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Breast Cancer Detection and Diagnosis Using Machine Learning: A Survey

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Abstract: **Breast cancer is one of the most widespread diseases causing death among women worldwide. Whenever a suspicion is raised, periodical exams usually including digital mammograms (DM), Infrared thermography, magnetic resonance imaging (MRI), ultrasound (US), microscopic (histological) images, microwave images, or other tools or tests might be recommended. Recently, many hardware and software have been applying different techniques for achieving high-quality results, especially the techniques of machine learning. In this paper, a comprehensive survey to review most of the accurate techniques being used for both detecting and diagnosing breast cancer is conducted. Besides, different commercial and non-commercial hardware and software are mentioned with their advantages and disadvantages in the process of detecting and diagnosing breast lesions. This study reveals that many techniques have been raised to help for breast cancer detection and diagnosis, however, there is no perfect modality that can detect and diagnose breast cancer alone. Moreover, a complete system that can deal with different modalities and gives 100% accuracy still a challenge, since the various structure of breast cancer and the different structure of images issued by a group of modalities that have been used.**

Index Terms: **Breast Cancer, Detection and Diagnosis Techniques, Medical Modalities, CAD systems, Machine Learning Techniques.**

I. Introduction

Breast Cancer is a disease that occurs in the glandular epithelium of the breast and afflicts a significant number of humans worldwide (Al-Tam, 2015; Harris & Vogel, 1997). Typically, this lesion reaches nearby tissues and can enter even the bloodstream or lymphatic system, which makes other organs vulnerable to the attack of this disease (Harris & Vogel, 1997). Whenever a suspicion is raised, periodical exams usually including digital mammograms (DM), Infrared thermography, magnetic resonance imaging (MRI), ultrasound (US), or microscopic (histological) images might be recommended by the expert of the domain (Harris & Vogel, 1997). Therefore, early detection and diagnosis of breast cancer is of major importance to increase the survival rate.

The appearance of breast cancer is influenced by many factors; however, the established researchers still cannot precisely know which factors make normal cells becoming cancerous. Generally, some factors such as breast density, certain inherited DNA mutations, and hormones can increase the appearance risk of cancer (American Cancer Society, 2020). The age of women might increase the likelihood of breast cancer, for instance, women whose age less than 45 years might have one over eight possibilities of invasive breast cancer. In comparison, there are about two over three possibilities of invasive breast cancers in women whose age is greater than or equal to 55 years (American Cancer Society, 2020). Besides, women who have dense breasts can develop cancer more than women with less dense breasts. Moreover, not having children, drinking alcohol, not being physically active, or being overweight or obese, might be led to the risk of developing breast cancer (Al-Tam, 2015; Harris & Vogel, 1997). Some studies have shown that breastfeeding at a young age reduces the risk of breast cancer (Al-Tam, 2015; Harris & Vogel, 1997). At the same time, the risk of breast cancer can be reduced to 18% by walking for a period between 1.25 to 2.5 hours per week (Al-Tam, 2015; Harris & Vogel, 1997).

There are many types of breast cancer, some of which are rare. The most common types are ductal carcinoma in situ (DCIS), lobular carcinoma in situ, and invasive (or infiltrating) ductal/lobular carcinoma (National Breast Cancer Foundation, 2020). On the other hand, there are fewer common types of cancer, such as inflammatory breast cancer, Triple-negative breast cancer, Phyllodes tumour, Paget disease of the nipple, and Angiosarcoma. Cancer can be non-invasive if the malignant cells have not passed through the basal membrane but are contained entirely in the lobule of the ducts, as well as cancer can be invasive when cancer has broken through the basal membrane and spread into the surrounding tissue (National Breast Cancer Foundation, 2020).

A doctor uses some devices called modalities to help in the detection and diagnosis of breast cancer. Mammography is the most popular modality used for detecting cancer; however, an efficient way to improve the accuracy of early detection is to combine different modalities such as x-ray (mammography), ultrasound, and/or magnetic resonance imaging jointly (Deo, 2015). For example, at first, a doctor can use mammography to detect breast cancer, and then if any suspected regions have appeared, US or MRI can be used as a complementary tool.

Machine learning (ML) models have been used to detect and diagnose breast cancer since the advancement in the medical modalities (Saxena & Gyanchandani, 2020). In 1993, Street et al., were developed an ML-based CAD model and was firstly used at the University of Wisconsin (Saxena & Gyanchandani, 2020). Accordingly, several researchers have been trying to develop varied CAD systems to be able to significantly reduce the danger of cancers that attack human kinds such as breast, skin, prostate, brain, colonial, cervical, bladder, and liver cancers.

This paper attempts to provide a comprehensive review to facilitate future research. Furthermore, in this survey, we present a taxonomy of medical modalities that will facilitate the study, analysis, and understanding of breast cancer detection and diagnosis by using the techniques of machine learning. The rest of this paper is organized as follows: Section II discusses the morphological and structural of breast cancer. Moreover, a group of old and new modalities has been using for detecting and classifying breast cancer are presented. Furthermore, the CAD system characteristics with its kinds are shown in section III. Besides, a set of detection and diagnosis CAD systems used for lesion detection and diagnosis are mentioned. On the other hand, BI-RADS assessment categories used by radiologists for creating breast cancer reports are summarized with details in section IV. Furthermore, the quality of screening test factors, the importance of DICOM standard, and a group of datasets with medical files or with only extracted features without medical files are mentioned and discussed in detail in sections V, VI, VII, respectively. Besides, dense breast kinds, search criteria, and machine learning in medicine are concluded in sections VIII, IX, X. Handcrafted feature-based algorithms being used in machine learning are shown in section XI. In section XII only the importance of learning feature-based algorithm technique is presented without details. The effects of reduction dimensions are summarized in section XIII, while the most commonly used measures of performance are briefly mentioned in section XIV. Finally, concluding remarks are presented in the last section.

II. BREAST IMAGING ANALYSIS

The main goal of imaging is to detect and diagnose cancer at its earliest and most treatable stage. Some techniques have been used to analyze breast imaging and mainly depend on three ideas: identify if tissue is normal or not, localize the abnormalities within the breast to help in further examination or treatment, and finally the abnormalities will be characterized to aid in the decision-making process after identification (Cancer et al., 2001).

