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REVIEW

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Systematic Review of Computing Approaches for Breast Cancer Detection Based Computer Aided Diagnosis Using Mammogram Images

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ABSTRACT

Breast cancer is one of the most prevalent types of cancer that plagues females. Mortality from breast cancer could be reduced by diagnosing and identifying it at an early stage. To detect breast cancer, various imaging modalities can be used, such as mammography. Computer-Aided Detection/Diagnosis (CAD) systems can assist an expert radiologist to diagnose breast cancer at an early stage. This paper introduces the findings of a systematic review that seeks to examine the state-of-the-art CAD systems for breast cancer detection. This review is based on 118 publications published in 2018–2021 and retrieved from major scientific publication databases while using a rigorous methodology of a systematic review. We provide a general description and analysis of existing CAD systems that use machine learning methods as well as their current state based on mammogram image modalities and classification methods. This systematic review presents all stages of CAD including pre-processing, segmentation, feature extraction, feature selection, and classification. We identify research gaps and outline recommendations for future research. This systematic review may be helpful for both clinicians, who use CAD systems for early diagnosis of breast cancer, as well as for researchers to find knowledge gaps and create more contributions for breast cancer diagnostics.

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Introduction

In 2015, the World Health Organization (WHO) announced that cancer is the second-largest contributor to global deaths. Breast cancer is the leading cause of cancer-related mortalities among women, trailed by colorectal and lung

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cancers (Mohammed et al. 2018) (Obaid et al. 2018). Breast cancer could be effectively diagnosed by employing a medical image examination. Various techniques of medical imaging may be used to examine Infrared Thermography (IRT), microscopic (histological) images, Magnetic Resonance Imaging (MRI), Ultrasound (US), and Digital Mammograms (DMs). To support radiologists in the method of interpreting images and identifying abnormalities, the usage of these modalities renders the process more effective by reducing mortality rates by 30–70%. Utilizing computerized feature extraction and classification that is devised as Computer-Aided Diagnosis (CAD) can become a beneficial technique for physicians in diagnosing and identifying abnormalities (Lahoura et al. 2021).

The primary role of a CAD system is to resolve the challenge of interpreting DMs. The goals of the system include effectively diagnose cancer and correctly interpret DMs. The CAD structures were developed to resolve the reliance of the operator in terms of diagnosis and decrease the cost of medical complementary technology (Mohanty, Senapati, and Lenka 2013). In the analysis on detecting cancer cells by CADs, 80% of the diagnosed cells were able to be detected without CAD, whereas the percent of tested tumor cells that were detected by CADs improved to 90% inside CAD (Horsch et al., 2011). Computerized diagnosis assesses the knowledge which a person or a computer gathers and offers an outcome to decide what kind of lesion is present and whether that is cancerous or not (Zeebaree et al., 2019).

Medical imaging technology with applying CAD-based Machine Learning Techniques (MLTs) is becoming common for cancer diagnosis and detection. To resolve the deficiency and ameliorate the efficiency of the CAD algorithms, the value of representation learning has been highlighted in recent years (Han et al., 2015) (Zeebaree et al., 2019). Deep Learning (DL) is one of representation learning strategies that use the hierarchical representations of image data as features. The main characteristic of DL is that it can take the content and encode it in a high-level of function representation (e.g., vector) without the need for post-processing (LeCun, Bengio, and Hinton 2015).

The main contribution of this review study is to introduce the recently introduced methods in state-of-art that concentrate on various Deep Learning Techniques (DLTs) and Machine Learning Techniques (MLTs) utilized in breast cancer identification based on DMs. The survey seeks to illustrate the issues that remain as to the applicability of DMs in the early detection of breast cancer. This study analyzes the most recent works that have discussed this topic and offers some perspective on current problems. We explore previous works that tackled these challenges, and eventually gives some observations and the potential directions of future study that would be taken to enable more progress. This systematic review is divided in two main parts. The first part introduces the methodology of this research and the CAD methodology with its steps as well as the ML and DL techniques. The second part of this research presents the review of each phase of the CAD system of the most recent studies.

Methodology

The main aim of this study is to identify state-of-the-art studies in the context of CAD systems, especially in the domain of breast cancer identification using DM images also, both Machine Learning (ML) and Deep Learning (DL) techniques as classifiers. To find the answer to the following research questions is the primary purpose of this study:

(1) What are DM breast cancer datasets mostly used on CAD systems?

(2) What techniques are used for each CAD stage?

(3) What challenges that are faced during each stage of CAD?

(4) What enhancement techniques are currently applied in the pre-processing stage?

(5) What segmentation techniques are applied to derive Region-of-Interest (ROI) in DM images?

(6) What type of features are extracted from DM images?

(7) What techniques are applied currently to extract features?

(8) What techniques are currently implemented to select the most relevant features?

(9) What classifiers are currently applied on DM breast cancer-based ML?

(10) What DL techniques are recently implemented for identifying breast cancer based on DM images?

(11) How they do their classification as benign/malignant, normal/abnormal, benign/ malignant/ normal, or Breast Imaging-Reporting and Data System (BI-RADS)?

(12) What are the evaluation measurements used for the evaluation of the mammogram imaging-based breast cancer CAD systems?

IEEE Xplore, Science Direct (Elsevier), Springer, and other databases were searched. Furthermore, these keywords and sentences were used:

mammogram breast cancer, mammogram classification, computer-aided diagnosis using mammogram, computer-aided detection using mammogram, CAD-based on mammogram, mammogram pre-processing for breast cancer, breast cancer segmentation using mammogram, breast cancer classification using mammogram, feature extraction technique for mammogram breast cancer, and feature selection technique for mammogram breast cancer.

Table 1 illustrates the number of articles published in each venue. All publications of this work were investigated and included in (Table) (5 -10) through the years from 2018 to 2020. Only works that have fulfilled the

Table 1. Published articles per year and journals.

Year	Journal	Publications	Year	Journal	Publications
2018	IEEE	15	2019	Springer Link	20
	Science Direct	12		Others	1
	Springer Link	5	2020	IEEE	8
	Others	8		Science Direct	10
2019	IEEE	11		Springer Link	10
	Science Direct	11		Others	7

following inclusion requirements are included: (1) Only breast cancer disease is included; (2) at least one CAD phase is considered; (3) utilized at least one method-based ML or DL as a classifier; (4) only DM modality is utilized; (5) the most popular performance measurement of the performed classifiers is presented; (6) only full published papers are included; (7) published papers between 2018 and 2020 with only one paper in 2021 are included. We excluded non-English papers, surveys, and books. At first, we retrieved 260 research papers, afterward, papers that irrelevant to the inclusion search criteria have been eliminated. Thus, this research includes only 118 papers (44.86%) whereas the rest of 145 papers are not well fitted for the quest criteria, then these papers have been excluded. The flow chart of the publication retrieval process is shown in Figure 1.

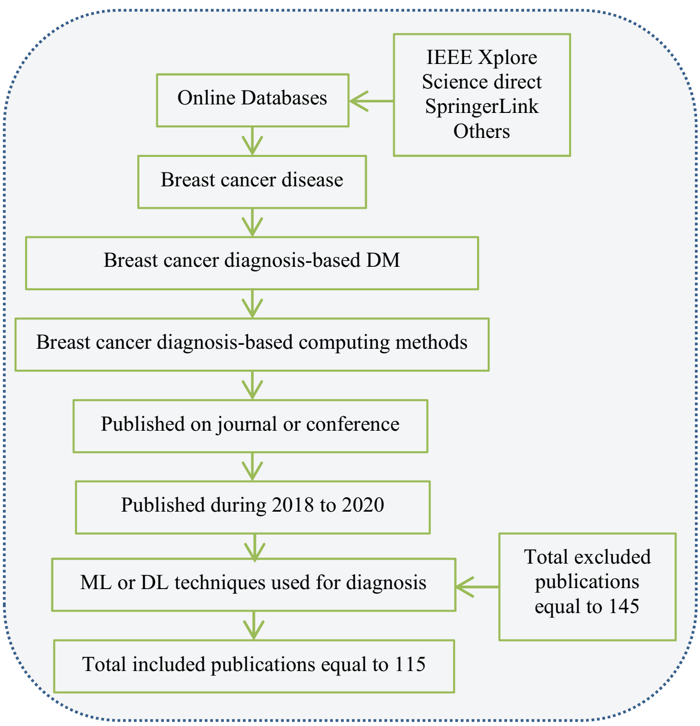

Figure 1. Flow chart-based summarization of publications selection process.

In this systematic review, more than hundreds of publications are reviewed from indexed and referred journals, conference proceedings and papers from main scientific databases such as IEEE Xplore, Web of Science, and Scopus previously mentioned. Scientific literature on mammographic image analysis contains informative and comprehensive studies. This review has been performed based on 12 main question that have been answered during the review process. We provide a survey-based CAD including pre-processing, segmentation, feature extraction and selection, and classification stages using both machine learning and deep learning techniques. Scope and algorithm of each stage has been presented with it is results. In feature extraction the type of extracted feature as well as the technique that has been used in feature extraction have been presented. Moreover, this systematic review presents the classification method, classifying classes and results are addressed. We also provided the contribution of each surveyed paper with used dataset and number of images in evaluation. (Sadoughi et al. 2018) artificial intelligence methods have been used to identify breast cancer utilizing a wide range of image processing methods. The paper provides relevant information, such as references, techniques used, work scopes, datasets, and various performance metrics, for a more comparative analysis between studies. (Oza et al., 2021) discussed about how to identify and classify suspect areas in mammograms using low-level image features, ML algorithms, and DL techniques from the literature utilizing various methods. Bottom-up survey will cover both low-level image analysis and artificial intelligence methods. Readers will be provided with everything they require to get started working on this topic right away after reading this paper. This review has been presented based on four main question including techniques to extract low-level features, machine learning methods used in identifying mistrustful region, deep learning methods in identifying and classifying breast cancer, and public database used in the evaluation of each work. (Jiménez-Gaona, Rodríguez-Álvarez, and Lakshminarayanan 2020) this paper conducts a crucial survey of the existing literature on the use of ultrasound and mammography images in breast tumor diagnosis using DL algorithms. CAD systems, which are using new DL methods to realize breast images automatically and improve the accuracy of radiologists' diagnoses, are also summarized. Two hundred and fifty research articles were obtained for this review, of which 59 were eligible for further examination after an eligibility process between 2010 and January 2020.

CAD Method

Generally, a standard CAD system covers operations encompassing segmenting structures, detecting abnormalities, and extracting characteristics of abnormalities towards classifying the problem. Figure 2 demonstrates algorithms that are commonly implemented in CAD systems (Memon et al., 2021).

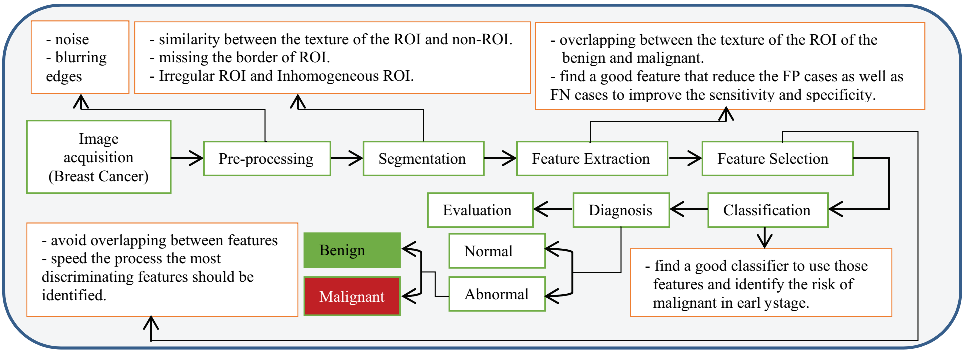

Figure 2. General block diagram of CAD methods.

Several phases in the block diagram include acquisition of the image, pre-processing, segmenting, extracting features, classifying, and evaluating. During pre-processing, the filter is applied to the image followed by a transformation towards improving the quality of mammograms and reducing noise level. Meanwhile, in segmenting, region-of-interest are separated from the background (Liu et al. 2020). In extracting features, lesions and normal breast tissue that are represented by certain features are taken for evaluations. While classifying step categories extracted features into classes of malignant and benign features. Finally, an algorithm that is proposed will be used to evaluate the classified features exploiting relevant methodologies. The evaluation step is critical as human lives and their well-being highly depend on the results of the assessments (Xi, Shu, and Goubran 2018) (Sajeev, Bajger, and Lee 2018). As such, any evaluation algorithms for CAD systems must consider sensitivity, specificity, and evaluation of positive predictions. Table 2 represents the recent major contributions of various CAD algorithms in the diagnosis of breast cancer infection. It has been illustrated from this systematic review that the proposed works was based on MLTs and DLTs.

Table 3 demonstrates that this research field has provided several widely published articles during the last two decades. An increase in scientific publications can be due to the improved ability of machines, developed methods of extracting features from images to perform image classification, and available more datasets being used in the research. This research performed the search in 2018 to 2020. Forty papers – 34.7% were published in 2018, 42 papers – 36.5% were published in 2019, and 32 papers – 27.8% were published in 2020. The research publication number was approximately the same in 2018 and 2019, whereas it has been decreasing slightly in 2020. Moreover, the most widely utilized datasets of the studies were shown in Table 3. The two most utilized were the Mammographic Image Analysis Society (MIAS) dataset that was used in 68 studies (59.13%) that 39 studies used only MIAS whereas 29 studies used MIAS with another dataset. The Digital Database for Screening

Table 2. Contributions of recent CAD approaches based on DM Images.

