
- [2] F. Bray, et al., Global estimates of cancer prevalence for 27 sites in the adult population in 2008, *Int. J. Cancer* 132 (5) (2013) 1133–1145.
- [3] M. Schneider, M. Yaffe, Better detection: improving our chances, *Digital Mammography: 5th International Workshop on Digital Mammography*, 2000.
- [4] H. Li, et al., Computerized radiographic mass detection. II. Decision support by featured database visualization and modular neural networks, *IEEE Trans. Med. Imaging* 20 (4) (2001) 302–313.
- [5] I. Leichter, et al., Optimizing parameters for computer-aided diagnosis of microcalcifications at mammography, *Acad. Radiol.* 7 (6) (2000) 406–412.
- [6] A.K. Mohanty, M.R. Senapati, S.K. Lenka, RETRACTED ARTICLE: an improved data mining technique for classification and detection of breast cancer from mammograms, *Neural Comput. Appl.* 22 (1) (2013) 303–310.
- [7] J. Tang, et al., Computer-aided detection and diagnosis of breast cancer with mammography: recent advances, *IEEE Trans. Inf. Technol. Biomed.* 13 (2) (2009) 236–251.
- [8] A. Horsch, A. Apfelmeier, M. Elter, Needs assessment for next generation computer-aided mammography reference image databases and evaluation studies, *Int. J. Comput. Assisted Radiol. Surg.* 6 (6) (2011) 749.
- [9] A. Sadaf, et al., Performance of computer-aided detection applied to full-field digital mammography in detection of breast cancers, *Eur. J. Radiol.* 77 (3) (2011) 457–461.
- [10] B. van Ginneken, et al., Comparing and combining algorithms for computer-aided detection of pulmonary nodules in computed tomography scans: the ANODE09 study, *Med. Image Anal.* 14 (6) (2010) 707–722.
- [11] K. Doi, Computer-aided diagnosis in medical imaging: historical review, current status and future potential, *Comput. Med. Imaging Graph.* 31 (4) (2007) 198–211.
- [12] K. Doi, Diagnostic imaging over the last 50 years: research and development in medical imaging science and technology, *Phys. Med. Biol.* 51 (13) (2006) R5.
- [13] M.L. Giger, H.P. Chan, J. Boone, Anniversary paper: history and status of CAD and quantitative image analysis: the role of medical physics and AAPM, *Med. Phys.* 35 (12) (2008) 5799–5820.
- [14] R. Fusco, et al., Pattern recognition approaches for breast cancer DCE-MRI classification: a systematic review, *J. Med. Biol. Eng.* 36 (4) (2016) 449–459.
- [15] A. Jalalian, et al., Computer-aided detection/diagnosis of breast cancer in mammography and ultrasound: a review, *Clin. Imaging* 37 (3) (2013) 420–426.
- [16] J. Han, M. Kamber, *Data Mining: Concepts and Techniques*, 2006.
- [17] S.A. Medjahed, T.A. Saadi, A. Benyettou, Breast cancer diagnosis by using k-nearest neighbor with different distances and classification rules, *Int. J. Comput. Appl.* 62 (1) (2013) 1–5.
- [18] F. Amato, et al., *Artificial Neural Networks in Medical Diagnosis*, Elsevier, 2013.
- [19] A. Thakur, V. Mishra, S.K. Jain, Feed forward artificial neural network: tool for early detection of ovarian cancer, *Sci. Pharm.* 79 (3) (2011) 493–506.
- [20] P. Bethapudi, E.S. Reddy, K.V. Varma, Classification of breast cancer using gini index based fuzzy supervised learning in quest decision tree algorithm, *Int. J. Comput. Appl.* 111 (14) (2015) 50–57.
- [21] M. Shouman, T. Turner, R. Stocker, Using decision tree for diagnosing heart disease patients, in: *Proceedings of the Ninth Australasian Data Mining Conference—Volume 121*, Australian Computer Society, Inc., 2011.
- [22] D. Tomar, S. Agarwal, Hybrid feature selection based weighted least squares twin support vector machine approach for diagnosing breast cancer, hepatitis, and diabetes, *Adv. Artif. Neural Syst.* 2015 (2015) 1.



- [23] X. Gao, et al., The method and efficacy of support vector machine classifiers based on texture features and multi-resolution histogram from 18 F-FDG PET-CT images for the evaluation of mediastinal lymph nodes in patients with lung cancer, *Eur. J. Radiol.* 84 (2) (2015) 312–317.
- [24] S.J.S. Gardezi, et al., Mammogram classification using dynamic time warping, *Multimedia Tools Appl.* 76 (282) (2017) 1–22.