Sometimes, breast cancer can be found after symptoms appear; however; some women who have cancer have no symptoms; therefore, regular breast cancer imaging is so important (Cancer et al., 2001). Some of the available medical imaging techniques are able to identify the structural or morphological differences in tumours, such as tissue masses, microcalcifications, asymmetry, angiogenesis, and architectural distortion (Cancer et al., 2001). These techniques are based on mechanical, chemical, physical, electrical, and biological characteristics of the tissue. Over the last two decades, many modalities have been used, but a few of them are recommended globally by physicians.

A. Old Breast Cancer Modalities

1) Mammograms

A mammogram is a device that lets a radiologist look for breast tissue (Helvie & Patterson, 2014). This device uses two plates to compress or flatten the breast to spread the tissue apart, which allows getting pictures as clear as possible (Helvie & Patterson, 2014). Two versions of a mammogram are available: analogue and digital mammography, as shown in figure 1 (LBN Medical, 2020). Analog mammography captures a low dose x-ray team on film cassettes, while x-ray beams are captured on a digital detector by digital mammography. The analogue device takes a longer time to get an image ready to be collected in the PACS system (Picture Archiving and Communications System) since it needs a CR reader such as Fuji Capsula XL II to convert the image into a digital one. Digital mammography is known as breast tomosynthesis or 3d mammogram, or called full-field digital mammography (FFDM), is able to create 3D breast images that can be stored in a computer, while analogue mammography only supports 2D images. Besides, the radiation dose of digital mammography is 30-40% lower than analogy mammography (Guo et al., 2018). Many studies have found that 3D mammography appears to find more breast cancer than 2D mammography, especially for women who have more dense breasts (Society, 2020). Both techniques are used to help in the early detection and diagnosis of breast cancer. The abnormal areas of the breast can be shown, however; it does mean that the suspected areas in images are 100% cancer. They help in determining whether more testing is needed or not. Physicians see the mammogram as the most technique used to early detect breast cancer worldwide (Helvie & Patterson, 2014). Nevertheless, not all kind of breast cancer can be shown by the mammogram, only some kinds of breast cancer can, such as calcifications and masses. The abnormalities in dense-breast are not seen well by using the mammogram, which can be painful for younger women and might lead to unnecessary biopsies. Therefore, extra modalities, such as Ultrasound and/or Magnetic Resonance Imaging (MRI) are recommended (Helvie & Patterson, 2014).

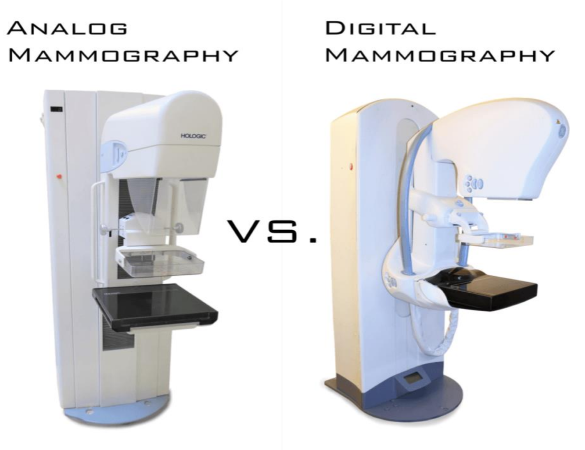

Fig. 1. Analog and digital mammography (LBN Medical, 2020).

2) Ultrasound

Ultrasound is a device that uses sound waves shown in figure 2, is mainly able to show certain breast changes that are more difficult to be identified by mammograms, like fluid-filled cysts, lumps, and some changes in dense breast tissues (Guo et al., 2018). Besides, it can be used to guide a biopsy needle into a suspicious area to take out some cells for cancer testing (Guo et al., 2018). This modality is available worldwide and has no radiation exposure and costs less than a lot of other imaging techniques (Guo et al., 2018). Ultrasound imaging includes some techniques to detect breast cancer such as ultrasound elastography, three-dimensional ultrasound, contrast-enhanced ultrasound, automatic breast ultrasound, and computer-aided detection of breast ultrasound (Guo et al., 2018). Elastosonography is a routine tool, is able to differentiate benign and malignant lesions by identifying the consistency or hardness of tissues (Guo et al., 2018). This technique is not perfect 100% and suffers from few drawbacks, for example, it cannot differentiate between lesions and surrounding tissues when lesions' elasticity properties are the same, as well as the quality of elastography image is restricted by the depth of the lesion. Therefore, many studies have been recommended combining both B-mode and elastography techniques, so the drawbacks of elastography could be overcome and also help decrease the rate of unnecessary biopsies (Guo et al., 2018). B-mode is a 2d image consists of bright dots of ultrasound echoes. The brightness of dots allows for anatomical structures to be visualized and quantified. Contrast-enhanced ultrasound is beneficial to distinguish between benign and malignant lesions too by its ability to show the vascular structure and perfusion of breast lesions, as well as quantitative parameters on the time or intensity curve, are supported (Guo et al., 2018). Moreover, automated and three-dimensional breast US present valuable information regarding breast lesions too, however the final decision to take the suitable test among the ultrasound techniques is back to the expert of a domain such as radiologists. Finally, three-dimensional ultrasound is a modality, which is able to show the anatomy and spatial locations of a tumour in the breast and thus potentially improve breast cancer detection and diagnosis. On the other hand, some studies are reviewed in (Guo et al., 2018) regarding the importance of using 3D modality- 3D is superior to 2D for discovering the area under the receiver operating characteristics curve (0.76, 0.51) respectively, but it will be better to combine 3D with mammography in which allows achieving to 0.90 (Guo et al., 2018). Moreover, the varieties of vascular heterogeneity for malignant and benign breast could be quantitatively assessed by using 3D ultrasound, which showed a noteworthy difference in vascularity between the central and peripheral for a benign lesion, while for a malignant lesion, it did not show any difference (Guo et al., 2018).

Fig. 2. Samsung WS80A Elite, an ultrasound modality (LBN Medical, 2020).