Ref.	Contribution	Ref.	Contribution
(Singh, Singh, and Bhatia 2018)	Retrieval of DM content utilizing wavelet CS-LBP and SOM	(Melekoodappattu et al., 2018)	ELM-FOA based on multi-scale features
(Berbar., 2018)	Three feature extraction methods based on WT	(Soulami et al. 2019)	ELM to extract suspicious region
(Suresh, Rao, and Reddy 2018)	Build IMEM enhancement technique	(Junior et al. 2019)	BC detection method based on Spatial diversity, geostatistics, and concave geometry
(Salama, Eltrass, and Elkamchouchi 2018)	CAD based on WBCT + GA-SVM-MI + SVM	(Matos et al., 2019)	BoF model based on SIFT, SURF, ORB, and LBP
(Charan, Khan, and Khurshid 2018)	CAD based on CNN	(Mohanty et al., 2019)	An efficient hybrid IGWO-ELM for classifying DMs
(Dallali et al. 2018)	CAD based on histogram thresholding in segmentation	(Yu et al., 2019)	Binary classification methods based on modifying DNN
(Tatikonda, Bhuma, and Samayamantula 2018)	CAD based on HOG and GLCM with different classifiers	(Liu et al., 2018)	Method called TWSVML21 for feature selection
(Routray et al., 2018)	LTEM based on energy map for feature calculation	(Gherghout, Tlili, and Souici 2019)	Classification method based on neural and queuing network
(Samant et al., 2018)	DCT and DFT transformation method with GLCM used in CAD	(Gewei et al., 2019)	An improved non-parametric method-based pixel intensity for BC-detection
(Shastri, Tamrakar, and Ahuja 2018)	DP-HOT and DP-PB-DCT feature descriptors	(Wang et al., 2019)	CAD based on several deep feature fusion
(Goudarzi et al., 2018)	Different feature extraction based on different concept levels using fuzzy rules	(Khan et al. 2019)	MVFF for CAD system based on CNN
(Sapate et al. 2018)	Hybrid system based on labelling and adaptive RG	(Li et al., 2019)	Improved U-Net architecture to segment masses
(Al-Masni et al., 2018)	CAD method based on YOLO	(Sun et al. 2019)	Multi-view CNN is Proposed for feature extraction from CC and MLO views
(Al-Antari et al. 2018)	Integrated CAD method and FrCN for segmentation	(Karthiga, Narasimhan, and Usha 2019)	CAD based on curvelet and regional features
(Sadad et al. 2018)	FCMRG segmentation method and hybrid LBP-GLCM+LPQ feature extraction method	(AlSalman et al.., 2019)	IDSS based on DWT and GLCM for BC diagnosis
(Uthoff et al.., 2018)	feature selection technique based on information measures	(Dabass et al.., 2019)	Enhancement method based on intuitionistic fuzzy logic
(Hussain et al., 2018)	Robust ML technique utilizing different features	(El-Sokkary et al., 2019)	CAD based PSO and GMM using texture and shape feature extraction
(Mohamed et al. 2018)	Features and classifiers used to improve a CAD	(Rahmatika, Handayani, and Setiawan 2019)	PM-segmentation based on histogram operation and K-means
(Mohanty et al., 2019)	Methods based on contourlet and FOA	(Zebari et al. 2019)	WT based enhancement model for segmentation and feature extraction
(Yousefi et al., 2018)	Full automated classification based on DCNN and MIL	(Rampunm et al., 2019)	Contour-based CNN relies on HED for PM-segmentation

(*Continued*)

Table 2. (Continued).

Ref.	Contribution	Ref.	Contribution
(Nedra et al., 2018)	CAD based on robust feature SURF efficient with K-means segmentation	(Shi et al., 2018)	Background and PM-segmentation based on pixel clustering
(Jiao et al. 2018)	Improved CNN based on parasitic metric learning net	(Shinde et al., 2019)	PM-SD based on RG, thresholding, and K-means
(Prathibha et al., 2018)	CAD utilizing different class classification of CNN	(Li et al., 2019)	Improved DenseNet and inventing a new DenseNet-II neural network models based on DL
(Yaşar, Kutbay, and Hardalaç 2018)	CAD based on ANN and complex WT combination	(Tariq et al. 2019)	CAD based on Global Discriminate Features
(Hazarika et al., 2018)	Method based on seeded RG segmentation	(Rampun et al. 2020)	LSP based on variant LBP, LTP, and LQP
(Shen et al. 2018)	A segmentation method based on GA morphological selection	(Mohanty et al., 2020)	KELM is Proposed based WC-SSA for DMs classification
(Mughal et al., 2018)	Discrete differentiation operator-based method to segmentation PM	(Al-Antari, Han, and Kim 2020)	An integrated CAD based on DL for BC classification
(Toz et al., 2018)	A SSEM method to segment PM	(MuduLi et al. 2020)	MFO-ELM for automated BC detection
(Esener et al., 2019)	RG method with line fitting to detect PM	(Li et al. 2020)	Bilateral mass detection based on registration and Siamese-Faster-RCNN networks
(Mohamed et al. 2018)	A deep learning-based approach using CNN to build a computerized reader for BI-RADS-based breast density categorization	(Zhang et al., 2020)	A method called DE-Ada* for mass detection
(Xu et al. 2018)	Residual based CNN method	(Shen et al. 2020)	An optimized classifying method based of DBN and SFO
(Zhu et al. 2018)	End-to-end system for mass segmentation using FCN+CRF	(Christopher et al., 2020)	An enhancement method called NLUML0GMIN
(Ribli et al., 2018)	Faster R-CNN method	(Arora, Rai, and Raman 2020)	DL-method based ensemble transfer learning and NN
(Singh, Singh, and Bhatia 2018)	cGAN for mass segmentation	(Nayak et al. 2020)	SRVFL-AE for multi-class abnormalities detection
(Gao et al., 2018)	CAD based Shallow-Deep CNN (SD-CNN)	(Rabidas et al., 2020)	A new local texture feature called LPA
(Hagos, Mérida, and Teuwen 2018)	Multi patch input based on CNN for segmentation	(Peng et al. 2020)	A mass detection-method based on DCN and NAS-FPN
(Teuwen et al. 2018)	A method of integration between candidate detector and the classification	(Patil and Biradar 2020)	Optimized RG-segmentation based on FC-CSO for BC detection
(Jung et al., 2018)	A new mass detection model based on RetinaNet	(Zeiser et al., 2020)	CAD based on U-Net for mass segmentation
(Samala et al.)	CNN based on learning multi-stage transfer	(Fanizzi et al., 2020)	CAD based on multiscale texture features
(Wang et al., 2018)	Integration of clinic, CC, MLO view features using DL	(Indra et al., 2020)	MTF based feature extraction and UTVO based classifier
(Mughal, Muhammad, and Sharif 2019)	Proposed curve stitching based on thresholding method for PM segmentation	(Ahmed et al. 2020)	Semantic segmentation and classification based on mask RCNN
(Mohanty et al., 2019)	Proposed different methods based on 2D-BDWT-GLCM and FOA	(Boudraa, Melouah, and Merouani 2020)	Improved a CAD based super-resolution reconstruction

(*Continued*)

Table 2. (Continued).

Ref.	Contribution	Ref.	Contribution
(Wang et al., 2019)	MNPNet method for mass segmentation	(Agnes et al. 2020)	Deep MA-CNN for DMs classification
(Shen et al., 2019)	cGNA method for mass segmentation	(Tavakoli et al. 2019)	CNN based deep feature for abnormalities detection
(Chen et al. 2019)	CAD-based feature pool containing various sets of features	(Song, Li, and Wang 2020)	Different models based on DCNN and XGBoost
(Ting, Tan, and Sim 2019)	Design effective CNNI-BCC for localize and classification	(Cheng et al. 2020)	An automated method called SERAN for mass segmentation
(Kaur, Singh, and Kaur 2019)	Automated method based on K-means clustering with MSVM	(Loizidou et al. 2020)	A method based on temporal subtraction for MCs detection
(Das and Das 2019)	KFCM based on entropy and brightness features	(Chen, Wang, and Chen 2020)	A multi-scale adversarial network based on improved U-Net for mass segmentation
(Mabrouk, Afify, and Marzouk 2019)	CAD using different features for MCCs detection	(Shen et al., 2019)	A segmentation mixed-supervision guided and ResCU-Net method
(Yin et al., 2019)	PM-segmentation based on improved iterative threshold	(Shu et al. 2020)	Pooling structures of CNN for DMs classifying
(Pavan et al. 2019)	PM-segmentation based on seed AC and Hough transform	(Zebari et al. 2020)	A method based an improved threshold and build ML system for background and PM segmentation
(Rahimeto et al. 2019)	Automated PM removal based on CCL method	(Suganthi et al. 2020)	A simple AC and intensity-based thresholding method is introduced for PM segmentation
(Gong et al. 2019)	A threshold method based on mixed features for PM-segmentation	(Ali et al., 2020)	Improved deep Res U-Net for PM segmentation
(Gu et al. 2019)	A mass segmentation-method based on super pixel generation and curve evolution methods	(Farhan et al., 2020)	CAD based on analyzing texture features
(Yu et al., 2019)	DL-method based on DenseNet201	(Albalawi et al., 2020)	CNN for DMs classification
(Zhang and Wang 2019)	FCE-Net and MFF method for MC detection	(Soleimani and Michailovich, 2020)	PM-segmentation method based on CNN
Shayma'a, 2019)	A mass detection-method based on MSER and feature matching	(Zhang et al. 2021)	BDR-CNN-GCN method based on DL for classification
(Pezeshki et al., 2019)	Spiculated parts extraction method based on FCM-GA	(Saffari et al. 2020)	Proposed CNN method classifies breast cancer into BIRADS
(Li, Mukundan, and Boyd 2021)	Proposed ML-LBP feature extraction	(Boumaraf et al. 2020)	Proposed a CAD method to classify DM massed into different BI-RADS categories

BC – Breast Cancer; PM – Pectoral Muscle; MC – Micro Calcification; WT – Wavelet Transform.

Table 3. Description of Used Dataset in the Recent CAD Approaches.

Ref.	Year	Dataset	Total no. of images	Resolution	Ref.	Year	Dataset	Total no. of images	Reso-lution
(Singh, Singh, and Bhatia 2018)	2018	MIAS	322	1024*1024	(Melekoodappattu et al., 2018)	2019	MIAS	184	N/A
(Berbar., 2018)	2018	DDSM-MIAS	768–291	128*128	(Soulami et al. 2019)	2019	MIAS-DDSM	N/A	N/A
(Suresh, Rao, and Reddy 2018)	2018	MIAS	306	1024*1024	(Junior et al. 2019)	2019	MIAS-DDSM	74–621	N/A
(Salama, Eltrass, and Elkamchouchi 2018)	2018	MIAS	100	128*128	(Matos et al., 2019)	2019	DDSM	1155	N/A
(Charan, Khan, and Khurshid 2018)	2018	MIAS	322	224*224	(Mohanty et al., 2019)	2019	MIAS-DDSM	314–1500	128*128
(Dallali et al. 2018)	2018	MIAS	N/A	1024*1024	(Yu et al., 2019)	2019	BCDR	406	N/A
(Tatikonda, Bhuma, and Samayamantula 2018)	2018	MIAS	126	1024*1024	(Liu et al., 2018)	2019	DDSM-INbreast BCDR	466–116-736	256*256
(Routray et al., 2018)	2018	MIAS	322	1024*1024	(Gherghout, Tlili, and Souici 2019)	2019	MIAS	322	1024*1024
(Samant et al., 2018)	2018	MIAS-DDSM	150–840	N/A	(Gewei et al., 2019)	2019	N/A	156	N/A
(Shastri, Tamrakar, and Ahuja 2018)	2018	MIAS-DDSM	150–2576	128*128	(Wang et al., 2019)	2019	N/A	400	N/A
(Goudarzi et al., 2018)	2018	MIAS	N/A	1024*1024	(Khan et al. 2019)	2019	MIAS-DDSM	322–2620	128*128
(Sapate et al. 2018)	2018	TCM-DDSM	360–100	multi	(Li et al., 2019)	2019	DDSM	400	512*512
(Al-Masni et al., 2018)	2018	DDSM	600	250*250	(Sun et al. 2019)	2019	MIAS-DDSM	N/A	180*180
(Al-Antari et al. 2018)	2018	INbreast	112	448*448	(Karthiga, Narasimhan, and Usha 2019)	2019	MIAS	322	1024*1024
(Sadad et al. 2018)	2018	MIAS-DDSM	109–72	N/A	(AlSalman et al.., 2019)	2019	MIAS	322	N/A
(Uthoff et al.., 2018)	2018	DDSM	287	N/A	(Dabass et al.., 2019)	2019	MIAS	322	1024*1024
(Hussain et al., 2018)	2018	DDSM	899	N/A	(El-Sokkary et al., 2019)	2019	MIAS	322	1024*1024
(Mohamed et al. 2018)	2018	DDSM	250	N/A	(Rahmatika, Handayani, and Setiawan 2019)	2019	MIAS	25	1024*1024
(Mohanty et al., 2019)	2019	MIAS-DDSM	314–1500	256*256	(Zebari et al. 2019)	2019	MIAS	200	1024*1024
(Yousefi et al., 2019)	2018	DBT	87	1270–2304	(Rampunm et al., 2019)	2019	MIAS-BCDR-INbreast	322–100-all	256*256
(Nedra et al., 2018)	2018	N/A	N/A	N/A	(Shi et al., 2018)	2019	MIAS-BCDR-INbreast	322–100-201	Multi
(Jiao et al. 2018)	2018	DDSM-MIAS	600–322	N/A	(Shinde et al., 2019)	2019	MIAS	322	1024*1024
(Prathibha et al., 2018)	2018	DDSM	N/A	128*128	(Li et al., 2019)	2019	FFDM	2042	1024*1024
(Yaşar, Kutbay, and Hardalaç 2018)	2018	MIAS	322	256*256	(Tariq et al. 2019)	2019	MIAS	322	1024*1024
(Hazarika et al., 2018)	2018	MIAS	150	1024*1024	(Rampun et al. 2020)	2020	MIAS-INbreast	272–206	1024*1024
(Shen et al. 2018)	2018	MIAS-DDSM INbreast	322–128-201	multi	(Mohanty et al., 2020)	2020	MIAS-DDSM-BCDR	314–1500-736	128*128
(Mughal et al., 2018)	2018	MIAS-FFDM	N/A-20	N/A	(Al-Antari, Han, and Kim 2020)	2020	DDSM-INbreast	600–112	Multi

(*Continued*)

Table 3. (Continued).