- [25] S. Khan, et al., A comparison of different Gabor feature extraction approaches for mass classification in mammography, *Multimedia Tools Appl.* 76 (1) (2017) 33–57.
- [26] N.F. Abubacker, et al., An integrated method of associative classification and neuro-fuzzy approach for effective mammographic classification, *Neural Comput. Appl.* 28 (12) (2016) 1–14.
- [27] S. Aminikhanghahi, et al., A new fuzzy Gaussian mixture model (FGMM) based algorithm for mammography tumor image classification, *Multimedia Tools Appl.* (2016) 1–15.
- [28] J. Diz, G. Marreiros, A. Freitas, Applying data mining techniques to improve breast cancer diagnosis, *J. Med. Syst.* 40 (9) (2016) 203.
- [29] A.C. Phadke, P.P. Rege, Fusion of local and global features for classification of abnormality in mammograms, *Sādhanā* 41 (4) (2016) 385–395.
- [30] M. Shibusawa, et al., The usefulness of a computer-aided diagnosis scheme for improving the performance of clinicians to diagnose non-mass lesions on breast ultrasonographic images, *J. Med. Ultrason.* 43 (3) (2016) 387–394.
- [31] S.P. Singh, S. Urooj, An improved CAD system for breast cancer diagnosis based on generalized pseudo-zernike moment and Ada-DEWNN classifier, *J. Med. Syst.* 40 (4) (2016) 105.
- [32] S.A. Waugh, et al., Magnetic resonance imaging texture analysis classification of primary breast cancer, *Eur. Radiol.* 26 (2) (2016) 322–330.
- [33] L. Cai, et al., Robust phase-based texture descriptor for classification of breast ultrasound images, *Biomed. Eng. Online* 14 (1) (2015) 26.
- [34] J.Y. Choi, A generalized multiple classifier system for improving computer-aided classification of breast masses in mammography, *Biomed. Eng. Lett.* 5 (4) (2015) 251–262.
- [35] J. de Nazaré Silva, et al., Automatic detection of masses in mammograms using quality threshold clustering, correlogram function, and SVM, *J. Digital Imaging* 28 (3) (2015) 323–337.
- [36] M. Dong, et al., An efficient approach for automated mass segmentation and classification in mammograms, *J. Digital Imaging* 28 (5) (2015) 613–625.
- [37] M. Hamoud, H.F. Merouani, L. Laimeche, The power laws: Zipf and inverse Zipf for automated segmentation and classification of masses within mammograms, *Evolving Syst.* 6 (3) (2015) 209–227.
- [38] X. Liu, et al., Microcalcification detection in full-field digital mammograms with PFCM clustering and weighted SVM-based method, *EURASIP J. Adv. Signal Process.* 2015 (1) (2015) 73.
- [39] K.M. Prabusankar, P. Thirumorthy, R. Manavalan, Assessment of combined textural and morphological features for diagnosis of breast masses in ultrasound, *Human-Centric Comput. Inf. Sci.* 5 (1) (2015) 12.
- [40] S. Sharma, P. Khanna, Computer-aided diagnosis of malignant mammograms using zernike moments and SVM, *J. Digital Imaging* 28 (1) (2015) 77–90.
- [41] W.-J. Wu, S.-W. Lin, W.K. Moon, An artificial immune system-based support vector machine approach for classifying ultrasound breast tumor images, *J. Digital Imaging* 28 (5) (2015) 576–585.
- [42] A.T. Azar, S.A. El-Said, Performance analysis of support vector machines classifiers in breast cancer mammography recognition, *Neural Comput. Appl.* 24 (5) (2014) 1163–1177.
- [43] S.M.A. Beheshti, et al., An efficient fractal method for detection and diagnosis of breast masses in mammograms, *J. Digital Imaging* 27 (5) (2014) 661–669.
- [44] H. Cai, et al., Diagnostic assessment by dynamic contrast-enhanced and diffusion-weighted magnetic resonance in differentiation of breast lesions under different imaging protocols, *BMC Cancer* 14 (1) (2014) 366.
- [45] Y.-H. Huang, et al., Computerized breast mass detection using multi-scale Hessian-based analysis for dynamic contrast-enhanced MRI, *J. Digital Imaging* 27 (5) (2014) 649–660.
- [46] G. Schaefer, ACO classification of thermogram symmetry features for breast cancer diagnosis, *Memetic Comput.* 6 (3) (2014) 207–212.
- [47] L. Vivona, et al., Fuzzy technique for microcalcifications clustering in digital mammograms, *BMC Med. Imaging* 14 (1) (2014) 23.