3) Magnetic Resonance Imaging (MRI)

MRI is a modality which able to evaluate tissue density of the breast, morphological changes, the state of the skin, armpit, and the pectoral muscle edge, as shown in figure 3 (Guo et al., 2018). When malignancy detection is clinically and mammographically occult, MRI is used, supporting a high negative predictive value (NPV) in which safely helps in the diagnosis of malignancy. Many studies have reported that MRI is a good method for screening the breast of young women who is at high-risk breast cancer. The American Cancer Society recommended using MRI to screen breast of patients who have a lifetime risk of breast cancer with greater than or equal to 20–25% (Guo et al., 2018), as well as women who have a strong family history of breast or ovarian cancer are recommended to use both MRI and mammogram tests every year (Guo et al., 2018).

However, using the MRI test does not mean that it will replace the mammography test; it should be complemented by the mammogram test. Annual screening of MRI and mammography improves the metastasis-free survival in women with BRCA1/2 mutation or a familial predisposition (Guo et al., 2018). Besides, the ability to diagnose ductal carcinoma in situ (DCIS) could be improved by using MRI (Guo et al., 2018). On the other hand, Sarica and Uluc (Sarica & Uluc, 2014), presented a study that MRI does not currently seem to be sufficient for removing the required biopsy to score sonographic BI-RADS 4 lesions. Moreover, the specificity (SP) of MRI was only 56.7% when using ultrasonographic BI-RADS 4 lesions (Sarica & Uluc, 2014). Therefore, there is still a need for biopsy in order to determine true positive lesions in MRI breast images (Guo et al., 2018). On other extremes, MRI is an expensive modality and is not available in many hospitals (Cancer et al., 2001).

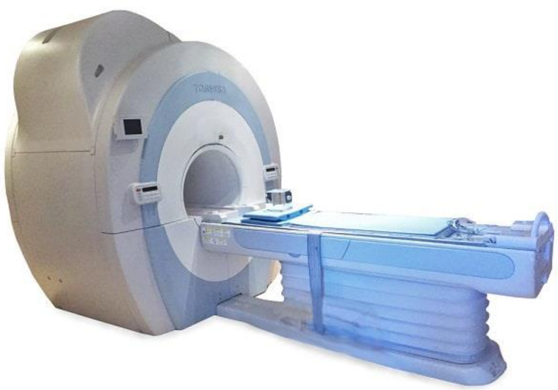

Fig. 3. Toshiba Vantage Titan 1.5T, an MRI modality (LBN Medical, 2020).

B. New Breast Cancer Modalities

For the time being, mammograms, ultrasound, and breast MRI are the most common modalities used to screen for breast cancer. However, new modalities have been developed, such as breast tomosynthesis (3D mammography), which is being used in some centres (Society, 2020). Moreover, other modalities have been studying to check if their performance and quality are as good as or might be better than those used today (Society, 2020):

- Molecular breast imaging (MBI) is also known as scintimammography or breastspecific gamma imaging (BSGI)),
- Positron emission mammography (PEM),
- Contrast-enhanced mammography (CEM) (also known as contrast-enhanced spectral mammography (CESM)),
- Optical imaging tests,
- Electrical impedance imaging (EIT),
- Elastography.

Another technique to detect and diagnose breast cancer is by using histopathology, which is a method to examine infected removed tissue of the breast under the microscope for advising treatment for the disease (Bagchi et al., 2020). However, the histopathology slide has complex visual patterns that make it complicated to distinguish malignant tissues from benign (Saxena & Gyanchandani, 2020). Therefore, modern research has focused on automating this process (Zhou et al., 2020).

DNA microarray technology is used for gene expression analysis, especially to determine a gene that has a mutation (Morais-Rodrigues et al., 2020). Some researchers believe that up to 60% of hereditary breast and ovarian cancers are occurred by a mutation in the genes BRCA1 and BRCA2 (National Human Genome Research Institute, 2020). This mutation can be discovered by taking a sample of DNA from the patient's blood. Then, the DNA molecules in the sample are cut into smaller manageable fragments, and the fluorescent dye is used to label these fragments: red for the control DNA and green for the DNA of a patient. Both red and green sets are entered into a chip to hybridize with artificial DNA on the chip. If both the red and green samples join to the normal sequences on the chip, this means that genes do not have a mutation; otherwise, genes have a mutation (National Human Genome Research Institute, 2020).

Fourier-transform infrared spectroscopy (FTIR) is a device that has been used for obtaining an infrared spectrum of absorption or emission of a liquid, gas, or solid. Some researchers used this device to classify breast cancer (Su & Lee, 2020).

Breast self-exam is a way for regularly examining your breasts on your own (Marcia Boraas, M.D., 2019). This process is very important since it helps to find breast cancer early, which increases the likelihood of treating cancer successfully. If the following changes have appeared in your breast, you must meet a doctor:

- Puckering, dimpling, or bulging of the skin
- Any change on the nipple might be occurred such as the position of the nipple is changed, or it might appear inverted (pushed interior instead of sticking out).
- soreness, Redness, rash, or swelling.

III. CAD SYSTEM

CAD is often used widely for both computer-aided detection and computer-aided diagnosis. In general, CAD is called computer-aided detection (CADe) when it is able to mark suspected abnormal areas of images and is called computer-aided diagnosis (CADx) when the ability to assess and classify benign and malignant breast cancer is supported (Yanase & Triantaphyllou, 2019). Moreover, CADt (Computer-aided simple triage) has appeared as a sub-class of the CAD system, is a system that analyzes and diagnoses the image immediately after radiographing and warms a radiologist about any suspected finding on the current image without the intervention of the radiologist by implementing the AI and image analysis techniques (Yanase & Triantaphyllou, 2019). CAD systems are created for two purposes: to help in identifying suspicious areas that might be missed on images that are created by modalities (detection schemes) and to distinguish benign from malignant breast lesions (diagnosis schemes) (Guo et al., 2018). Basically, a CAD system consists of four stages: preprocessing, segmentation, feature extraction and selection, and classification. A radiologist can use a CAD system as a second reader to detect and diagnose breast cancer, however; not all suspected areas are correctly marked, so radiologists must decide which marks are rightly placed (Cancer et al., 2001). Reading suspected areas by more than one radiologist definitely will improve the rate of cancer detection (Cancer et al., 2001).