Ref.	Year	Dataset	Total no. of images	Resolution	Ref.	Year	Dataset	Total no. of images	Reso-lution
(Toz et al., 2018)	2018	INbreast	60	512*512	Muduli et al., 2020)	2020	MIAS-DDSM	326–1500	1024*1024
(Esener et al., 2019)	2018	MIAS	322	256*256	(Li et al. 2020)	2020	INbreast-TXMD BCPKUPH	88–2089-200	Multi
(Mohamed et al. 2018)	2018	Private	22,000	227*227	(Zhang et al., 2020)	2020	DDSM-INbreast	2781–387	Multi
(Xu et al. 2018)	2018	INbreast	410	224*224	(Shen et al. 2020)	2020	MIAS	322	1024*1024
(Zhu et al. 2018)	2018	INbreast-DDSM	116–158	N/A	(Christopher et al., 2020)	2020	MIAS	N/A	1024*1024
(Ribli et al., 2018)	2018	INbreast	115	N/A	(Arora, Rai, and Raman 2020)	2020	DDSM	1318	256*256
(Singh, Singh, and Bhatia 2018)	2018	DDSM – private	567–194	N/A	(Nayak et al. 2020)	2020	MIAS	322	256*256
(Gao et al., 2018)	2018	Private-INbreast	49–89	224*224	(Rabidas et al., 2020)	2020	MIAS-DDSM	58–500	1024*1024
(Hagos, Mérida, and Teuwen 2018)	2018	Private	28,294	300*300	(Peng et al. 2020)	2020	DDSM-INbreast	1592–410	1333*800
(Jung et al., 2018)	2018	Private	23,405	N/A	(Patil and Biradar 2020)	2020	MIAS	N/A	N/A
(Teuwen et al. 2018)	2018	INbreast – private	410–222	N/A	(Zeiser et al., 2020)	2020	DDSM	7989	1024*1024
(Samala et al.)	2018	Private – DDSM	4039	128*128	(Fanizzi et al., 2020)	2020	BCDR	260	N/A
(Wang et al., 2018)	2018	BCDR	763	r*r	(Indra et al., 2020)	2020	DDSM	126	N/A
(Mughal, Muhammad, and Sharif 2019)	2019	MIAS-DDSM	322–400	multi	(Ahmed et al. 2020)	2020	MIAS-DDSM	322–2620	512*512
(Mohanty et al., 2019)	2020	MIAS-DDSM	N/A	128*128	(Boudraa, Melouah, and Merouani 2020)	2020	MIAS	93	1024*1024
(Wang et al., 2019)	2019	INbreast-DDSM	410–316	256*256	(Agnes et al. 2020)	2020	MIAS	322	192*192
(Shen et al., 2019)	2019	INbreast-Private	112–376	256*256	(Tavakoli et al. 2019)	2020	MIAS	322	1024*1024
(Chen et al. 2019)	2019	N/A	275	N/A	(Song, Li, and Wang 2020)	2020	DDSM	11562	N/A
(Ting, Tan, and Sim 2019)	2019	MIAS	221	1024*1024	(Cheng et al. 2020)	2020	DDSM	400	224*224
(Kaur, Singh, and Kaur 2019)	2019	MIAS	322	N/A	(Loizidou et al. 2020)	2020	N/A	320	4096*3328
(Das and Das 2019)	2019	MIAS	N/A	N/A	(Chen, Wang, and Chen 2020)	2020	DDSM-INbreast	762–107	256*256
(Mabrouk, Afify, and Marzouk 2019)	2019	MIAS	181	N/A	(Shen et al., 2019)	2020	INbreast	112	256*256
(Yin et al., 2019)	2019	N/A	720	N/A	(Shu et al. 2020)	2020	CBIS-DDSM-INbreast	3071–410	800*800
(Pavan et al. 2019)	2019	Unspecified	30	N/A	(Zebari et al. 2020)	2020	MIAS-BCDR-INbreast	322–100-200	1024*1024
(Rahimeto et al. 2019)	2019	MIAS-BGH DADC	N/A	512*512	(Suganthi et al. 2020)	2020	MIAS	322	1024*1024
(Gong et al. 2019)	2019	MIAS-DDSM GPCH (private)	209–240-128	Multi	(Ali et al., 2020)	2020	MIAS-INbreast	322–416	N/A

(*Continued*)

Table 3. (Continued).

Ref.	Year	Dataset	Total no. of images	Resolution	Ref.	Year	Dataset	Total no. of images	Reso-lution
(Gu et al. 2019)	2019	MIAS	322	1024*1024	(Farhan et al., 2020)	2020	MIAS	322	30*30
(Yu et al., 2019)	2019	MIAS	322	N/A	(Albalawi et al., 2020)	2020	MIAS	322	11,024*1024
(Zhang and Wang 2019)	2019	MIAS	322	512*512	(Soleimani and Michailovich, 2020)	2020	MIAS-INbreast DDSM	322–208 457	Multi
Shayma'a, 2019)	2019	MIAS-DDSM	85–100	Multi	(Zhang et al. 2021)	2021	MIAS	322	1024*1024
(Pezeshki et al., 2019)	2019	MIAS-DDSM	58–200	1024*1024	(Saffari et al. 2020)	2020	INBreast	410	256*256
(Li, Mukundan, and Boyd 2021)	2021	INBreast	409	1024*1024	(Boumaraf et al. 2020)	2020	DDSM	500	N/A

Table 4. Summary of surveyed studies based pre-processing phase in the literature.

Ref.	Technique	Scope	Evaluation results (%)
(Singh, Singh, and Bhatia 2018)	CCL, morphological operations, adaptive K-means, adaptive median filter	Labels and artifact suppression, Pectoral muscle removal, and noise reduction	PT 10
(Berbar., 2018)	Contrast stretching	Contrast ROI	PT 10
(Suresh, Rao, and Reddy 2018)	Intelligibility mammogram enhancement method	Image enhancement	PSNR = 9.103MSE = 8.54
(Salama, Eltrass, and Elkamchouchi 2018)	2-D median filter and connected component labelling	Remove noise and artifact sources also to suppress the pectoral muscle	PT 10
(Dallali et al. 2018)	Histogram equalization and adaptive limited contrast and thresholding	Contrast enhancement and pectoral muscle removal	MSE = 0.125374 RMSE = 0.354082 PSNR = 4.508960 SSIM = 0.206977
(Tatikonda, Bhuma, and Samayamantula 2018)	Median filter and CLAHE	Improve image quality	PT 10
(Shastri, Tamrakar, and Ahuja 2018)	Normalization and TS-CLAHE	Image enhancement	PT 10
(Goudarzi et al., 2018)	Thresholding, shrinkwrap, wavelet, HE, and median filter	Pectoral muscle, labels, and noise removal also improving the image contrast	PT 10
(Yousefi et al., 2018Youse)	Nonlinear Anscombe transformation, adaptive wiener filter, Hough transform	Noise and pectoral muscle removal also	PT 10
(Esener et al., 2019)	Median filter	Noise reduction	PT 8
(Mughal, Muhammad, and Sharif 2019)	optimized Bayesian non-local means filter (OBNLM)	Unwanted noise removal	Sn = 96.6, Sn = 96.4
(Kaur, Singh, and Kaur 2019)	Median filter and morphological operations	Reduce image redundancy	PT 10
(Mabrouk, Afify, and Marzouk 2019)	Full-Scale Histogram Stretching (FSHS), Histogram Equalization (HE), Morphological, WT	to enhance the fineness of mammogram image	PT 10
(Rahimeto et al. 2019)	Wiener filter and Otsu's thresholding	Noise and tags removal	PT 8
(Gong et al. 2019)	Otsu threshold	Remove unwanted area	PT 10
(Yu et al., 2019)	Morphological operations and threshold	Remove noise and region of breast extraction	PT 10
Shayma'a, 2019)	Median filter and SEBHE	Noise removal and image enhancement	PT 10
(Pezeshki et al., 2019)	CLAHE	enhance the significant features of the mass	PT 10
(Melekoodappattu et al., 2018)	Wiener filter, CLAHE	smoothing, sharpening, noise removal and edge detection	PT 10
(Soulami et al. 2019)	low threshold, labelling, 2D – median filter	Artifacts, background, and noise removal	PT 10
(Matos et al., 2019)	Logarithmic transformation	Image enhancement	PT 10
(Gherghout, Tlili, and Souici 2019)	anisotropic diffusion filter	Reduce noise and preserve edges	PT 10
(Wang et al., 2019)	Adaptive mean filter, algorithm (Junior et al. 2019)	avoid the impact of noise, enhancement	PT 10
(Karthiga, Narasimhan, and Usha 2019)	Top-hat and bottom-hat transforms, morphological and curvelet transforms	Contrast enhancement, sharpen and wrapping	PT 10
(AlSalman et al.., 2019)	Thresholding and, Weiner filter and CLAHE filters	Artifacts, pectoral muscle, and noise removal	PT 10

(*Continued*)

Table 4. (Continued).

Ref.	Technique	Scope	Evaluation results (%)
(Dabass et al.., 2019)	CLAHE and entropy based Intuitionistic Fuzzy Method	Contrast enhancement	Entropy = 4.8868 PSNR = 22.4759
(El-Sokkary et al., 2019)	Threshold and method of (Memon et al., 2021)	Artifact and pectoral muscle removal	PT 10
(Rahmatika, Handayani, and Setiawan 2019)	Median filter	Noise reduction	PT 8
(Zebari et al. 2019)	Wavelet transform	Image enhancement for segmentation and feature extraction	Segmentation: Ac = 90.5 Feature extraction: PSNR = 69.95
(Rampun et al. 2020)	Active counter, restricted contour growing incorporating edge information, and median filter	Breast region segmentation and Noise reduction	PT 10
(Al-Antari, Han, and Kim 2020)	multi-threshold peripheral equalization	enhance the peripheral regions of breast images	PT 10
(Shen et al. 2020)	Wang-Mendel	breast image noise removal	PT 10
(Christopher et al., 2020)	NLUMLOGMIN	Mammogram enhancement	EME = 3.89, AME = 23.92, SDME = 49.36
(Arora, Rai, and Raman 2020)	Histogram equalization	improve upon the contrast and dynamic range of an image	PT 10
(Patil and Biradar 2020)	Median filter	Noise elimination	PT 10
(Zeiser et al., 2020)	CLAHE	removal of irrelevant information	PT 8
(Indra et al., 2020)	Adaptive median filter	Remove speckle, salt, and pepper noises	PT 10
(Ahmed et al. 2020)	Binarization, Median filter, HE, morphological operations, savitzky golay filter, masking,	Artifact, noise, and pectoral muscle removal	PT 8
(Agnes et al. 2020)	Median filter, global thresholding, morphological operations, and single seeded region growing	Noise reduction, background, and pectoral muscle removal	PT 10
(Tavakoli et al. 2019)	Otsu's thresholding CLAHE	eliminates irrelevant areas from the image and enhances the contrast	PT 10
(Cheng et al. 2020)	Gamma transformation and OTSU	Enhance details of image and extract breast region	PT 10
(Loizidou et al. 2020)	Border removal function, Otsu's thresholding, Demons	Background and pectoral muscle removal, image registration	PT 10
(Zebari et al. 2020)	Wavelet transform	Highlight breast region	PT 8
(Ali et al., 2020)	Gaussian, median filters, and CLAHE	Noise reduction and image sharpening	PT 8
(Farhan et al., 2020)	CLAHE	Image enhancement	PT 10
(Albalawi et al., 2020)	Wiener filter	Noise reduction	PT 10
(Li, Mukundan, and Boyd 2021)	LBP	ROI	PT10
(Boumaraf et al. 2020)	Histogram equalization	Image enhancement	PT10

PT 8 means the results are presented in Table 5, and PT 10 means results are presented in Table 7. CLAHE – contrast limited adaptive histogram equalization.