- [48] M. Tan, J. Pu, B. Zheng, Optimization of breast mass classification using sequential forward floating selection (SFFS) and a support vector machine (SVM) model, *Int. J. Comput. Assisted Radiol. Surg.* 9 (6) (2014) 1005–1020.
- [49] A.T. Azar, S.M. El-Metwally, Decision tree classifiers for automated medical diagnosis, *Neural Comput. Appl.* 23 (7) (2013) 2387–2403.
- [50] A.T. Azar, S.A. El-Said, Probabilistic neural network for breast cancer classification, *Neural Comput. Appl.* 23 (6) (2013) 1737–1751.
- [51] K. Drukker, et al., Quantitative ultrasound image analysis of axillary lymph node status in breast cancer patients, *Int. J. Comput. Assisted Radiol. Surg.* 8 (6) (2013) 895–903.
- [52] A. García-Manso, et al., Consistent performance measurement of a system to detect masses in mammograms based on blind feature extraction, *Biomed. Eng. Online* 12 (1) (2013) 2.
- [53] A. Hizukuri, et al., Computerized determination scheme for histological classification of breast mass using objective features corresponding to clinicians' subjective impressions on ultrasonographic images, *J. Digital Imaging* 26 (5) (2013) 958–970.
- [54] S. Hoffmann, et al., Automated analysis of non-mass-enhancing lesions in breast MRI based on morphological, kinetic, and spatio-temporal moments and joint segmentation-motion compensation technique, *EURASIP J. Adv. Signal Process.* 2013 (1) (2013) 172.
- [55] R. Hupse, et al., Standalone computer-aided detection compared to radiologists' performance for the detection of mammographic masses, *Eur. Radiol.* 23 (1) (2013) 93–100.
- [56] A.D. Masmoudi, et al., LBPV descriptors-based automatic ACR/BIRADS classification approach, *EURASIP J. Image Video Process.* 2013 (1) (2013) 19.
- [57] A.K. Mohanty, et al., RETRACTED ARTICLE: mass classification method in mammograms using correlated association rule mining, *Neural Comput. Appl.* 23 (2) (2013) 273–281.
- [58] W.K. Moon, et al., Quantitative ultrasound analysis for classification of BI-RADS category 3 breast masses, *J. Digital Imaging* 26 (6) (2013) 1091–1098.
- [59] F. Retter, et al., Computer-aided diagnosis for diagnostically challenging breast lesions in DCE-MRI based on image registration and integration of morphologic and dynamic characteristics, *EURASIP J. Adv. Signal Process.* 2013 (1) (2013) 157.
- [60] M.R. Senapati, P.K. Dash, Local linear wavelet neural network based breast tumor classification using firefly algorithm, *Neural Comput. Appl.* 22 (7) (2013) 1591–1598.
- [61] M.R. Senapati, et al., Local linear wavelet neural network for breast cancer recognition, *Neural Comput. Appl.* 22 (1) (2013) 125–131.
- [62] K.P. Sidiropoulos, et al., Multimodality GPU-based computer-assisted diagnosis of breast cancer using ultrasound and digital mammography images, *Int. J. Comput. Assisted Radiol. Surg.* 8 (4) (2013) 547–560.
- [63] U.R. Acharya, et al., Thermography based breast cancer detection using texture features and support vector machine, *J. Med. Syst.* 36 (3) (2012) 1503–1510.
- [64] J. Dheeba, S.T. Selvi, A swarm optimized neural network system for classification of microcalcification in mammograms, *J. Med. Syst.* 36 (5) (2012) 3051–3061.
- [65] J. Dheeba, S. Tamil Selvi, An improved decision support system for detection of lesions in mammograms using differential evolution optimized wavelet neural network, *J. Med. Syst.* 36 (5) (2012) 3223–3232.
- [66] J. Ding, et al., Breast ultrasound image classification based on multiple-instance learning, *J. Digital Imaging* 25 (5) (2012) 620–627.
- [67] W. Jian, X. Sun, S. Luo, Computer-aided diagnosis of breast microcalcifications based on dual-tree complex wavelet transform, *Biomed. Eng. Online* 11 (1) (2012) 96.
- [68] J.-B. Li, Mammographic image based breast tissue classification with kernel self-optimized fisher discriminant for breast cancer diagnosis, *J. Med. Syst.* 36 (4) (2012) 2235–2244.
- [69] R. Ramos-Pollán, et al., Discovering mammography-based machine learning classifiers for breast cancer diagnosis, *J. Med. Syst.* 36 (4) (2012) 2259–2269.
- [70] F.S. Zakeri, H. Behnam, N. Ahmadinejad, Classification of benign and malignant breast masses based on shape and texture features in sonography images, *J. Med. Syst.* 36 (3) (2012) 1621–1627.