Several detections and diagnosis CAD systems are being developed by some companies, such as ICAD, which is a global medical technology that offers a range of computer-aided detection (CAD) solutions to help in early breast cancer detection and diagnosis (ICAD, 2020). ICAD developed a ProFound AI tool for both 2D and 3D mammography, is able to detect both malignant soft-tissue densities and calcifications (ICAD, 2020). Basically, ProFound AI not only improves cancer detection rates but also reduce false-positive and reading time for mammography images (ICAD, 2020). Another tool is developed by ICAD, namely SecondLook, is a tool that is built based on sophisticated patented algorithms for analyzing data, which can identify and mark suspicious areas in 2D mammography image (ICAD, 2020). Moreover, ProFound AI™ Risk is also created by ICAD, which is a decision support tool for radiologists or physicians for helping them to accurately estimate breast cancer risk from only mammography images (ICAD, 2020).

R2 technology develops and markets computer-aided detection systems for the early detection of breast cancer (R2 Technologies Corporation, 2020).

JBD-01K is a tool developed by JLK Inc company, and the ability to present the location of breast tumours and microcalcifications is provided by using AI-based analysis of mammography images (van Leeuwen et al., 2021). This tool deals with mammography DICOM files by accessing and retrieving these files from the PACS (Picture Archiving and Communications System) systems (van Leeuwen et al., 2021).

Lunit is a Korean company that launches the Lunit INSIGHT MMG tool, which is built based on deep learning techniques, assists radiologists to interpret mammography images (Lunit, 2020). The training set used contains 200000 total cases, of which greater than 50000 are cancer cases. This tool can automatically mark lesions suspicious of breast cancer on mammograms, including mass, calcification, distortion, and asymmetry. Basically, it localizes suspicious regions in mammography images using colour or outline and shows abnormality score determining the probability of breast cancer for the detected region (Lunit, 2020). Generally, this tool is developed to increase the detection rate and reduce the recall rate when mammography images are interpreting. Besides, it can achieve 96% accuracy ROC AUC (Area Under the Receiver Operating Characteristic Curve) (Lunit, 2020).

The company of Olea Medical created Breastscape product which supports radiologists with two applications: BreastApp and BreastLoc. BreastApp is an application responsible for automatically detect breast cancer in MRI images, as well as a BI-RADS score report is supported (Olea Medical, 2020). On the other hand, BreastLoc is a diagnostic biopsy tool that deals with MRI images too. Moreover, all the catalogue of grids and needles is loaded within this application (Olea Medical, 2020).

QUIBIM company has developed five applications to be used for breast cancer detection in MRI images: Textures analysis, T2 Mapping, Perfusion-Pharmacokinetics modelling, Body Diffusion-Weighted Imaging (DWI) - IVIM, and Body Diffusion-Weighted Imaging (DWI) - ADC (Quibim, 2020). Textures analysis is able to determine a lesion heterogeneity that can be an aggressive tumour (Quibim, 2020). In comparison, T2 Mapping is mainly created for providing relaxometry measurements and parametric maps. Moreover, to compute the water molecules diffusivity of tissues, Body Diffusion-Weighted Imaging (DWI) - IVIM application is implemented, permitting to distinguish fast water molecules diffusivity from slow ones (Quibim, 2020). While Perfusion-Pharmacokinetics modelling application can be used to classify the different biological behaviour of tumour in phenotypes (Quibim, 2020). Finally, Body Diffusion-Weighted Imaging (DWI) - ADC is built for computing the water molecules diffusivity in tissues too (Quibim, 2020).

ScreenPoint company lunches a few tools such as Transpara™ CAD, Transpara™ Decision Support, and Transpara™ Score, in which AI techniques and image analysis are implemented to support radiologists in early breast cancer detection and diagnosis using both 2D and 3D mammography (ScreenPoint Medical, 2020). Transpara uses a dataset trained with over one million trusted images, as well as got "Class IIa" certification and classified as "Class II" by Food and Drug Administration (FDA) (Radboud university medical, 2020). However, this kind of product only deals with 2D and 3D mammography images (Radboud university medical, 2020). On the other hand, the authors in (Rodriguez-Ruiz et al., 2019) presented a comparative study to investigate the performance of Transpara, including its used AI techniques with 101 radiologists, promising results were reflected as this product achieves an average breast radiologist level in cancer detection accuracy.

Volpara Solutions has developed the VolparaDensity application, which uses smart AI techniques to assess breast density and provides consistent scoring for breast density (Volpara Health, 2020). Besides, this application is compatible with most 2D and 3D digital modalities and has got "Class I" certification and classified as "Class II" by FDA (Radboud university medical, 2020). Moreover, Aspen® Breast is the most advanced product created by Volpara Solutions too. It has been said that Aspen® Breast is a warning system, which is able to estimate the probability of women who can develop breast cancer especially in the period within ten years of their current age and throughout their life (Volpara Health, 2020). Besides, lifetime risk and high-risk estimations have appeared, for example, warning estimations will be provided for a woman who at average risk for developing breast cancer or has a family history of breast cancer (Volpara Health, 2020). On the other hand, a study was presented showing the importance of using MRI screening as a supplemental unit to work jointly with mammography screening in women with extremely dense breasts (Bakker et al., 2019). Besides, Volpara 1.5 was used to grade a group of mammography images which had four density scores, and then women of these images were invited to undergo MRI screening. By using this method, the diagnosis number of women is fewer than using only a mammography unit (Bakker et al., 2019). As well, Volpara was used to measure risk factors in the dense breast using Full-field digital mammograms in which help to guide precision medicine (Brentnall et al., 2019).

Densitas lunches Densitasai solutions, which consist of Densitas densityai™, Densitas qualityai™, and Densitas riskai™, mainly have been developed to support radiologists for breast cancer detection and diagnosis using mammography images (Densitas® Inc, 2020). In general, these solutions are created for controlling diagnostic images by managers, controlling quality by technologists, implementing an advanced analytics platform, and managing health system administrators (Densitas® Inc, 2020). Densityai™ tool provides BI-RADS density scale assessments, while qualityai™ is created to control the quality of images. In addition, Densitas riskai™ can assess breast cancer risk using image-derived factors and only two clinical factors (Densitas® Inc, 2020). Densitasai solutions got "Class II" by FDA and also certified, but the classification of certification is unknown (Radboud university medical, 2020).