Table 5. Summary of Surveyed Studies based Segmentation Phase in the Literature.

Ref.	Technique	Scope	Evaluation results (%)
(Singh, Singh, and Bhatia 2018)	Threshold based seeded region growing	ROI extraction	PT 10
(Salama, Eltrass, and Elkamchouchi 2018)	Watershed	ROI extraction	PT 10
(Charan, Khan, and Khurshid 2018)	Morphological closing operation and masking	ROI extraction	PT 10
(Dallali et al. 2018)	Histogram thresholding	Mass detection	Contrast = 0.0018, Correlation = 0.9665, Energy = 0.9998, Homogeneity = 1.0000
(Samant et al., 2018)	Otsu's thresholding	Remove unwanted labels	PT 10
(Sapate et al. 2018)	Automatic seed selection, adaptive fuzzy region growing, region merging	Identifying the suspicious region	TMC: Ac = 75, Sens = 91.67, Sp = 58.33, PPV = 68.75, NPV = 87.50, FPsI = 1.12 DDSM: Ac = 74.13, Sn = 90.87, Sp = 57.39, PPV = 68.08, NPV = 86.27, FPsI = 1.13
(Al-Masni et al., 2018)	Deep learning-based YOLO	ROI extraction	Ac = 99.71
(Al-Antari et al. 2018)	Deep learning-based YOLO and FrCN	To segment the mass	Ac = 92.97, Sens = 92.72, Sp = 93.21, Dice = 92.69, Jac = 86.37, AUC = 92.97, MCC = 85.93
(Sadad et al. 2018)	Fuzzy C-Means (FCM) and region-growing (RG) algorithm called FCMRG	Tumor segmentation	PT 10
(Uthoff et al.., 2018)	Otsu's thresholding and region growing	Lesion segmentation	PT 10
(Yousefi et al., 2018Youse)	Level set	ROI selection	PT 10
(Nedra et al., 2018)	K-means	Breast tissues segmentation	PT 10
(Hazarika et al., 2018)	Region growing	Pectoral muscle removal	Ac = 92
(Shen et al. 2018)	Polynomial fitting/Curve Estimation, genetic algorithm, and morphological selection	Pectoral muscle removal	MIAS: FP = 2.03, FN = 6.9, Jac = 91.25, Dice = 94.96 DDSM: FP = 1.6, FN = 4.03, Jac = 94.48, Dice = 97.15 INbreast: FP = 2.42, FN = 13.61, Jac = 84.61, Dice = 89.1
(Mughal et al., 2018)	Convex hull	Pectoral muscle removal	MIAS: FP = 0.99, FN = 5.67 FFDM: FP = 0.98, FN = 5.66
(Toz et al., 2018)	Geometrical properties	Pectoral muscle segmentation	Sn = 95.6
(Esener et al., 2019)	Region growing	Pectoral muscle segmentation	Ac = 94.4, Sn = 89.62, Sp = 99.99
(Zhu et al. 2018)	FCN+ CRF	Lesion segmentation	INbreast: Dice = 90.97 DDSM: Dice = 91.3
(Singh, Singh, and Bhatia 2018)	cGAN-Unet	Lesion segmentation	DDSM: Ac = 0.97, dice = 0.94, Jac = 0.89, Sn = 0.92, Sp = 0.98 Private: Ac = 0.95, dice = 0.86, Jac = 0.76, Sn = 0.85, Sp = 0.97
(Mughal, Muhammad, and Sharif 2019)	Curve stitching and adaptive hysteresis thresholding (CSAHT)	Separation of breast region and internal details of breast parenchyma from background	PT 10
(Wang et al., 2019)	MNPNet	Breast mass segmentation	INbreast: Dice = 91.1 DDSM: Dice = 91.69

(*Continued*)

Table 5. (Continued).

Ref.	Technique	Scope	Evaluation results (%)
(Shen et al., 2019)	Improved U-net by combining conditional generative adversarial network (cGAN) and original dataset	Breast mass segmentation	INbreast: Ac = 92, Sn = 90.57, Sp = 93.09, Jac = 78.47, Dice = 87.58, MCC = 82.14 Private: Ac = 88.82, Sn = 95.61, Sp = 83.41, Jac = 79.35, Dice = 88.2, MCC = 78.8
(Das and Das 2019)	Kernel based fuzzy c-means (FCM)	Detection of masses	
(Mabrouk, Afify, and Marzouk 2019)	Local threshold and Otsu method	MCC extraction	PT 10
(Yin et al., 2019)	Active counter	Pectoral muscle removal	Ac = 94.6, Dice = 0.986
(Pavan et al. 2019)	Active counter	Pectoral muscle removal	Jac = 0.92
(Rahimeto et al. 2019)	Otsu's multi-thresholding technique and CCL	Automatic pectoral muscle removal	Ac = 98.62, IoU = 0.8362, RMSE = 0.1033
(Gong et al. 2019)	New threshold method	segment the breast glandular tissue	PT 10
(Gu et al. 2019)	Superpixel generation based SLIC and DBSCAN, and curve evolution method	Breast mass segmentation	TP = 86.76, FP = 13.24, SI = 86.33, DSC = 90.12
Shayma'a, 2019)	MSER detector-based SURF and features matching	Breast cancer mass detection	DDSM: Ac = 96 MIAS: Ac = 96.47
(Pezeshki et al., 2019)	FCM	Tumor segmentation	PT 10
(Melekoodappattu et al., 2018)	Gray level and global thresholding	Background and pectoral muscle region segmentation	PT 10
(Soulami et al. 2019)	EML	To segment breast area	PT 10
(Junior et al. 2019)	Combination of MeanShift and Fast Scanning	Lesion detection	MIAS: Dr = 97.3, FP = 0.89 DDSM: Dr = 91.63, FP = 0.86
(Gherghout, Tlili, and Souici 2019)	non-parametric method and level-set function	Tumor detection	Ac = 94.937
(Wang et al., 2019)	Adaptive mass region detection	Extract breast mass region	PT 10
(Li et al., 2019)	combines densely connected U-Net with attention gates (AGs)	Breast mass segmentation	Ac = 78.38, Sn = 77.89, Sp = 87.62, F1-score = 82.24
(AlSalman et al., 2019)	k-means	Segment ROI	PT 10
(El-Sokkary et al., 2019)	PSO and GMM	ROI segmentation	PT 10
(Rahmatika, Handayani, and Setiawan 2019)	Histogram operation and k-means clustering	Breast tissue segmentation	
(Rampunm et al., 2019)	CNN with modified HED	Pectoral muscle segmentation	MIAS: Ac = 99.3, Sn = 98.2, SP = 99.5, Jac = 94.6, Dice = 97.5; BCDR: Ac = 99.6, Sn = 95.2, Sp = 99.8, Jac = 92.6, Dice = 95.6; INbreast: Ac = 99.9, Sn = 99.6, Sp = 99.6, Jac = 96.9, Dice = 98.8
(Shi et al., 2018)	Pixel-wise clustering	Pectoral muscle segmentation	MIAS: Ac = 97.08, Jac = 94.89, Dice = 96.4; BCDR: Ac = 97.38, Jac = 95.96, Dice = 97.6; INbreast: Ac = 97.91, Jac = 96.22, Dice = 97.66
(Shinde et al., 2019)	Machine learning	Pectoral muscle segmentation	Ac = 93.71

(*Continued*)

Table 5. (Continued).

Ref.	Technique	Scope	Evaluation results (%)
(Al-Antari, Han, and Kim 2020)	Deep learning YOLO	detection of suspicious breast lesions	DDSM: Ac = 99.17, MCC = 98.36, Dice = 99.28; INbreast: Ac = 97.27, MCC = 93.93, Dice = 98.02
(Li et al. 2020)	Combining self-supervised learning network and Siamese-Faster-RCNN	bilateral mass detection	INbreast: TP = 0.88, FP = 1.12 BCPKUPH:TP = 0.85, FP = 1.86 TXMD: TP = 0.85, FP = 2.70
(Shen et al. 2020)	Otsu thresholding and mathematical morphology	Separate useful part of image	PT 10
(Peng et al. 2020)	Faster R-CNN (DCN C3–C5 NAS-FPN OHEM)	Mass detection	DDSM: TPR = 0.9345 INbreast: TPR = 0.9554
(Patil and Biradar 2020)	Optimized region growing based on FC-CSO	Tumor segmentation	Ac = 0.98, Sn = 0.59, Sp = 0.99, Pre = 0.99, F1-score = 0.74, MCC = 0.76
(Zeiser et al., 2020)	Data augmentation and U-Net model	Mass diagnosis	Ac = 85.95, Sn = 92.32, Sp = 80.47, Dice = 79.39, AUC = 86.40
(Indra et al., 2020)	Multi scale invariant threshold	detecting cancer	PT 10
(Ahmed et al. 2020)	DeepLab RCNN	Mass segmentation	Ac = 0.98, pre = 0.8
(Cheng et al. 2020)	Spatial Enhanced Rotation Aware Network (SERAN)	Breast mass segmentation	Ac = 99.84, Sn = 87.7, Sp = 99.9, IOU = 73.95, Dice = 84.3
(Chen, Wang, and Chen 2020)	Improved U-Net	Breast mass segmentation	DDSM: Ac = 0.9981, Sn = 0.8523, Sp = 0.9986, Dice = 0.8216 INbreast: Ac = 0.9943, Sn = 0.8272, Sp = 0.9956, Dice = 0.8164
(Shen et al., 2019)	MS-ResCU-Net	Simultaneous segmentation and classification	Ac = 94.16, Sn = 93.11, Sp = 95.02, Dice = 91.78, Jac = 85.13, MCC = 87.22, AUC = 94.57
(Zebari et al. 2020)	New threshold technique based on texture features Machine learning based on HOG and NN	BS segmentation PM segmentation	BS: Ac = 99.31, Sn = 99.54, Sp = 99.41, Jac = 98.67, Dice = 99.14; PM: Ac = 98.64, Sn = 98.25, Sp = 99.63, Jac = 96, Dice = 98.5
(Suganthi et al. 2020)	Contrast enhancement and intensity-based thresholding	Breast region segmentation	Ac = 92.55
(Ali et al., 2020)	Fully convolutional network	Pectoral muscle segmentation	MIAS: Ac = 96, Dice = 94.5 INbreast: Ac = 95, Dice = 94
(Albalawi et al., 2020)	K-means clustering	Mass segmentation	PT 10
(Soleimani and Michailovich, 2020)	CNN	PM segmentation	Dice = 97.22, Ac = 99.64
(Saffari et al. 2020)	conditional Generative Adversarial Networks (cGAN) network	Breast tissue segmentation	Ac = 98, Dice = 88, Jaccard index = 78
(Boumaraf et al. 2020)	Region growing	ROI segmentation	PT10

Table 6. Summary of surveyed studies for feature extraction and feature selection methods.