- [71] Y. Zhang, et al., Building an ensemble system for diagnosing masses in mammograms, *Int. J. Comput. Assisted Radiol. Surg.* 7 (2) (2012) 323–329.
- [72] W.K. Moon, et al., The adaptive computer-aided diagnosis system based on tumor sizes for the classification of breast tumors detected at screening ultrasound, *Ultrasonics* 76 (2017) 70–77.
- [73] T. Kooi, et al., Large scale deep learning for computer aided detection of mammographic lesions, *Med. Image Anal.* 35 (2017) 303–312.
- [74] P. Casti, et al., Towards localization of malignant sites of asymmetry across bilateral mammograms, *Comput. Methods Prog. Biomed.* 140 (2017) 11–18.
- [75] M. Abdel-Nasser, et al., Breast tumor classification in ultrasound images using texture analysis and super-resolution methods, *Eng. Appl. Artif. Intell.* 59 (March) (2017) 84–92.
- [76] Q. Zhang, et al., Deep learning based classification of breast tumors with shear-wave elastography, *Ultrasonics* 72 (2016) 150–157.
- [77] W. Xie, Y. Li, Y. Ma, Breast mass classification in digital mammography based on extreme learning machine, *Neurocomputing* 173 (2016) 930–941.
- [78] W. Sun, et al., Enhancing deep convolutional neural network scheme for breast cancer diagnosis with unlabeled data, *Comput. Med. Imaging Graph.* (2016).
- [79] J. Shan, et al., Computer-aided diagnosis for breast ultrasound using computerized BI-RADS features and machine learning methods, *Ultrason. Med. Biol.* 42 (4) (2016) 980–988.
- [80] R. Rouhi, M. Jafari, Classification of benign and malignant breast tumors based on hybrid level set segmentation, *Expert Syst. Appl.* 46 (2016) 45–59.
- [81] U. Raghavendra, et al., Application of gabor wavelet and locality sensitive discriminant analysis for automated identification of breast cancer using digitized mammogram images, *Appl. Soft Comput.* 46 (2016) 151–161.
- [82] W. Peng, R. Mayorga, E. Hussein, An automated confirmatory system for analysis of mammograms, *Comput. Methods Prog. Biomed.* 125 (2016) 134–144.
- [83] H. Mahersia, H. Boulehmi, K. Hamrouni, Development of intelligent systems based on Bayesian regularization network and neuro-fuzzy models for mass detection in mammograms: a comparative analysis, *Comput. Methods Prog. Biomed.* 126 (2016) 46–62.
- [84] Z. Jiao, et al., A deep feature based framework for breast masses classification, *Neurocomputing* 197 (2016) 221–231.
- [85] J. Arevalo, et al., Representation learning for mammography mass lesion classification with convolutional neural networks, *Comput. Methods Prog. Biomed.* 127 (2016) 248–257.

- [86] D.O.T. Bruno, et al., LBP operators on curvelet coefficients as an algorithm to describe texture in breast cancer tissues, *Expert Syst. Appl.* 55 (2016) 329–340.
- [87] W. Sun, et al., Computerized breast cancer analysis system using three stage semi-supervised learning method, *Comput. Methods Prog. Biomed.* 135 (2016) 77–88.
- [88] L. Jeleń, et al., Influence of feature set reduction on breast cancer malignancy classification of fine needle aspiration biopsies, *Comput. Biol. Med.* 79 (2016) 80–91.
- [89] C.-M. Lo, et al., Feasibility testing: three-dimensional tumor mapping in different orientations of automated breast ultrasound, *Ultrasound Med. Biol.* 42 (5) (2016) 1201–1210.
- [90] M. Abdel-Nasser, et al., Analysis of tissue abnormality and breast density in mammographic images using a uniform local directional pattern, *Expert Syst. Appl.* 42 (24) (2015) 9499–9511.
- [91] C.-M. Lo, et al., Quantitative breast lesion classification based on multichannel distributions in shear-wave imaging, *Comput. Methods Prog. Biomed.* 122 (3) (2015) 354–361.
- [92] X. Liu, Z. Zeng, A new automatic mass detection method for breast cancer with false positive reduction, *Neurocomputing* 152 (2015) 388–402.
- [93] A. Gubern-Mérida, et al., Automated localization of breast cancer in DCE-MRI, *Med. Image Anal.* 20 (1) (2015) 265–274.
- [94] Q. Huang, et al., Automatic segmentation of breast lesions for interaction in ultrasonic computer-aided diagnosis, *Inf. Sci.* 314 (2015) 293–310.