Mia product is created by Kheiron Medical Technologies company, which is mainly focused on breast screen to be recalled or not (Kheiron medical, 2020). Basically, it works as an expert mammographer to take a decision for recalling of breast screening. Moreover, suspicious areas can be marked by this product (Kheiron medical, 2020). In addition, both novel deep learning and radiologist insights are combined for use in early detect breast cancer in mammography images (Kheiron medical, 2020).

On the other extreme, normal mammograms are detected and flagged to be reviewed by human experts using a product called Vara, which is developed by Merantix Healthcare (Vara, 2020). Normally, this product generates pre-written reports for human experts enforcing them to check the exams of the generated reports, while the rest exams can be read using the screening workflow of Vara without issuing any flags or pre-written reports (Vara, 2020). Finally, Vara is implemented using machine learning techniques, can be used as a viewer and reporting product for mammography images (Vara, 2020).

Zebra Medical Vision develops an automatic AI tool, namely, Triage Mammography, which can identify suspicious regions in 2D mammography images (Zebra Medical Vision, 2020). Generally, mammograms are sent to zebra's analytics imaging platform in which a suspicious region in the breast can be detected, and then an alerting result will be created to radiologist's workstation by Triage Mammography product (Zebra Medical Vision, 2020).

The QVCAD System is mainly devoted to assisting radiologists to detect breast lesions using 3D breast ultrasound images (QView Medica, 2020). In general, women who undergo 3D breast ultrasound modality, have negative mammograms because of their dense breast tissues, which makes it difficult for distinguishing normal tissue from malignant (QView Medica, 2020). The techniques of pattern recognition processes and artificial neural networks are implemented, which makes the QVCAD able to differentiate suspicious and normal regions in the breast (QView Medica, 2020). Moreover, it has been given the "ClassII" classification by the FDA (Radboud university medical, 2020).

In (Calisto et al., 2020), the authors proposed a new application called BreastScreening, which is responsible for the multimodal diagnosis of breast cancer and is able to show different medical images (US, MRI, Mammography) in one interface. The time for reviewing lesions in different medical images is reduced by using this application. This work proofs that using multimodal view for medical images is better than using the signal-modal view.

A CADe system was proposed in (Moon et al., 2020), which can effectively not only reduce the reviewing time but also misdetection rate is decreased too. Automated breast ultrasound (ABUS) 3-D images were used as inputs to this system, while convolutional neural network (CNN) used as a classifier.

A CAD system based on YOLO (you only look once) deep learning techniques for detecting and diagnosis breast cancer was proposed (Al-Antari et al., 2020). DDSM and INbreast datasets are used to provide this system with a group of mammography images. ResNet-50, Regular feedforward CNN, and InceptionResNet-V2 classifiers were implemented based on YOLO detector, but the InceptionResNet-V2 classifier achieves the highest accuracy of all with values 97.50% for DDSM dataset and 95.32% for INbreast dataset.

Moreover, in (Aly et al., 2021), the authors suggested a CAD system based on YOLO deep learning methods to distinguish between cancer or benign masses in full-field digital mammograms images collected from INbreast dataset. The overall accuracy of the suggested system was 94.2% by using YOLO v3 algorithm to detect masses, ResNet and Inception methods for feature extraction, and k-means clustering for generating anchors that corresponding the original dataset used.

A new trend was investigated where the authors used CNN with SE-Attention mechanism to automatically classify breast density images (J. Deng et al., 2020). A new dataset was created using 18157 beast mammography images. This system can provide radiologists with a reliable breast density diagnosis by determining the patients who need more care than others (J. Deng et al., 2020).

The writers focused on finding a way to help for breast density classification in mammography images by applying texture analysis with the diffuse division technique and fuzzy classifier (Valencia-Hernandez et al., 2021). The images were collected from Breast Cancer Digital Repository (BCDR) and InBreast datasets. The proposed system shows reliable outcomes when compared with LIBRA, which is a software for fully-automatic breast density prediction developed by a computational group at the University of Pennsylvania (Valencia-Hernandez et al., 2021).

IV. BI-RADS

The Breast Imaging Report and Data System (BI-RADS) is developed by the American College of Radiology, has been used in most countries worldwide to reduce variability in creating reports for mammography, MRI, or ultrasonography by radiologists (Bell & Weerakkody, 2013). BI-RADS consists of seven assessment categories starting from 0 to 6, as shown in table I. Not only the standard DICOM (Digital Imaging and Communications in Medicine) supports BI-RADS assessment categories, but also it is included in the digital mammography modalities and the computer-aided diagnosis (Guo et al., 2018). If more than one finding has appeared, BI-RADS categories are assigned from lowest to the highest: 1, 2, 3, 6, 0, 4, 5 (Bell & Weerakkody, 2013). A biopsy is done when it is the only way to know that a current imaging test or a physical exam is cancer.

Table I. BI-RADS assessment categories (Bell & Weerakkody, 2013).

Category	Finding	Description
BI-RADS 0	Incomplete	In this stage, additional imaging evaluation is needed, probably Mammography, MRI, or Ultrasound
BI-RADS 1	Negative	symmetrical and no masses, architectural distortion, or suspicious calcifications (Bell & Weerakkody, 2013).
BI-RADS 2	Benign	The probability of malignancy is 0%.
BI-RADS 3	Probably benign	The probability of malignancy is less than 2%.
BI-RADS 4	suspicious for malignancy	The probability of malignancy is greater than or equal to 2-94%. For mammography and ultrasound, these can be further divided as follow: 1. BI-RADS 4A: means that low suspicion for malignancy, which can be between 2-9%. 2. BI-RADS 4B: moderate suspicion for malignancy with values between 10-49%. BI-RADS 4C: high suspicion for malignancy with values between 50-94%.
BI-RADS 5	highly suggestive of malignancy	The probability of malignancy is greater than or equal 95%
BI-RADS 6	known biopsy-proven malignancy	A cancer has already shown on a mammogram by a previous biopsy. In this situation, it might be recommended to use mammography test to see the effective of treatment against the cancer of breast.