Ref.	Feature	Feature extraction	Feature selection
(Singh, Singh, and Bhatia 2018)	Texture	LBP, CS-LBP, WLBP, and WCS-LBP	N/A
(Berbar., 2018)	Texture and statistical	ST-GLCM, wavelet-CT1, and wavelet-CT2,	N/A
(Salama, Eltrass, and Elkamchouchi 2018)	Texture, Statistical, and shape	GLCM and improved WBCT	GA+SVM+MI and PSO+SVM+MI
(Tatikonda, Bhuma, and Samayamantula 2018)	Texture	Combination of HOG and GLCM	N/A
(Routray et al., 2018)	Texture	Laws Texture Energy Measure (LTEM)	N/A
(Samant et al., 2018)	22 Texture	GLCM	N/A
(Shastri, Tamrakar, and Ahuja 2018)	Texture	Combination of HOG with Gabor filter (HOT) and PB-DCT	DP
(Goudarzi et al., 2018)	Geometric and texture	Compactness, entropy, mean, and smoothness	N/A
(Sapate et al. 2018)	Geometric and texture	N/A	N/A
(Al-Masni et al., 2018)	Deep feature	CNN	N/A
(Sadad et al. 2018)	Texture	Hybrid LB-GLCM+LPQ	mRMR
(Uthoff et al.., 2018)	13 Histogram, texture, 18 shape	GLRL, GLSZ, NGTD, LTEM	k-melodies clustering, IO
(Hussain et al., 2018)	Texture	Morphological, SIFT, and EFDs	N/A
(Mohamed et al. 2018)	50 texture, shape	GLCM, GLRLM, wavelet	Two sample T-test with PVE
(Mohanty et al., 2019)	Texture	Contourlet transform	Forest optimization
(Yousefi et al., 20189)	Statistical, texture, gray level, morphological	Hand-crafted	N/A
(Nedra et al., 2018)	Texture	SURF and BoW	N/A
(Mohanty et al., 2019)	480 Texture	2D-BDWT and GLCM	PCA + FOA
(Chen et al. 2019)	59 Shape and density	FFT features, DCT features and WT features	PSO
(Mabrouk, Afify, and Marzouk 2019)	Shape, texture, and invariant moment	Morphological and GLCM	Fisher score
(Gong et al. 2019)	Texture and statistical	GLCM	N/A
(Pezeshki et al., 2019)	34 intensity histograms, texture, margin and shape	FD, GLCM, LBP	GA
(Melekoodappattu et al., 2018)	Texture	SURF, Gabor filter, GLCM	GWO
(Soulami et al. 2019)	Shape	N/A	N/A
(Matos et al., 2019)	Texture	SIFT, SURF, ORB, LBP, SIFT+LBP	BOF
(Mohanty et al., 2019)	Texture	Discrete Tchebichef transform (DTT)	PCA and LDA
(Liu et al., 2018)	Texture and geometric	GLCM	TWSVML21
(Gherghout, Tlili, and Souici 2019)	Texture	GLCM, GLRLM	RELIEF and MRMR
(Wang et al., 2019)	Deep learning, morphological, texture, and density	CNN, GLCM	N/A
(Karthiga, Narasimhan, and Usha 2019)	14 textural	GLCM	N/A
(AlSalman et al.., 2019)	22 statistical	DWT and GLCM	N/A
(El-Sokkary et al., 2019)	Texture and shape	GLCM	N/A
(Tariq et al. 2019)	20 textural	GLCM	N/A
(Rampun et al. 2020)	Texture	Local septenary patterns (LSP)	Dominant patterns
(Mohanty et al., 2020)	Shannon entropy, Tsallis entropy, Renyi entropy, and energy	Block-based discrete wavelet packet transforms (BDWPT)	Principal component analysis (PCA)
(Muduli et al., 2020)	Lifting wavelet transform (LWT)		PCA + LDA
(Zhang et al., 2020)	Texture, shape, and deep learning	SIFT, GIST, HOG, LBP, ResNet, DenseNet, and VGG	N/A
(Shen et al. 2020)	Statistical textural	DWT + GLCM	N/A

(*Continued*)

Table 6. (Continued).

Ref.	Feature	Feature extraction	Feature selection
(Arora, Rai, and Raman 2020)	Deep learning	AlexNet, VGG16, GoogLeNet, ResNet18, and Inception ResNet	N/A
(Rabidas et al., 2020)	Texture	Local Photometric Attributes (LPA)	Stepwise logistic regression
(Patil and Biradar 2020)	Texture	GLCM and GLRM	N/A
(Fanizzi et al., 2020)	Texture	Haar wavelet decompositions	Embedded and filter
(Indra et al., 2020)	Texture	MTF based matrix vectors	MTF based feature
(Boudraa, Melouah, and Merouani 2020)	Statistical texture	GLCM, GLRLM	N/A
(Tavakoli et al. 2019)	Deep learning	CNN	N/A
(Song, Li, and Wang 2020)	Deep learning and texture	DCNN, GLCM, GOG	N/A
(Loizidou et al. 2020)	Shape, intensity, texture	FOS, GLCM	t-test, MANOVA
(Farhan et al., 2020)	Texture	LBP, HOG, and GLCM	N/A
(Albalawi et al., 2020)	Deep	CNN	N/A
(Li, Mukundan, and Boyd 2021)	texture	M-FD + MLBP	PCA
(Boumaraf et al. 2020)	handcrafted	Shape, density, margin	GA

N/A – not available.

Mammography (DDSM) was cited in 45 papers (40%), whereas 12 studies used only DDSM, and 33 studies used DDSM with another dataset. These databases are most popular not only because they included a large set of images but also because they permitted free usage of such images provided the licenses are respected. For INbreast dataset, 23 studies (20%) used to evaluate their study, where only 5 studies used only INbreast, while 18 studies used INbreast with another dataset. Only eight studies (7%) used Braset Cancer Digital Repository (BCDR) dataset. Some research used private datasets and databases, such as those supplied by the Alberta Program for Early Detection of Breast Cancer and the database given by the University of Chicago. Private datasets seem to surface less often in the studies relative to public ones, so it is more challenging to get access to them. Only seven publications (6%) utilized 100 or less images in the training phase to perform the testing phase. Moreover, 12 publications (11%) utilized between 101 and 200 images, 44 publications (38.26%) used between 200 and 500 images and 42 papers (36.52%) used 500 or more images in their performance evaluation. Furthermore, 11 publications (10%) did not determine the utilized image number. 68.69% of the publications utilize 200 or more than 200 images.

Generally, the CAD method includes segmented systems, the identification of anomalies, and the extraction of their characteristics for the corresponding classification. CAD systems typically reach four main phases. The first phase of pre-processing involves improving the contrast and tuning out the noise to prepare the dataset images for the following phases through a set of image pre-processing operations as illustrated in Table 4. The second phase is the segmentation allows the system to extract features more easily from ROI as illustrated in Table 5. The third phase is the feature extraction and selection

Table 7. Summary of surveyed studies for classification based on ML and DL techniques.

Ref.	ML/ DL	Technique	Class	Scope	Evaluation results (%)
(Singh, Singh, and Bhatia 2018)	ML	SOM	N/AB	Content retrieval system	Precision = 79.61
(Berbar., 2018)	ML	SVM	N/AB	Breast mass classification	DDSM: Ac = 98.69, Sn = 98.82, AUC = 0.98637 MIAS: Ac = 97.89, Sn = 96.12, AUC = 0.8769
(Salama, Eltrass, and Elkamchouchi 2018)	ML	Linear SVM, kernel SVM, and KNN	N/AB B/M	Breast cancer diagnosis	Ac = 97.5, Sn = 93.75, Sp = 100 Ac = 96, Sn = 100, Sp = 93.3
(Charan, Khan, and Khurshid 2018)	DL	CNN	N/AB	Early detection of cancer	Ac = 65
(Tatikonda, Bhuma, and Samayamantula 2018)	ML	KNN, CT, SVM, ANN, LDA, and NB	B/M	Benning and malignant classification	Ac = 99.11, Sn = 98.11, Ap = 100
(Routray et al., 2018)	ML	ANN	B/M/N	Breast cancer detection	Ac = 94.4, Sn = 90.9, Sp = 99.99
(Samant et al., 2018)	ML	SVM and KNN	B/M/N	detect and classify tumours	Ac = 93.89
(Shastri, Tamrakar, and Ahuja 2018)	ML	SVM	N/AB	Breast cancer classification into normal and abnormal also further classification into benign and malignant	MIAS: Ac = 97.33, Sn = 97.18, Sp = 98.89, AUC = 100 DDMS: Ac = 84.84, Sn = 87.18, Sp = 79.37, AUC = 92.2
			B/M		MIAS: 100 all metrics DDSM: Ac = 72.43, Sn = 73.53, Sp = 71.33, AUC = 82.93
(Goudarzi et al., 2018)	ML	Combination of fuzzy, discretization and bagging	N/AB	Breast cancer classification	Ac = 89.37, Sn = 88.23, Sp = 84.07
(Sapate et al. 2018)	ML	SVM and KNN	B/M	Early detection is the important key to reduce breast cancer mortality rate	TCM: Ac = 88.61, Sn = 85.56, Sp = 91.67, TP = 154, FP = 15, TN = 165, FN = 26, AUC = 0.868, FPsI = 0.54 DDSM: Ac = 87, Sn = 82, Sp = 92, TP = 41, FP = 4, TN = 46, FN = 9 AUC = 0.856, FPsI = 0.54
(Al-Masni et al., 2018)	DL	FC-NNs	B/M	Classification of breast masses	Ac = 97, Sn = 100, Sp = 94, AUC = 96.45
(Al-Antari et al. 2018)	DL	CNN	B/M	Benign and malignant classification	AUC = 94.78, MCC = 89.91, F1 score = 96.84
(Sadad et al. 2018)	ML	DT, LDA, SVM, KNN, Ensemble, Logistic regression	B/M	Classification of breast masses	MIAS: Ac = 98.2, Sn = 100, Sp = 97, F-score = 98, MCC = 96 DDSM: Ac = 93.1, Sn = 95, Sp = 88, F-score = 93, MCC = 85

(*Continued*)

Table 7. (Continued).

Ref.	ML/ DL	Technique	Class	Scope	Evaluation results (%)
(Uthoff et al., 2018)	ML	ANN	B/M	Breast mammogram lesion classification	Ac = 96.2, Sn = 97.6, Sp = 95.2, AUC = 0.971
(Hussain et al., 2018)	ML	SVM, DT, Bayesian	N/AB	Automated BC detection	Sn = 1, Sp = 1, AUC = 1, PPV = 1NPV = 1, FPR = 0
(Mohamed et al. 2018)	ML	ANN, SVM, KNN	B/M	Automatic mass classification	Ac = 98.9, Sn = 100, Sp = 97.8
(Mohanty et al., 2019)	ML	SVM, KNN, Na¨ıve-Bayes, C4.5	N/AB B/M N/AB	Classify suspicious regions	N/AB for both dataset: Ac = 100, Sn = 1, Sp = 1, MCC = 1 MIAS B/M: Ac = 98.74, Sn = 0.97, Sp = 1, MCC = 0.97
(Yousefi et al., 2018Youse)	DL	MI-RF	B/M	Mass detection in DBT	Ac = 86.81, Sn = 86.6, Sp = 87.5, AUC = 0.87
(Nedra et al., 2018)	ML	SVM	B/M	Classification of breast abnormalities	Ac = 99, Sn = 99.49, Sp = 95.53
(Jiao et al. 2018)	DL	Deep CNN and parasitic metric learning network	B/M	Distinguish Malign cases from Benign ones	DDSM: Ac = 97.4 MIAS: Ac = 96.7
(Prathibha et al., 2018)	DL	CNN-Bandelet, CNN-ORT II, and CNN-Tetrolet	B/M/N	Mammogram classification	Ac = 85.4
(Yaşar, Kutbay, and Hardalaç 2018)	ML	ANN+ complex wavelet transforms	F/D/G	Tissue density classification	Ac = 94.79
(Mohamed et al. 2018)	DL	CNN (AlexNet) (Transfer learning)	BI-RADS	Breast density estimation	AUC = 0.9882
(Xu et al. 2018)	DL	CNN	BI-RADS	Breast density estimation	Ac = 92.63
(Ribli et al., 2018)	DL	Faster R-CNN		Detection and classification	AUC = 0.95
(Gao et al., 2018)	DL	SD-CNN	B/M	Lesion classification	Ac = 09, AUC = 0.92
(Hagos, Mérida, and Teuwen 2018)	DL	Multi-input CNN	B/M	Lesion detection and classification	AUC = 0.93
(Jung et al., 2018)	DL	Fast R-CNN and mask R-CNN with ResNet	B/M	Lesion detection and classification	Sn = 0.97, FP = 3.56 per image
(Teuwen et al. 2018)	DL	RetinaNet	B/M	Mass detection and classification	Ac = 0.98, FP = 1.3 per image
(Samala et al.)	DL	Multistage finetuned CNN	B/M	Classification performance on varying sample sizes	AUC = 0.91
(Wang et al., 2018)	DL	CNN and LTSM	B/M	Classification of breast masses using contextual information	AUC = 0.89
(Mohanty et al., 2019)	DL	Deep SRVFL-AE	N/AB	Mass classification	Ac = 94.79
(Chen et al. 2019)	ML	SVM	B/M	Predict the likelihood of case being malignant	Sn = 81, Sp = 77
(Ting, Tan, and Sim 2019)	DL	CNNI-BCC	B/M/N	Improves the breast cancer lesion classification	Ac = 90.5, Sn = 89.47, Sp = 90.71

(*Continued*)

Table 7. (Continued).