- [95] F. Pak, H.R. Kanan, A. Alikhassi, Breast cancer detection and classification in digital mammography based on non-sampled contourlet transform (NSCT) and super resolution, *Comput. Methods Prog. Biomed.* 122 (2) (2015) 89–107.
- [96] S. Dhahbi, W. Barhoumi, E. Zagrouba, Breast cancer diagnosis in digitized mammograms using curvelet moments, *Comput. Biol. Med.* 64 (2015) 79–90.
- [97] F.S.S. de Oliveira, et al., Classification of breast regions as mass and non-mass based on digital mammograms using taxonomic indexes and SVM, *Comput. Biol. Med.* 57 (2015) 42–53.
- [98] C.-M. Lo, et al., Quantitative breast mass classification based on the integration of B-mode features and strain features in elastography, *Comput. Biol. Med.* 64 (2015) 91–100.
- [99] S.K. Wajid, A. Hussain, Local energy-based shape histogram feature extraction technique for breast cancer diagnosis, *Expert Syst. Appl.* 42 (20) (2015) 6990–6999.
- [100] M. Pratiwi, J. Harefa, S. Nanda, Mammograms classification using gray-level co-occurrence matrix and radial basis function neural network, *Proc. Comput. Sci.* 59 (2015) 83–91.
- [101] S.S. Venkatesh, et al., Going beyond a first reader: a machine learning methodology for optimizing cost and performance in breast ultrasound diagnosis, *Ultrasound Med. Biol.* 41 (12) (2015) 3148–3162.
- [102] A. Chmielewski, P. Dufort, A.M. Scarnelo, A computerized system to assess axillary lymph node malignancy from sonographic images, *Ultrasound Med. Biol.* 41 (10) (2015) 2690–2699.
- [103] C.-M. Lo, et al., Intensity-invariant texture analysis for classification of bi-rads category 3 breast masses, *Ultrasound Med. Biol.* 41 (7) (2015) 2039–2048.
- [104] W. Sun, et al., Prediction of near-term risk of developing breast cancer using computerized features from bilateral mammograms, *Comput. Med. Imaging Graph.* 38 (5) (2014) 348–357.
- [105] N. Váñez, et al., Breast density classification to reduce false positives in CADE systems, *Comput. Methods Prog. Biomed.* 113 (2) (2014) 569–584.
- [106] S. Ergin, O. Kilinc, A new feature extraction framework based on wavelets for breast cancer diagnosis, *Comput. Biol. Med.* 51 (2014) 171–182.
- [107] Z. Wang, et al., Breast tumor detection in digital mammography based on extreme learning machine, *Neurocomputing* 128 (2014) 175–184.
- [108] H. Mohamed, M.S. Mabrouk, A. Sharawy, Computer aided detection system for micro calcifications in digital mammograms, *Comput. Methods Prog. Biomed.* 116 (3) (2014) 226–235.
- [109] M.Z. Do Nascimento, et al., Classification of masses in mammographic image using wavelet domain features and polynomial classifier, *Expert Syst. Appl.* 40 (15) (2013) 6213–6221.
- [110] M. Kowal, et al., Computer-aided diagnosis of breast cancer based on fine needle biopsy microscopic images, *Comput. Biol. Med.* 43 (10) (2013) 1563–1572.
- [111] D.R. Ericeira, et al., Detection of masses based on asymmetric regions of digital bilateral mammograms using spatial description with variogram and cross-variogram functions, *Comput. Biol. Med.* 43 (8) (2013) 987–999.
- [112] J. Milenković, et al., Characterization of spatiotemporal changes for the classification of dynamic contrast-enhanced magnetic-resonance breast lesions, *Artif. Intell. Med.* 58 (2) (2013) 101–114.
- [113] M. Tan, et al., Prediction of near-term breast cancer risk based on bilateral mammographic feature asymmetry, *Acad. Radiol.* 20 (12) (2013) 1542–1550.
- [114] A.E. Hassanien, T.-H. Kim, Breast cancer MRI diagnosis approach using support vector machine and pulse coupled neural networks, *J. Appl. Logic* 10 (4) (2012) 277–284.
- [115] S. Suzuki, et al., Mass detection using deep convolutional neural network for mammographic computer-aided diagnosis, 2016 55th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE), IEEE, 2016.
- [116] G. Quellec, et al., Multiple-instance learning for anomaly detection in digital mammography, *IEEE Trans. Med. Imaging* 35 (7) (2016) 1604–1614.
- [117] C. Hiba, Z. Hamid, A. Omar, An improved breast tissue density classification framework using bag of features model, 2016 4th IEEE International Colloquium on Information Science and Technology (CISIT), IEEE, 2016.