V. QUALITY OF SCREENING TESTS

Two important factors should be reviewed in this part: sensitivity and specificity of a test and False-negative/positive of a test. At conventional, the quality of modalities' images using for breast cancer tests, is dependent on two measures: sensitivity and specificity. Sensitivity shows anyone who truly has a disease, while specificity shows who indeed does not have a disease (Susan G. Komen, 2020). Both measures are calculated from 0 to 100 percent. Moreover, False-negative/positive of a test should be taken into consideration. False-negative means that test results for someone show no sign of breast cancer, but this person has breast cancer. While False-positive means that breast cancer exists in the test results, but in reality, this person does not have breast cancer (Susan G. Komen, 2020). No modalities have 100 % sensitivity and specificity; therefore, extra tests will be performed.

The sensitivity of mammography declines significantly when breast tissues become denser — the higher the density of the breast, the lower sensitivity of mammography (Guo et al., 2018). Mammography sensitivity in women over age 50 years is more than ultrasound (US) sensitivity, 95%, and 85% respectively (Guo et al., 2018). However, in women less than or equal to 45 years old, the sensitivity of ultrasound is 13.3% that is greater than the sensitivity of mammography (Guo et al., 2018). Recently, many studies recommend combining both mammography and US tests that can improve the early detection and diagnosis of breast cancer (Guo et al., 2018). By combining both mammography and US, the diagnostic accuracy of tests is more accurate than using mammography alone (Guo et al., 2018).

VI. DICOM STANDARD

DICOM stands for Digital Imaging and Communications in Medicine, is mainly created to be standard for the communication and management of medical imaging information in healthcare (Medical Imaging Technology Association, 2020). This technique was introduced for doing consistency over the varied types of medical imaging modalities. Recently, all modalities create images that store in DICOM format and need special software known as a medical DICOM viewer to retrieve, view, and access these images. DICOM file contains two parts: the header and the body parts (Al-Tam, 2015). The header contains some data that are related to the stored image in the body part. This data can be a patient, doctor data, type of the image (like JPEG, TIFF), type of modality (like US, MRI). The body contains the pixel of the stored image. Generally, modalities create DICOM files, then exporting them to a server to be accessed by anyone anywhere and anytime. This server is called PACS server, which is a software responsible for collecting DICOM files from modalities to be used later by anyone. Many hospitals usually have their own PACS server to collect the generated medical image to be retrieved, viewed, or annotated later by radiologists (Brühschwein et al., 2020). For the time being, many PASC server and DICOM viewers have already existed, some of them are free of charge, while others are not and required much money to be installed and maintained (Al-Tam, 2015; Brühschwein et al., 2020; Wadali et al., 2020).

VII. DATASETS

A few standard datasets have been collected with a set of DICOM files, some of these files have been annotated by radiologists. The datasets of breast cancer can be divided into groups: datasets with medical files and datasets with extracted features without medical files. A few datasets with medical images are existed such as CBIS-DDSM, INbreast, Mini Mammographic Image Analysis Society (Mini-MIAS), while the well-known extracted features datasets are Wisconsin Breast Cancer Dataset (WBCD) and SEER cancer databases. Curated Breast Imaging Subset of DDSM (CBIS-DDSM) is a refreshed and standardized version of the Digital Database for Screening Mammography (DDSM) that includes 2620 scanned film mammography (TCIA, 2020). Also, this dataset collects different normal, benign, and malignant cases with verified pathology information. CBIS-DDSM only collect malignant medical images cases and increase the quality of the collected images by convert to DICOM files (TCIA, 2020). At the other extreme, Wisconsin Breast Cancer Dataset (WBCD) is another dataset that contains extracted features from 699 images obtained from the University of Wisconsin Hospitals (Frank & Asuncion, 2010). The Digital Database for Screening Mammography (DDSM) contains approximately 2500 mammography images, while the MIAS Mini-Mammographic Database has 322 digitized films (VCL, 2020). The INbreast database contains 410 mammography images, where 360 images have been used for generating 90 women cases for both breasts (4 images per case), the rest form 25 cases for mastectomy patients (2 images per case) (Moreira et al., 2012). SEER collects thousands of extracted features collected from breast cancer images and other cancers types (National Cancer Institute, 2020). In addition, the Breast Cancer Histopathological Image Classification (BreakHis) contains 9109 microscopic images of breast lesion tissue, which were gathered using different enlarging factors (40X, 100X, 200X, and 400X) from 82 patients (Spanhol et al., 2015). Essentially, this dataset assembles 2480 benign and 5429 malignant samples, where each image has some properties: 3-channel RGB, 700X460 pixels, 8-bit depth for each channel, and PNG file format (Spanhol et al., 2015). On the other hand, The Stanford Tissue Microarray Database contains annotated tissue images and associated expression data (Marinelli et al., 2007).

A survey was conducted and mentioned a group of datasets used by researchers. ISPY1, Breast-MRI-NACT-Pilot, TCGA-BRCA, BREAST-DIAGNOSIS, QIN Breast DCE-MRI are datasets contain hundreds of thousands of images mixed between CT, MR, SEG, MRI (Nahid & Kong, 2017; TCIA, 2020).

The MIAS and DDSM datasets are the most ones that have been utilized to detect and diagnose breast cancer according to the papers published in Elsevier (https://www.elsevier.com), Springer (http://www.springer.com), and IEEE (http://www.ieeexplore.ieee.org) web sites (Nahid & Kong, 2017).

VIII. DENSE BREAST

The breast consists of ducts, lobules, and fatty and fibrous tissue, and it is called a dense breast when a lot of fibrous or glandular tissues more than fats have been found (Society, 2020). Dense breast is common; however, the breasts become less dense with age for most women (Society, 2020). The more dense breast is, the more difficult it is to reveal some regions of the breast to distinguish abnormal from normal tissue on a mammogram. There are four types of the dense breast: entirely fatty as shown in figure 4.a, scattered areas of fibrous and glandular tissue as shown in figure 4.b, heterogeneously dense (dense glandular and fibrous tissue) as shown in figure 4.d, and extremely dense as shown in figure 4.c. Heterogeneously dense tissues make it difficult to see small lesions in the breast. While extremely dense breast makes it worse than the heterogeneously dense breast for reading tumours on mammograms.