Ref.	ML/ DL	Technique	Class	Scope	Evaluation results (%)
(Kaur, Singh, and Kaur 2019)	ML	K-mean clustering + MSVM/ decision tree	B/M/N	Detection and validation of automated mammogram breast cancer	Ac = 95.6, Sn = 98.6, Sp = 97.6, ROC = 0.99
(Mabrouk, Afify, and Marzouk 2019)	ML	ANN, KNN, SVM	B/M/N	micro calcifications cancer	Ac = 96, Sn = 98, Sp = 94
(Gong et al. 2019)	ML	SVM ELM	Density	Classify breast density	MIAS: Ac = 96.19 DDSM: Ac = 96.36
(Yu et al., 2019)	DL	DenseNet201-c	N/AB	Diagnosis of breast abnormality	Ac = 92.73, Sn = 94.58, Sp = 91.67
(Zhang and Wang 2019)	DL	FCE-Net + MFF		Identify microcalcification clusters and detect breast cancer	Ac = 97.16
(Pezeshki et al., 2019)	ML	SVM	B/M	Tumor classification	MIAS: Ac = 91.37, Sn = 92.1, Sp = 90, AUC = 0.9776 DDSM: Ac = 93.22, Sn = 92.06, Sp = 94.54, AUC = 0.9752
(Melekoodappattu et al., 2018)	ML	ELM-FOA	B/M	Automatic Micro Calcification Detection	Ac = 99.04,
(Soulami et al. 2019)	ML	SVM	N/AB	Detection abnormalities	
(Matos et al., 2019)	ML	SVM, AdaBoost, RF	B/M	discrimination of malignancy and benignity	Ac = 99.65, Sn = 100, Sp = 99.24, Pre = 0.99, F1-score = 0.99,
(Mohanty et al., 2019)	ML	LGWO-ELM	N/AB	Automated and accurate classification	MIAS: Ac = 100, AUC = 1 DDSM: Ac = 99.5, AUC = 0.9931
			B/M		MIAS: Ac = 100, AUC = 1 DDSM: Ac = 98.5, AUC = 0.9910
(Yu et al., 2019)	DL	GoogLeNet, AlexNet, CNN2, CNN3, SVM	B/M	Differentiation of breast lesions	Ac = 0.81, AUC = 0.88
(Liu et al., 2018)	ML	TWSVML21	B/M	Mass classification	DDSM: Ac = 88.66, Sn = 88.06, Sp = 89.26 INbreast:Ac = 87.05 BCDR: Ac = 89.13
(Gherghout, Tlili, and Souici 2019)	ML	BPNN	N/AB B/M	Classification of breast mass	Pre = 98.1, AUC = 0.965 Pre = 95.2, AUC = 0.92
(Wang et al., 2019)	ML	ELM, SVM	B/M	Breast cancer classification	Ac = 86.5, Sn = 85.1, Sp = 88.02, AUC = 0.923
(Khan et al. 2019)	DL	MVFF based CNN	N/AB	Mammogram classification	Ac = 93.73, Sn = 96.31, Sp = 90.47, AUC = 0.934
			B/M		Ac = 77.66, Sn = 81.82, Sp = 72.02, AUC = 0.769
(Sun et al. 2019)	DL	MVMDCNN-LOSS	B/M	Mammogram classification	Ac = 0.8282

(*Continued*)

Table 7. (Continued).

Ref.	ML/DL	Technique	Class	Scope	Evaluation results (%)
(Karthiga, Narasimhan, and Usha 2019)	ML	SVM	N/AB	Breast cancer diagnosis	Ac = 98
(AlSalman et al.., 2019)	ML	ANN	B/M/N	Breast cancer diagnosis	Ac = 96.5625
(El-Sokkary et al., 2019)	ML	Non-linear SVM	B/M/N	Breast cancer detection and diagnosis	Ac = 85
(Mohanty et al., 2019)	ML	SVM, KNN, C4.5	N/AB	DM identification	MIAS: Ac = 100, Sn = 1, Sp = 1, MCC = 1, F-score = 1, AUC = 1 DDSM: same results as MIAS with SVM and KNN
			B/M		MIAS: Ac = 100, Sn = 1, Sp = 1, MCC = 1, F-score = 1, AUC = 1 DDSM: same results as MIAS with KNN
(Li et al., 2019)	DL	DenseNet neural network	B/M	DM classification	Ac = 94.55
(Tariq et al. 2019)	ML	ANN	B/M	Breast cancer classification	Ac = 99.4, Sn = 99.58, SP = 99.37
(Rampun et al. 2020)	ML	SVM	BI-RADS	Breast density classification	Ac = 83.3, Ac = 80.5
(Mohanty et al., 2020)	ML	WC-SSA-KELM	N/AB	correctly classify digital mammograms	MIAS: Ac = 99.62, AUC = 0.99, Sn = 0.99, Sp = 0.97, MCC = 0.98, F-measure = 0.99 DDSM: Ac = 99.92, AUC = 0.99, Sn = 1, Sp = 0.99, MCC = 0.99, F-measure = 0.99
			B/M		MIAS: Ac = 99.28, AUC = 0.99, Sn = 0.99, Sp = 0.99, MCC = 0.98, F-measure = 0.99 DDSM: Ac = 99.63, AUC = 0.99, Sn = 0.99, Sp = 0.99, MCC = 0.99, F-measure = 0.99 BCDR: Ac = 99.60, AUC = 0.99, Sn = 1, Sp = 1, MCC = 0.99, F-measure = 0.99
(Al-Antari, Han, and Kim 2020)	DL	Regular feedforward CNN, ResNet-50, and InceptionResNet-V2	B/M	improve the diagnostic performance of breast lesions	DDSM: Ac = 97.5 INbreast: Ac = 95.32
(Muduli et al., 2020)	ML	MFO-ELM	N/AB	Classification of breast masses	MIAS: Ac = 100, AUC = 1 DDSM: Ac = 99.76, AUC = 0.9958
			B/M		DDSM: Ac = 100, AUC = 1 DDSM: Ac = 98.8, AUC = 0.9927
(Zhang et al., 2020)	DL	AdaBoost	B/M	Breast mass classification	DDSM: Ac = 90.91, Sn = 82.96, Sp = 98.38 INbreast: Ac = 87.93, Sn = 57.20, Sp = 97.73
(Shen et al. 2020)	DL	Deep Belief Network (DBN)		automatic diagnosis of breast cancer	Ac = 91.5, Sn = 94.1, Sp = 72.4

(*Continued*)

Table 7. (Continued).

Ref.	ML/ DL	Technique	Class	Scope	Evaluation results (%)
(Arora, Rai, and Raman 2020)	ML	NN	B/M	Automatic classification	Ac = 0.88, AUC = 0.88
(Rabidas et al., 2020)	ML	SVM, RF, FLDA	B/M	Characterization of mammographic masses	MIAS: ROC = 0.94, Ac = 86.90 DDSM: ROC = 0.89, Ac = 80.76
(Patil and Biradar 2020)	DL	CNN + recurrent neural network (RNN) = CRNN	B/M/N	Breast cancer detection	Ac = 0.90, Sn = 0.92, Sp = 0.89, Pre = 0.78, F1-score = 0.84, MCC = 0.78
(Fanizzi et al., 2020)	ML	Binary RF	N/AB B/M	Breast microcalcification diagnosis	Ac = 97.31, AUC = 98.16 Ac = 88.46, AUC = 92.08
(Indra et al., 2020)	ML	UTVO, ANN, ANN+PSO	B/M	diagnosis system for healthcare applications	Ac = 97.12, Sn = 90.06, Sp = 99.52
(Boudraa, Melouah, and Merouani 2020)	ML	Simple logistic	B/M	Automatic differentiation	Ac = 96.7, Sn = 100, Sp = 94.7
(Agnes et al. 2020)	DL	Multiscale All Convolutional Neural Network (MA-CNN)	B/M/N	Mammogram classification	Ac = 96.47, Sn = 96, Sp = 96, AUC = 0.99
(Tavakoli et al. 2019)	DL	Fully connected layer with sigmoid function	N/AB	Detect and diagnose breast masses	Ac = 94.68, Sn = 93.33, Sp = 95.31, AUC = 0.95
(Song, Li, and Wang 2020)	ML	SVM, XGBoost	B/M/N	Mass classification	Ac = 92.80
(Loizidou et al. 2020)	ML	LDA, KNN, NB, SVM, DT, EDT	B/M	Micro-calcification detection and classification	Ac = 99.55, Sn = 98.82, Sp = 99.72
(Shen et al., 2019)	DL	MS-ResCU-Net	B/M	Simultaneous segmentations and classification	Ac = 94.12, Sn = 97.56, Sp = 88.89, Pre = 93.02, F1-score = 95.24, AUC = 96.16
(Shu et al. 2020)	DL	RGP and GGP	B/M	Mammographic diagnosis	CBIS-DDSM: Ac = 0.767, AUC = 0.823, p-value = 0.009 INbreast: Ac = 0.922, AUC = 0.924, p-value = 0.011
(Farhan et al., 2020)	ML	SVM, LR, and KNN	B/M	Breast cancer detection	Ac = 92.5, Sn = 88, SP = 97
(Albalawi et al., 2020)	DL	CNN	N/B/M	Cancer classification	Ac = 97.14, Sn = 96.52, Sp = 98.88
(Zhang et al. 2021)	DL	Net-5	N/AB	Cancer detection	Ac = 96.1, Sn = 96.2, Sp = 96
(Saffari et al. 2020)	DL	CNN	BIRADS	Cancer classification	Pre = 97.85, Sn = 97.85, Sp = 99.28
(Li, Mukundan, and Boyd 2021)	ML	SVM	BIRADS	Cancer classification	Ac = 84.6, AUC = 95.3
(Boumaraf et al. 2020)	ML	BPN	BIRADS	Mass classification	Ac = 84.5, PPV = 84.4, NPV = 94.8, MCC = 79.3

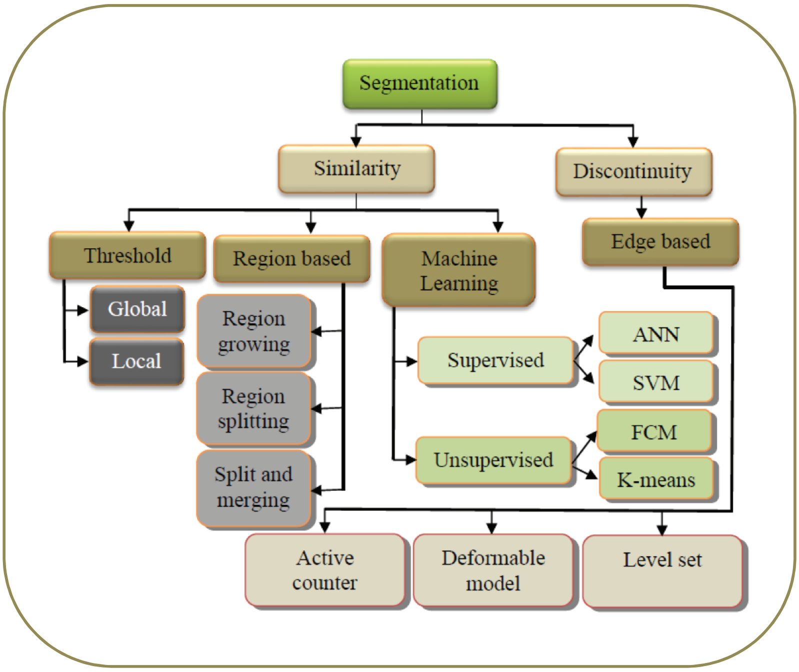

Figure 3. Segmentation Techniques.

teach the system to detect the same suspicious features that are assessed by radiologists. Features that have been selected can distinguish between benign and malignant regions to reduce errors of classification. Despite considerable effort, no consensus has been reached as of yet about those functions, which are needed, as illustrated in Table 6. The last phase of the CAD system which is considered as the CAD heart is classification. It is a data mining operation that is an effective means of finding and extracting trends from broad datasets using various methods of ML and DL.

Pre-processing (Enhancement)

In the data processing procedure for image processing, pre-processing is regarded as critical. The ultimate goal is to enhance the quality of the images produced. A pre-processing step is used in image processing techniques to either improve image quality by suppressing unwanted distortions or to improve image features before any further processing is performed (Zebari et al. 2019). The success of subsequent image processing steps, such as segmentation, feature extraction, feature selection, and classification is highly dependent on the accuracy of pre-processing. Inhomogeneity, low contrast, and unidentified noise are all common characteristics of clinical images that necessitate pre-processing. Pre-processing can help suppress these problems in medical images where they affect analysis. Many techniques are used in pre-processing, such as manual correction and mathematical operations, noise removal and enhancement (George et al., 2017).

In this systematic review, 45 of the 107 studies using DMs in the first phase were pre-processed to improve the following phases of the 107 studies on breast cancer that were surveyed. DM's pre-processing stage is compared among recent publications in Table 4. The pre-processing phase was used by some publications, but evaluation was done in a later phase, as shown by the segmentation results in this paper. The pre-processing techniques used by most DMs consist of three stages. Remove radiopaque artifacts and labels by denoising the mammogram, enhancing the contrast, and applying these techniques. Median, Gaussian, Morphological and Wiener filters are commonly used for denoising DMs. Many publications use contrast enhancing algorithms such as contrast stretching, histogram equalization, contrast limited adaptive histogram equalization, logarithmic contrast enhancement, and exponential contrast enhancement, among others Exponential Contrast Enhancement (ECE). These algorithms are used to enhance the DMs so that specific ROIs or microcalcifications or masses visible in the image can be displayed more clearly. Whopping 46 papers (40%) of the papers in this sample had some form of pre-processing done. This filter has the highest rate of use for denoising DMs in the literature with 14 papers (30.04%), while the Contrast Limited Adaptive Histogram Equalization (CLAHE) filter has the highest rate of use for improving contrast with nine papers (19.56%). Additionally, the pre-processing phase is used to narrow down the ROI by

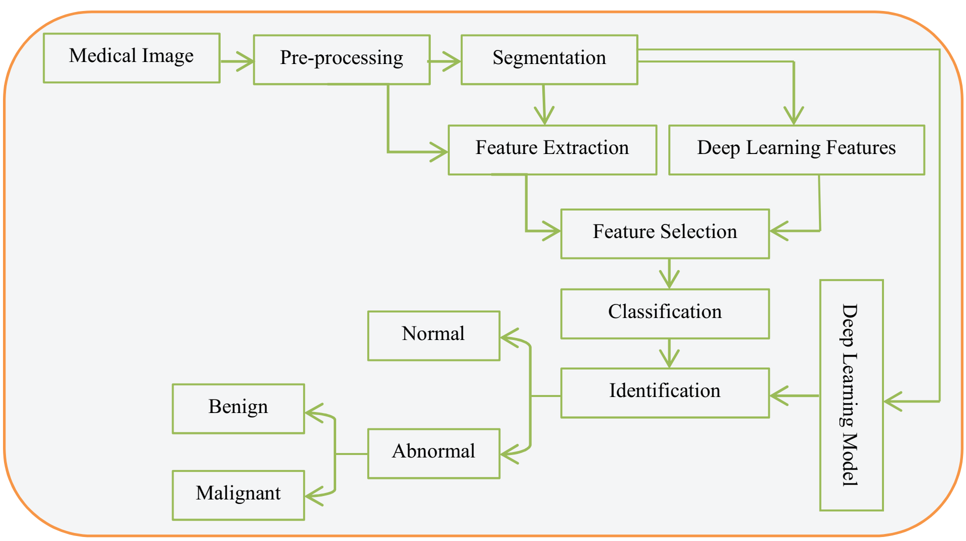

Figure 4. CAD pipelines based on ML and DL models.

eliminating regions with artifacts, noise, or pectoral muscle. The detection of ROI is made possible by the thresholding technique, which removes artifacts, background, and noise from images of the pectoral muscle (11% – 23.91%).