- [118] Y. Chen, Q. Huang, An approach based on biclustering and neural network for classification of lesions in breast ultrasound, *International Conference on Advanced Robotics and Mechatronics (ICARM)*, IEEE, 2016.
- [119] F. Burling-Claridge, M. Iqbal, M. Zhang, Evolutionary algorithms for classification of mammographic densities using local binary patterns and statistical features, 2016 IEEE Congress on Evolutionary Computation (CEC), IEEE, 2016.
- [120] F.A. Spanhol, et al., A dataset for breast cancer histopathological image classification, *IEEE Trans. Biomed. Eng.* 63 (7) (2016) 1455–1462.
- [121] N. Zemmam, N. Azizi, M. Sellami, CAD system for classification of mammographic abnormalities using transductive semi supervised learning algorithm and heterogeneous features, 2015 12th International Symposium on Programming and Systems (ISPS), IEEE, 2015.
- [122] K. Vaidehi, T. Subashini, Automatic classification and retrieval of mammographic tissue density using texture features, 2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO), IEEE, 2015.
- [123] G. Schaefer, T. Nakashima, Strategies for addressing class imbalance in ensemble classification of thermography breast cancer features, 2015 IEEE Congress on Evolutionary Computation (CEC), IEEE, 2015.
- [124] P.B. Ribeiro, et al., Unsupervised breast masses classification through optimum-path forest, 2015 IEEE 28th International Symposium on Computer-Based Medical Systems (CBMS), IEEE, 2015.
- [125] V. Ponomaryov, Computer-aided detection system based on PCA/SVM for diagnosis of breast cancer lesions, 2015 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON), IEEE, 2015.
- [126] L.M. Mina, N.A.M. Isa, Breast abnormality detection in mammograms using Artificial Neural Network, 2015 International Conference on Computer, Communications, and Control Technology (I4CT), IEEE, 2015.
- [127] A.F. Khalaf, I.A. Yassine, Novel features for microcalcification detection in digital mammogram images based on wavelet and statistical analysis, 2015 IEEE International Conference on Image Processing (ICIP), IEEE, 2015.
- [128] A.F. Khalaf, I.A. Yassine, Spectral correlation analysis for microcalcification detection in digital mammogram images, 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI), IEEE, 2015.
- [129] I.I. Esener, S. Ergin, T. Yüksel, A new ensemble of features for breast cancer diagnosis, 2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), IEEE, 2015.
- [130] M.E. Elmann, Y.M. Kadah, Implementation of practical computer aided diagnosis system for classification of masses in digital mammograms, 2015 International Conference on Computing, Control, Networking, Electronics and Embedded Systems Engineering (ICCNSEE), IEEE, 2015.
- [131] R.S. de la Rosa, et al., Multiple-instance learning for breast cancer detection in mammograms, 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2015.
- [132] J.D. Calderón-Contreras, et al., A fuzzy computer aided diagnosis system using breast thermography, 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI), IEEE, 2015.
- [133] N.G.B. Ayed, et al., New developments in the diagnostic procedures to reduce prospective biopsies breast, 2015 International Conference on Advances in Biomedical Engineering (ICABME), IEEE, 2015.
- [134] A. Addoui, et al., A comparison of multi-resolution and multi-orientation for breast cancer diagnosis in the full-field digital mammogram, 2015 27th International Conference on Microelectronics (ICM), IEEE, 2015.
- [135] H. Su, et al., Robust automatic breast cancer staging using a combination of functional genomics and image-omics, 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2015.
- [136] S.K. Wajid, A. Hussain, B. Luo, An efficient computer aided decision support system for breast cancer diagnosis using echo state network classifier, 2014 IEEE Symposium on Computational Intelligence in Healthcare and e-health (CICARE), IEEE, 2014.
- [137] A. Tashk, et al., A CAD mitosis detection system from breast cancer histology images based on fused features, 2014 22nd Iranian Conference on Electrical Engineering (ICEE), IEEE, 2014.
- [138] F. Soares, et al., Classification of breast masses on contrast-enhanced magnetic resonance images through log detrended fluctuation cumulant-based multifractal analysis, *IEEE Syst. J.* 8 (3) (2014) 929–938.
- [139] B. Sanae, A.K. Mounir, F. Youssef, Statistical block-based DWT features for digital mammograms classification, 2014 9th International Conference on Intelligent Systems: Theories and Applications (SITA-14), IEEE, 2014.
- [140] E. Rodrigues, et al., Comparing results of thermographic images based diagnosis for breast diseases, 2014 International Conference on Systems, Signals and Image Processing (IWSSIP), IEEE, 2014.