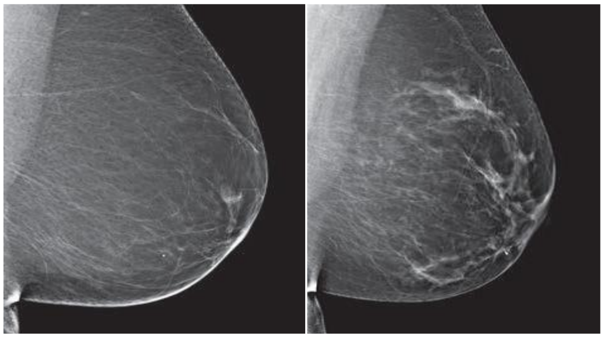

Fig. 4.a: Entirely fatty ((ACS), 2020). Fig. 4.b: Dense glandular and fibrous tissue ((ACS), 2020).

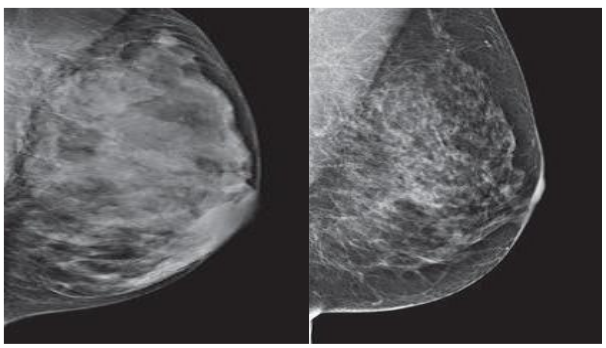

Fig. 4.c: Extremely dense ((ACS), 2020). Fig. 4.d: Heterogeneously dense ((ACS), 2020).

IX. Dense breast

Radiologists use BI-RADS assessment to score breast density: BIRADS A or 1, BI-RADS B or 2, BI-RADS C or 3, BI-RADS D or 4 (American College of Radiology, 2019). BI-RADS A refers that a breast is a fatty breast, while BI-RADS B means that a breast is composed of fatty tissues with some scattered areas of dense tissue. Besides, BI-RADS C means that the breast consists of a mixture of fatty and dense tissues. Finally, BI-RADS D denotes that a breast is composed of almost entirely dense tissues.

X. Search criteria

This survey aims to review various studies related to breast cancer detection and diagnosis using CAD systems that implement machine learning techniques on medical images issued from different modalities. A few questions should be taken into consideration in which does this survey as useful as possible:

- What are the modalities of medical imaging that have been used for early detection and diagnosis of breast cancer?
- What are the most popular CAD systems being implemented in hospitals?
- What are the machine learning techniques currently used by CAD systems?
- What are the evaluation criteria for breast cancer, or how to evaluate that an image of the breast is malignant or benign?
- What are the popular datasets used by CAD systems or researchers for breast cancer detection and diagnosis?
- What are the evaluation criteria used to assess the CAD system's performance?

Some electronic databases were explored, Springer (http://www.springerlink.com), ACM Digital Library (https://dl.acm.org/), Science Direct (Elsevier) (http://www.sciencedirect.com), Microsoft academic (https://academic.microsoft.com/home), Pubmed (https://www.ncbi.nlm.nih.gov/pubmed/), and IEEE Xplore (http://www.ieeexplore.ieee.org). At first, a search was conducted through a period starting from January 2017 to August 2020 to find any related survey or review to this survey. Three thousand five hundred five studies were found using the search terms criteria in table II. Most studies did not contain "survey" or "review" on the title of these papers. Therefore, https://academic.microsoft.com/ was used to search related papers with a title that contains "survey" or "review" word, only 45 studies were retrieved. Besides, another search criteria with the same conditions of the first search criteria performed in the rest list of databases in table II for creating a complete list of related papers without repetition. Of 45 studies, only 12 studied are considered related to this survey. Finally, (Bagchi et al., 2020; Bharati et al., 2020; Das et al., 2020; Gardezi et al., 2019; Kajala & Jain, 2020; Nahid & Kong, 2017; Raghavendra et al., 2019; Saxena & Gyanchandani, 2020; Yassin et al., 2018; Zhou et al., 2020; Zou et al., 2019; Zuluaga-Gomez et al., 2019) papers were included. The main goal is to cover all machine learning methods that have been used in researchers' papers without any repetition. Therefore, any repeated methods mentioned many times in the collected papers is only mentioned once in this survey. The final stage is to find any recent papers that have used the collected machine learning methods between 2017-2020 based on the same databases list and the same search terms mentioned down in table II but without "survey" or "review" words. The criteria of search are conducted based on a certain standard that include a group of terms used in the research engine of each database in which help us to collect as many machine learning methods as possible in this survey.

Table II. The search terms used in the destination databases.

Database	Search in	Search terms
IEEE	http://www.ieeexplore.ieee.org	(("Document Title":"breast cancer") AND "All Metadata":"machine learning"), 312 results were founded.
Science Direct	http://www.sciencedirect.com	1. "breast cancer" "machine learning" "review", 2072 results were founded. 2. "breast cancer" "machine learning" "survey", 690 results were founded. 1. Year: 2017-2020 Title: "breast cancer" "machine learning", in this criterion, the final number of founded papers were reduced to only 31 papers compared to the previous criteria.

ACM	https://dl.acm.org	[Publication Title: "breast cancer"] AND [Publication Title: "machine learning"] AND [Publication Date: (01/01/2017 TO 12/31/2020)], 10 results were founded.
Microsoft Academic	https://academic.microsoft.com/	1. "breast cancer" "machine learning" "review", 26 results were founded. 2. "breast cancer" "machine learning" "survey", 19 results were founded.
Springer	http://www.springerlink.com	1. '"machine learning" AND ("survey")' within 2017-2020, 66 results were founded. Where the title contains= "breast cancer", with the exact phrase = "machine learning", start year="2017" and end year="2020", with at least one of the words= "survey". 2. "machine learning" AND ("review") within 2017-2020, 195 results were founded.
Pubmed	https://www.ncbi.nlm.nih.gov/pubmed/	(("breast cancer"[Title]) AND ("machine learning"[Title])), 84 results were founded, in period between 2017-2020.

However, it might have happened unintentionally that some relevant studies may not have been reviewed.