Segmentation

The process of segmentation involves splitting an image into several areas that share common characteristics including contrast, brightness, texture, color, and grey level. Segmentation aims to perform manipulation of an image's representation towards easier analysis and improved meaningful content (Sharma and Preet 2016). Each segmented area is allocated with pixels from an image. During the enhancing process of an image, segmentation typically comes after pre-processing. The primary purpose of executing image segmentation is not to produce an image with higher quality, rather the step is carried out to delineate and discover observable structures and regions of focus (Zebari et al. 2020).

Segmentation can be broadly categorized into two image intensity characteristics, namely discontinuity and similarity. Similarity divides an image into several areas based on similarity, dependent on pre-set criteria. Meanwhile, discontinuity refers to dividing an image according to rapid intensity fluctuations (Patil and Deore 2013). Figure 3 illustrates primary segmentation types that have been widely utilized in the segmentation of medical images.

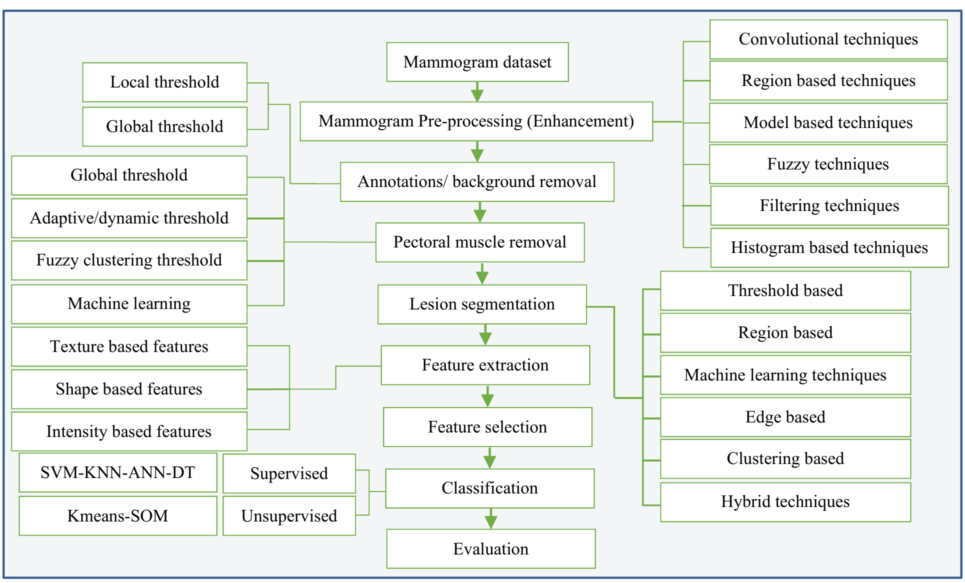

Figure 5. Medical Image processing using CAD Based on ML techniques.

Threshold Based Segmentation

Pixel-based segmentation technique falls under the sub-category of segmentation techniques (Patil and Deore 2013). The pixel-based technique is considered the most rudimentary image segmentation technique attributed to the simplicity of its implementation concept. Despite this, the technique is effective in segmenting images containing bright objects that are surrounded by a dark background. In the pixel-based technique, thresholding is used to calculate the value where an object should be separated from the background. Thresholding may be subdivided into two, namely, local thresholding and global thresholding (Zebari et al. 2020). Thresholding via global thresholding exploits global information. As abnormalities appear lighter than tissues around them, thresholding is thus a viable solution to perform separation of objects from background in segmentation. Local thresholding is also labeled as adaptive thresholding. In operations, adaptive thresholding dynamically alters the values of thresholding, conditional on local properties of an image's subregions. Specifically, the division of an image into regions is followed by a determination of a threshold value that is contingent on the properties of local pixels in a specific region of interest (Triyani et al. 2016). Heuristic optimisation methods can be used to perform thresholding (Kadry et al. 2021).

Region-Based Segmentation

Similarity-based segmentation divides an image into several regions depending on criteria of similarity that have been pre-set. The technique begins either with an individual pixel or a cluster of pixels, which are also known as seeds. Through this technique, neighboring seeds are examined, and subsequently, only seeds that meet the criteria of similarity for a structure would be considered for inclusion (Zeebaree et al., 2019a). Similarity can be described based on an image's edges and/or intensities. Reiteration of examination of seeds that meet a set of pre-set criteria is ended when no new pixels are included in a structure of interest. A primary distinctive feature of this technique is its ability to perform segmentation of similar regions and generating relevant regions (Sadad et al. 2018).

Machine Learning-Based Segmentation

One of the most potent techniques in automating analysis and segmenting medical images is machine learning. The technique can perform learning on complex relationships from empirical data to derive decisions accurately (Liu et al., 2014). Machine learning-based techniques for segmentation may be further classified into supervised and non-supervised techniques. Supervised machine learning primarily thrives in performing a different set of tasks via only altering the training set. Segmentation training data are labelled automatically by grouping identical pixels under unsupervised learning (Gordillo et al., 2013).

Edge Based Segmentation

Segmentation based on edges is the most widely utilized technique for detecting edges, such as boundaries that are responsible for delineating different regions. Edge-based segmentation operates based on discovering dissimilarities of pixels towards determining nearby boundaries that correspond to objects within an image (Gupta and Anand 2017). The technique achieves a fast computation and is operable without needing historical information about an image's content (Thanh et al. 2020). Furthermore, the technique is designed, such that it is highly perceptive to substantial fluctuations in grey level values and in a way that allows it to independently evaluate whether an edge falls within an edge or otherwise (Liu et al. 2020). This technique is effective in overcoming the consequence of size changes in the segmented object that is caused by the incompatible thresholding strategy utilized in segmenting an image.

Deep Learning Based Segmentation

DL-based image segmentation techniques have achieved good results in the field of image segmentation with artificial intelligence's rapidly developing. Deep learning has some benefits in segmentation accuracy and speed over traditional machine learning and computer vision methods. This can help doctors verify the size of tumors and quantify the treatment effect before and after using deep learning to segment medical images. This reduces the amount of work that doctors have to do by a great deal (Liu et al. 2021).

Despite the fact that traditional image segmentation methods no longer hold a candle to the cutting-edge deep learning-based segmentation methods currently in use, the concepts still hold value. For example, the presented threshold-based image segmentation algorithm, the region-based image segmentation technique, and the edge detection-based segmentation method (He et al. 2017). To segment an image, these techniques draw on expertise in digital image processing and mathematics. It is easy to calculate and quick to segment, but there is no way to insure the segmentation is accurate down to the last detail. Deep learning models for image segmentation have made significant progress recently. The accuracy of their segmentation has outperformed that of conventional techniques. Image semantic segmentation was first effectively implemented with a fully convolutional network. This was the first time convolutional neural networks were used for image segmentation, and it was a breakthrough (Lin et al. 2017). Researchers proposed the use of full convolutional networks, which were developed by the authors. In addition to these, there are a number of segmentation networks that excel at processing fine edges, including U-Net, Mask R-CNN, RefineNet, and DeconvNet.

Based on the literature review of segmentation techniques for DMs of breast cancer, several segmentation methods typically utilized by various researchers such as neural networks, level set, watershed algorithm, clustering, thresholding, hybrid techniques, etc. as shown in Table 5. It is shown that the surveyed papers introduced efficient automated CAD systems for the identification of breast cancer. From this systematic review it is observed that (59 papers – 51.3%) performed segmentation methods in CAD systems. The researchers used an adaptive thresholding method to segment the DMs of breast cancer. This method will also aid in distinguishing between the various forms of the tumors, e.g., benign and malignant. Based on the surveyed papers (8 papers – 13.55%) used thresholding technique to segment ROI from DMs. Clustering is a mathematical study from unsupervised learning, this technique deals with discovering a hidden structure from an unlabeled data set. Since clusters are divided from each other by regions of the comparatively low density of point, clusters define as "continuum-like regions of this space," or areas surrounded by space that have a high density of points, which are separated from other high-density functions by low-density regions of the point. Accurate and efficient techniques to detect ROI in DMs based clustering were presented, 5 papers – 8% from the surveyed studies used clustering methods. Similarly, the surveyed papers used edge detection-based segmentation methods to segment ROI from DMs. Moreover, Table 5 showed that (8 papers – 13.55%) of researchers were introduced different automatic computing system based on region-based segmentation as well as hybrid techniques to extract ROI from DMs to improve a classification method which could predict breast cancer. Furthermore, recently DLTs were used widely in image processing fields, from our surveyed papers it has been investigated that DLTs were used widely in the segmentation of DMs (15 papers – 25.42%). Eventually, (10 papers – 16.94%) used other segmentation techniques to segment DMs for further processing.

Feature Extraction

Image processing tasks regularly involve a large corpus, which consumes a significant amount of time and is less practical for the task of efficiently classifying objects from background in segmentation. One strategy to reduce computation time is to perform the transformation of input data by reducing the number of feature vectors. The process of transforming the input data is known as feature extraction. Feature vectors typically hold related information and are exploited as input vectors in classification tasks. Classification of features could be performed based on shape, texture, and color (Tatikonda, Bhuma, and Samayamantula 2018). As seen on mammogram DMs of the individual body, various organs and tissues have very various texture detail. Texture has traditionally been a significant diagnostic function since texture analysis is a good method for lesion identification and disease diagnosis. Computerized feature extraction from mammography images is the most promising strategy to be used in performing breast cancer diagnosis. This is attributed to faster analysis and higher accuracy in diagnosing possible signs of breast cancer. The features hold vital information about digital images that are useful in analyzing images. Primary criteria which have been utilized to discriminate malignant and benign masses include shape and texture (Goudarzi et al., 2018) (Chaieb and Kalti 2019).

Texture Features

Among the most essential characteristics considered for distinguishing ROI or artifacts in the image is the texture feature. The estimation of most of the textural features is performed utilizing values of gray level from the entire image or the ROIs only. During this accelerated phase within cancerous tumors, there is the development of a growing number of nuclei in cancerous tissue. Therefore, it is possible to distinguish various stages of cancer with the aid of texture characteristics (Sajeev, Bajger, and Lee 2018) (Saleck, ElMoutaouakkil, and Mouçouf 2017). An explanation of such characteristics involves resemblance, variance, curvature, comparison, etc. Features of texture may be categorized into two including frequent and statistical features. Statistical features utilized in this study comprised five classes, namely, First-Order Statistics (FOS), Gray-Level Run-Length Matrices (GLRLM), Gray-Level Difference Matrices (GLDM), Gray-Level Co-occurrence Matrices (GLCM), and Tamura features (Chaieb and Kalti 2019). Frequency features are a texture that is transformed into the frequency domain, which does not involve an image's spatial domain. Two structural transformation techniques are studied including 2D wavelet transform and Gabor transform (Bagchi et al. 2020).

Feature selection is a technique used to reduce the dimension of data, which is widely utilized in the areas of data mining, statistics, pattern recognition, and machine learning. In operations, the technique reduces a set of features into a subset of important features that are dependent on certain criteria. Typically, a set of features consumes a large dimensionality space attributed to large variations of abnormalities and normal tissues (Mohanty et al., 2019) (Tubishat et al., 2020). Thus, it becomes necessary to remove features deemed insignificant and perform selection on features that are deemed most promising to be used to discriminate tumors from a set of all features. This comes with its inherent challenge to select features that are capable of uplifting accuracy while at the same time can improve searching time (Shastri, Tamrakar, and Ahuja 2018) (Kou et al. 2020).

Morphological Features

Geometric features have also been termed as shape or morphological features. The features take after the shapes of regions of interest (Vikhe and Thool 2018). Analyzing geometric features of suspected lesions that are identified from views in mammograms meticulously is useful, as this may be able to positively envisage the probability of abnormality and substantiate subsequent necessity to conduct a biopsy. Along with density, lesion's margin, size, and shape are critical in defining the probability of a lesion falling either under a malignant tumor or a benign mass category (Sapate et al. 2018).