- [141] H.A. Nugroho, et al., Analysis of computer aided diagnosis on digital mammogram images, 2014 International Conference on Computer, Control, Informatics and Its Applications, IEEE, 2014.
- [142] H.A. Nugroho, et al., Identification of malignant masses on digital mammogram images based on texture feature and correlation based feature selection, 2014 6th International Conference on Information Technology and Electrical Engineering (ICITEE), IEEE, 2014.
- [143] C.-M. Lin, et al., Breast nodules computer-aided diagnostic system design using fuzzy cerebellar model neural networks, *IEEE Trans. Fuzzy Syst.* 22 (3) (2014) 693–699.

- [144] J.A. Jaleel, S. Salim, S. Archana, Textural features based computer aided diagnostic system for mammogram mass classification, 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICICCT), IEEE, 2014.
- [145] R. Chaieb, et al., Image features extraction for masses classification in mammograms, 2014 6th International Conference of Soft Computing and Pattern Recognition (SoCPar), IEEE, 2014.
- [146] N. Azizi, et al., A new hybrid method combining genetic algorithm and support vector machine classifier: application to CAD system for mammogram images, 2014 International Conference on Multimedia Computing and Systems (ICMCS), IEEE, 2014.
- [147] X. Liu, et al., An iterated Laplacian based semi-supervised dimensionality reduction for classification of breast cancer on ultrasound images, 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2014.
- [148] J. Wang, Y. Yang, R.M. Nishikawa, Reduction of false positive detection in clustered microcalcifications, 2013 IEEE International Conference on Image Processing, IEEE, 2013.
- [149] M. Radovic, et al., Application of data mining algorithms for mammogram classification, 2013 IEEE 13th International Conference on Bioinformatics and Bioengineering (BIBE), IEEE, 2013.
- [150] S. Liu, et al., An effective computer aided diagnosis system using B-Mode and color Doppler flow imaging for breast cancer, Visual Communications and Image Processing (VCIP), 2013, IEEE, 2013.
- [151] N. Azizi, et al., Kernel based classifiers fusion with features diversity for breast masses classification, 2013 8th International Workshop on Systems, Signal Processing and their Applications (WoSSPA), IEEE, 2013.
- [152] C. Yao, et al., Adaptive kernel learning for detection of clustered microcalcifications in mammograms, 2012 IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI), IEEE, 2012.
- [153] M. Rizzi, et al., Health care improvement: comparative analysis of two CAD systems in mammographic screening, IEEE Trans. Syst. Man Cybern. Part A Syst. Humans 42 (6) (2012) 1385–1395.
- [154] Y. Kabbadj, F. Regragui, M.M. Himmi, Microcalcification detection using a fuzzy inference system and support vector machines, 2012 International Conference on Multimedia Computing and Systems (ICMCS), IEEE, 2012.
- [155] M.I. Daoud, et al., A fusion-based approach for breast ultrasound image classification using multiple-ROI texture and morphological analyses, Comput. Math. Methods Med. 2016 (2016) 1–12.
- [156] H. Rezaeilouyeh, A. Mollahosseini, M.H. Mahoor, Microscopic medical image classification framework via deep learning and shearlet transform, J. Med. Imaging 3 (4) (2016) 044501.
- [157] J.J. Mordang, et al., Reducing false positives of microcalcification detection systems by removal of breast arterial calcifications, Med. Phys. 43 (4) (2016) 1676–1687.
- [158] M. Radovic, et al., Parameter optimization of a computer-aided diagnosis system for detection of masses on digitized mammograms, Technol. Health Care 23 (6) (2015) 757–774.
- [159] C. Gallego-Ortiz, A.L. Martel, Improving the accuracy of computer-aided diagnosis for breast MR imaging by differentiating between mass and nonmass lesions, Radiology 278 (3) (2015) 679–688.
- [160] W.K. Moon, et al., Computer-aided diagnosis for distinguishing between triple-negative breast cancer and fibroadenomas based on ultrasound texture features, Med. Phys. 42 (6) (2015) 3024–3035.
- [161] M.M. Fernández-Carrobles, et al., A CAD system for the acquisition and classification of breast TMA in pathology, Stud. Health Technol. Inf. 210 (2015) 756–760.
- [162] M. Tan, et al., A new approach to develop computer-aided detection schemes of digital mammograms, Phys. Med. Biol. 60 (11) (2015) 4413.
- [163] D.-R. Chen, C.-L. Chien, Y.-F. Kuo, Computer-aided assessment of tumor grade for breast cancer in ultrasound images, Comput. Math. Methods Med. 2015 (2015) 1–6.