Intensity Features

Intensity characteristics exclude from the voxel depiction of ROI. Although several visualizations are built upon the local features (median, mode, and variance), typically ROI visualizations are built upon the intensity-based features (Mohamed et al. 2018). Regardless of the data or the likelihood class, the values of gray-scale values inside an ROI are represented by a statistical model. The histogram of the intensities helps describes the structure of the area, the details of each pixel, and other suspicious characteristics (Berbar., 2018). These features and properties help detect and define the ROI. In two dimensions, an image is a function that maps the spatial coordinates x and y into a value *f(x, y)* that represents the image's gray level intensity at that point. An image is a function in two dimensions. A digital image is one in which *x, y*, and *f(x, y)* are all discrete and finite quantities. Each pixel in a digital image has a specific position and gray intensity value, and together they make up a digital image. The spatial domain refers to the area covered by an image's coordinates (Massafra et al. 2021). In general, statistical features may be produced from the histogram of an image, such as, mean, variance, skewness, kurtosis, entropy, and capacity (Kaushal et al., 2019) (Pashoutan, Shokouhi, and Pashoutan 2017).

Deep Features

Machine learning has a connection to the problem of learning from input data samples because of the unified rule base that are used in it. This method includes analytical, statistical, and mathematical methods instead of explicitly programming the machines to learn from the training data. In the improvement of computer-aided breast cancer identification methods, machine learning techniques such as SVM, nave Bayes, artificial neural networks (ANNs), and set classifiers were becoming popular (Oza et al., 2021). Machine learning algorithms begin with the extraction of image features. Image features are frequently defined using arrays or descriptors, which training processes can then make use of. Choosing the right features is critical for training accuracy. Due to a variety of issues, the traditional machine learning paradigm has evolved into deep learning. Deep learning is more general than conventional machine learning because it focuses on mechanisms for drawing inferences from data and achieves higher generalization levels. One of the most influential deep learning networks is the so-called CNN, which has convolutional layers (Pillai et al., 2019) (Oza et al., 2021). To the contrary of traditional machine learning approaches, deep learning techniques do not require feature extraction steps because of the large number of inner layers that extract features as they pass through layer-embedded operators. By studying thousands of images during the training process (Sechopoulos, Teuwen, and Mann 2020), DL-based algorithms learn what an abnormal mass looks like instead of inserting data on its shape, size, pattern as well as other features.

Table 6 observed that various researchers utilized various methods for feature extraction purposes. Many researchers used texture features (26 papers – 53.06%) as classifier input and obtained good results. GLCM is a method that is mostly utilized to extract texture features based on the surveyed papers (20 papers – 40.81%). Shape features are terminology used to characterize the shape of masses such as circularity, convexity or concavity indexes, spiculation index, perimeter, and more. Cancerous masses are more irregular and spiculated whereas healthy ones are rounder and more oval. Due to this reality, shape features are commonly utilized as identifiers in mass classification. This consistency includes the use of an appropriate segmentation method that can extract the ROI from unwanted regions. The most widely utilized methods for feature extraction in DMs are texture and morphological methods. Therefore, the combination between both features texture and morphological is regarded as the best method. Seven papers – 14.28% have used the integration of texture and morphological features. Moreover, DL is also used to extract features (7 papers – 14.28%) as an input to the classifier.

Breast Cancer Diagnosis

The most advanced sense of a human being is vision, but sometimes, the human vision is limited in it is capacity to process images. Therefore, through the concept of image processing and ML, computerized systems can acquire information about a problem that the human vision cannot acquire (Yadav and Jadhav 2020). This means that sometimes computerized systems are required in cases whereby the human vision is limited and cannot distinguish a problem. Analysis of medical images for instance X-rays, ultrasound (Irfan et al. 2021), thermal (Rajinikanth et al. 2021) images and scanners can help in radiologic diagnosis (Saxena et al., 2020). Figure 4 presents steps involved in a CAD system using the ML and DL techniques. The pre-processing and segmentation stages can be used for both ML and DL.

Machine learning techniques and image processing have made great contributions to the area of medicine through the digitalization of medical images, which allows the analysis and investigation of phenomena using a computer. The basic capability of ML is that it can discover new models without learning much about the underlying structures (Gardezi et al. 2019). This sort of research can extract complicated knowledge from noise or other details with a great deal of success. As the usage of statistical models for expert systems eliminates subjective assessments, these models provide excellent insight into the clinical analysis of provided diseases (Singh, Singh, and Bhatia 2018) (Asri et al. 2016). The ML techniques may be used to find the breast lesion trends since these algorithms are used in the processing and forecasting of medical images. Therefore, much research has also utilized various machine learning methods in the prediction and diagnosis of breast cancer. Figure 5 shows a step of CAD system-based machine learning in medical image processing.

Deep learning strategies are representation-learning methods that consist of complex yet basic components and are utilized to change the representation at one stage into a more complex presentation at marginally more intellectual stages. The incredibly Deep Neural Network (DNN) framework made it capable of high-level inference and advanced artificial intelligence functions (Murtaza et al., 2019). DL paradigms provide new opportunities in the area of biomedical informatics due of its features for instance excellent results, end-to-end learning model with integrated learning feature, capacity to manage complex and multi-modal data and so on. DL methods have been utilized in the productive classification and interpretation of DMs of breast cancer (Zheng et al., 2020).

DL differs from ML because it addresses data in the method in a certain way, it is described a bit differently. Whilst Artificial Neural Networks (ANN) are employed to replicate the convolutions of the nociceptor neuron, ML approaches are based on certain standardized knowledge regarding the data that they operate upon. Unlike supervised learning, which is the process of learning a mapping function input to an output based on previously seen input-output pairs, unsupervised learning is not characterized by minimal human control and may be characterized as a kind of ML that occurs when a machine looks for unknown trends in data without prior labeling (Dembrower et al., 2020) (Sharma and Mehra 2020) (Hussein, 2012) (Kim-Soon, Abdulmaged, and Mostafa 2021).

When performing classification on suspected lesions, the goal is to identify those with a high likelihood of being correctly identified and the lowest risk of leading to diagnostic errors. Textural and geometric features' values are utilized to proceed with classification, as elaborated earlier (Sapate et al. 2018). In this section, general classification techniques that are utilized to differentiate between the types or subtypes of cancers are briefly described. In essence, two learning algorithms are commonly widely used in the task of classifying tumors namely supervised and unsupervised algorithms. Most of the CAD systems for breast cancer detection from mammogram images used ML techniques to classify cancer subtypes. Several supervised and unsupervised techniques were used: Support Vector Machine (SVM), K-nearest Neighbor (KNN), Neural Network (NN), Naıve-Bayes (NB), C4.5, Decision Tree (DT), Linear Discriminant Analysis (LDA), Ensemble, Logistic regression, ANN, Bayesian, Multilayer Perceptron (MLP), Self-Organizing Map (SOM), Neuro-Fuzzy System (ANFIS), Probabilistic Neural Network (PNN), Fully Connected Neural Networks (FC-NNs), Multiple-Instance Random Forest (MI-RF), and Convolutional Neural Network (CNN) on breast cancer databases to compare the performance of those algorithms. The surveyed papers have used different techniques as classifiers from two main groups including MLTs and DLTs. From Table 7 it is shown that (44 papers – 57.14%) used MLTs whereas (33 papers – 42.85%) used DLTs. We categorized the analyzed studies based on the technique used to discriminate breast masses. We extracted the techniques they used in each paper, the classes used in the classification, the scope of the study, and the results they achieved. From the 118 papers analyzed in this study, 80 papers presented in Table 7, 35% (27 papers), 11.68% (9 papers), 14.28% (11 papers), 24.67% (19 papers) used SVM, KNN, ANN, and CNN as a single classifier to distinguish mammographic masses, respectively. We analyzed 34 papers (44.15%) that used more than one method to classify mammographic masses. Some of these studies proposed a hybrid classifier that combined different methods, while other studies examined different classifiers for classification. The studies (Melekoodappattu et al., 2018) (Mohanty et al., 2019) (Mohanty et al., 2020) (Muduli et al., 2020) (Patil and Biradar 2020) (Indra et al., 2020) (Kaur, Singh, and Kaur 2019) (Zhang and Wang 2019) created a hybrid classifier based on using different classifiers, an overview of papers that used one or more than one technique is given in Table 7. SVM has a higher rate of use whereas KNN and ANN have a lower rate.

Typically, the classification process is binary, i.e., benign and malignant (46.75% – 36 papers). However, (12 papers – 15%) papers used the class normal and abnormal, and (12 papers – 15%) used three classes (benign, malignant, and normal). Moreover, we showed that (10 papers – 12.5%) used multi-classes in the classification while at the first step, the classification has been done into normal and abnormal then the abnormal has classified into benign and malignant. Also, some studies (8 papers – 10%) also used BI-RADS classes (2, 3, 4, and 5) for classification. In terms of results, accuracy was reported in 69 papers (94%). Most of the surveyed papers (38 papers – 52%) presented their performance evaluation based on accuracy, sensitivity, and specificity, while (36 papers – 49%) used AUC in their evaluation.

Discussion

In this paper, various techniques employed in different stages of the CAD system to diagnose breast cancer using DMs images have been discussed. Preprocessing is the initial step in digital image analysis which is performed after the image acquisition. It plays an important role in diagnosing the biological tissues captured in an image by refining the quality of the image without destroying the important features. The current study shows that most of the researchers use a median filter to reduce noise as well as CLAHE as a contrast enhancement technique. Several surveyed papers used pre-processing methods to segment pectoral muscle, artifacts, and image background in DMs.

To classify breast cancer into different classes, feature extraction is essential. Textural and morphological features were used for early diagnostics of DMs of the breast. The textural features can aid in the grading of the cancerous tissue. GLCM technique has a superior rate in using feature extraction technique based on the surveyed papers. In classification, both MLTs and DLTs are used to classify extracted features into different classes. As per the surveyed papers, SVM has the maximum rate in using as a classifier from MLTs whereas CNN has a higher rate from DLTs. SVM can recognize non-linear boundaries between classes in feature space and have many kernels to be used. They also can deal well with overfitting, particularly in the high-dimensional feature space.

We epitomize the recommendations as well as review the guidelines on how to boost the efficiency of breast cancer diagnosis and classification utilizing DMs. During the survey of this SR, it is noticed that most of the publications utilized datasets from one database only. Moreover, the pre-processing stage is a crucial stage to improve the performance of further stages, wherein most publications do not utilize any method of this stage; e.g., CLAHE to ameliorate the contrast of DMs, to smooth the DMs based on unsharp masking method, and to reduce noise from the image using noise reduction filters. Furthermore, to increase the generalization and reduce the overfitting of the system, both augmentation and drop-out are recommended to utilize. For mathematically practical it is preferred to utilize better image quality or full resolution whereas many researchers reduced image resolution. Another problem according to the dataset is that utilizing only one database or format during the evaluation. The classifier would have an easier time dealing with this, whereas DMs from different databases and the use of both formats Screen-Film Mammography (SFM) and Full-Field Digital Mammography (FFDM) together would be problematic.

Further, some recurring issues have been noticed in some of the surveyed publications. The issue outlined here is the challenge in contrasting the sensibility and specificity of a report that presents only the Area Under the Curve (AUC) with another that presents only the sensibility and specificity. This challenge in the study fields renders it challenging to figure out the literature in this research domain. Another supposed issue with this analysis is that the researchers do not equate the findings by the classifier with the results that are collected by the clinician for the reasons of whether the classifier is more reliable. The next issue we noticed was the fact that in several publications the approach utilized during the experiments is not explicit or was not present e.g., k-fold cross-validation, a left one out technique, a holdout technique, and so on. Over the above, one standard repository which is generated along with the ground truth of the images is needed to test and verify the segmentation results; thus, it helps in successful diagnosis. Despite this, it is suggested to provide uniform open-access image datasets that include images from various image modalities for the same case to endorse the dependence on more than one image modality in the classification role and merge the details from several views. CAD systems enable to provide results relying on various perspectives related to various image modalities.

Conclusion

The results of this systematic review can help to support inventive research efforts for improving automated CAD systems to help the medical research community in the identification of breast cancer at an early stage. Current MLTs have utilized various image modalities in CAD systems for breast cancer detection. The basic components of the CAD system for breast cancer diagnosis are based on DMs including the pre-processing, segmentation, feature extraction, feature selection, and classification stages. Recent trends have been analyzed for pre-processing techniques that show that it needs more quality of the image before segmentation or feature extraction phases. To explore new developments regarding segmentation and classification methods, this analysis examined the influences of CAD schemes. The research reveals that the potential CAD method can be independent of the magnification factor and dataset. ML classifiers based on DL that were built by adding several layers in the framework become more computationally challenging as the number of layers increase. For the conventional methods, it is rather complicated to compare to DL. It also needs a massive number of datasets for training. However, the data augmentations that come from the assistance of numerous deep learning algorithms have contributed to delivering more consistent and accurate performance. While there are some effective approaches in the literature, there is also a potential to explore more efficient strategies in future work to aid with breast cancer detection at an early level. We hope that this study will guide the breast tissue research community to continue to improve their methods of diagnosing breast cancer.

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