- [164] Q. Yang, et al., A new quantitative image analysis method for improving breast cancer diagnosis using DCE-MRI examinations, Med. Phys. 42 (1) (2015) 103–109.
- [165] P. Li, et al., Breast cancer early diagnosis based on hybrid strategy, Biomed. Mater. Eng. 24 (6) (2014) 3397–3404.
- [166] D. Saraswathi, E. Srinivasan, A CAD system to analyse mammogram images using fully complex-valued relaxation neural network ensembled classifier, J. Med. Eng. Technol. 38 (7) (2014) 359–366.
- [167] S.C. Agner, et al., Computerized image analysis for identifying triple-negative breast cancers and differentiating them from other molecular subtypes of breast cancer on dynamic contrast-enhanced MR images: a feasibility study, Radiology 272 (1) (2014) 91–99.
- [168] W.A. Weiss, et al., Residual analysis of the water resonance signal in breast lesions imaged with high spectral and spatial resolution (HiSS) MRI: a pilot study, Med. Phys. 41 (1) (2014) 012303–1–012303–6.
- [169] N. Bhooshan, et al., Potential of computer-aided diagnosis of high spectral and spatial resolution (HiSS) MRI in the classification of breast lesions, J. Magn. Reson. Imaging 39 (1) (2014) 59–67.
- [170] C. Loukas, et al., Breast cancer characterization based on image classification of tissue sections visualized under low magnification, Comput. Math. Methods Med. 2013 (2013) 1–7.
- [171] R.M. Rangayyan, S. Banik, J.L. Desautels, Detection of architectural distortion in prior mammograms via analysis of oriented patterns, J. Visual. Exp. (78) (2013) e50341, 1–19, doi:10.3791/50341.
- [172] K. Ganesan, et al., Decision support system for breast cancer detection using mammograms, Proc. Inst. Mech. Eng. Part H 227 (7) (2013) 721–732.
- [173] H.C. Cho, et al., A similarity study of content-based image retrieval system for breast cancer using decision tree, Med. Phys. 40 (1) (2013) 012901–1–012901–13.
- [174] W.J. Singh, B. Nagarajan, Automatic diagnosis of mammographic abnormalities based on hybrid features with learning classifier, Comput. Methods Biomech. Biomed. Eng. 16 (7) (2013) 758–767.
- [175] H. Jing, Y. Yang, R.M. Nishikawa, Retrieval boosted computer-aided diagnosis of clustered microcalcifications for breast cancer, Med. Phys. 39 (2) (2012) 676–685.
- [176] H.S. Tseng, et al., Speckle reduction imaging of breast ultrasound does not improve the diagnostic performance of morphology-based CAD system, J. Clin. Ultrasound 40 (1) (2012) 1–6.
- [177] D. Saslow, et al., American Cancer Society guidelines for breast screening with MRI as an adjunct to mammography, CA Cancer J. Clin. 57 (2) (2007) 75–89.
- [178] V. Corsetti, et al., Evidence of the effect of adjunct ultrasound screening in women with mammography-negative dense breasts: interval breast cancers at 1 year follow-up, Eur. J. Cancer 47 (7) (2011) 1021–1026.
- [179] C.K. Kuhl, et al., Dynamic breast MR imaging: are signal intensity time course data useful for differential diagnosis of enhancing lesions? Radiology 211 (1) (1999) 101–110.
- [180] N. Pérez, et al., Improving the performance of machine learning classifiers for breast cancer diagnosis based on feature selection, 2014 Federated Conference on Computer Science and Information Systems (FedCSIS), IEEE, 2014.
- [181] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (7553) (2015) 436–444.
- [182] L. Deng, D. Yu, Deep learning: methods and applications, Found. Trends Signal Process. 7 (3–4) (2014) 197–387.
- [183] M. Heath, et al., The digital database for screening mammography, in: Proceedings of the 5th International Workshop on Digital Mammography, Medical Physics Publishing, 2000.
- [184] J. Suckling, et al., Mammographic Image Analysis Society (MIAS) Database v1. 21, 2015.
- [185] J.E. Oliveira, et al., Toward a standard reference database for computer-aided mammography, Medical Imaging, International Society for Optics and Photonics, 2008.
- [186] B.R.N. Matheus, H. Schiabel, Online mammographic images database for development and comparison of CAD schemes, J. Digital Imaging 24 (3) (2011) 500–506.
- [187] I.C. Moreira, et al., Inbreast: toward a full-field digital mammographic database, Acad. Radiol. 19 (2) (2012) 236–248.
- [188] M.G. Lopez, et al., BCDR: a breast cancer digital repository, 15th International Conference on Experimental Mechanics, 2012.