In general, all relevant studies were examined, but only studies that satisfied the following criteria are included:

- This survey is built based on (Bagchi et al., 2020; Bharati et al., 2020; Das et al., 2020; Gardezi et al., 2019; Kajala & Jain, 2020; Nahid & Kong, 2017; Raghavendra et al., 2019; Saxena & Gyanchandani, 2020; Yassin et al., 2018; Zhou et al., 2020; Zou et al., 2019; Zuluaga-Gomez et al., 2019) papers at first stage. Words such as "survey" or "review" were searched in the title of the papers to get these papers. Besides, "breast cancer" words should be mentioned in the title too.
- The published works should be between January 2017 and August 2020.
- At least one medical modality was used.
- Almost all breast cancer kinds that are detected and diagnosed before biopsies test are included. In contrast, other papers were working with other tests like histopathology medical images (images are created using the microscopic examination of a biopsy or surgical specimen) are mentioned without extensive detail (Saxena & Gyanchandani, 2020).
- One or more machine learning techniques must be implemented.
- Papers without performance measures like sensitivity and specificity are excluded.
- Papers that are not in the journal list mentioned in table II are excluded.

XI. Machine Learning in Medicine

Machine learning has been widely implemented in many areas such as speech recognition, object detection, predict the protein structure, and it is used to detect and diagnose human cancers especially lung, liver, brain, and breast cancers (C. Deng et al., 2020). Its ability to learn from a tremendous amount of data makes it a powerful tool to support decision making in recent decades. For the time being, many methods of machine learning have been used to help a physician in breast cancer detection and diagnosis. The capability of these methods not only helps for revealing the early stage of breast cancer but also the prediction of cancer occurrence and the possibility of the recurrence of cancer after treatment can be provided (Kajala & Jain, 2020). Moreover, during a specific time, the possibility of the death or survival rate can be addressed. Besides, using machine learning can significantly reduce the mistakes taken by humans and enhance the robustness and reliability of outcomes to help to build stable systems (Kajala & Jain, 2020). However, with all of these abilities of machine learning techniques, it still far away from behaving smartly like what human beings do.

XII. Handcrafted Feature-Based Algorithms

Machine learning methods need previous steps on the input images to classify these images as cancerous or not. Recent systems developments based on machine learning have been applied different techniques, such as cropping, remove noise, and enhance the input images' quality, which is performed during the pre-processing stage (Bagchi et al., 2020; Kajala & Jain, 2020). Accordingly, CAD systems depend on a few steps to be fulfilled, such as pre-processing, segmentation, feature extraction and selection, and finally, classification, as shown in figure 5.

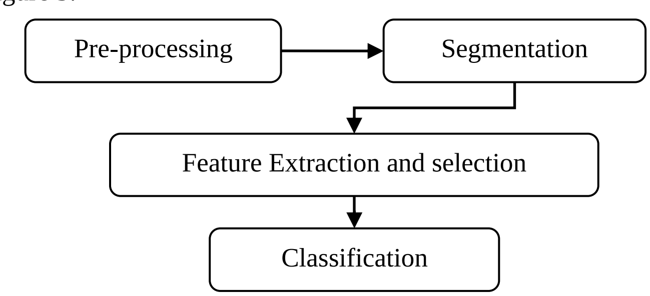

Fig. 5. CAD systems stages.

Each stage has different methods that can be applied. The pre-processing phase has procedures such as cropping, de-noising, image enhancement, while the segmentation phase has other procedures such as thresholding, boundary-based, region-based, template matching. Besides, Feature extraction and selection contains procedures to extract colour, shape, and texture from images. Finally, the classification uses the techniques of machine learning, such as supervised and unsupervised methods to classify images into cancer, benign or normal.

A. Pre-Processing stage

Medical images such as mammography, ultrasound, MRI images have noise, and they required some procedures to remove this noise with unwanted labels, as well as improves the contrast level of the images which makes the features of these images are more selectable (Kajala & Jain, 2020). Many methods were applied during this stage, such as Additive, Multiplicative, Impulse, Shot, Uniform, Periodic noise. Besides, some filters can be implemented, such as Mean, Median, Wiener, Gaussian filters (Bagchi et al., 2017).

The pre-processing stage is necessary since of detection of masses in the medical images is far complicated because traits of the masses are hard to be seen and sometimes appear like normal breast cells (Kajala & Jain, 2020). Moreover, the microcalcifications of the breast have higher contrast than the surrounding regions; therefore, some methods can be applied to detect this region such as dyadic wavelet processing (Kajala & Jain, 2020). Meanwhile, On the contrary to microcalcifications, masses have spiculated structures, varying densities, and low contrast. Therefore, the detection rate of masses can be achieved to 96.2% for sensitivity and 94.4% for specificity by applying Contrast Limited Adaptive Histogram equalization (CLAHE) along with Median filtering (Kajala & Jain, 2020).

B. Segmentation stage

This stage is responsible for segmenting images to choose the region of interest (ROI) in medical images. Common procedures might be implemented to get the desired ROI, including thresholding, boundary-based segmentation, template matching, and region-based segmentation.

1) Thresholding

The thresholding can be performed by some methods such as Gray Level Thresholding, Maximum Entropy Method, Minimum Error Method, and Otsu's Method (Kajala & Jain, 2020). The thresholding procedures are commonly used to remove the parts of images that do not contain any vital information based on the grey level histogram, and the threshold value is chosen. Then the segmenting occurred between the difference between required and background image pixel intensities. However, the main drawback of the threshold, it ignores the spatial data of images, and hence, the contiguousness of the segmented regions is excluded. Furthermore, different methods can be applied along with thresholding to enhance the output as can be found in (Bagchi et al., 2020), which corrects the threshold procedure to avoid over-segmentation. Moreover, in (Bagchi et al., 2020), the writers mentioned that researchers used thresholding to segment mammography images and achieved 80% sensitivity and 0.32% as false-positive per image. Besides, other researchers implemented three classes threshold method with edge detection to segment the chosen images (Bagchi et al., 2020).

In (Torres et al., 2019), the writers proposed a fully-automated thresholding technique by using the morphological analysis of the mammogram, which makes the proposed algorithm is able to estimate the breast density. Other researchers suggested that radiologists can do manual segmentation for dense tissues, which makes the classifiers work faster compared to without segmentation (Torres et al., 2019); unfortunately, this procedure is time-consuming and needs training from the specialist.

2) Boundary-based segmentation

Generally, an image intensity has edges and discontinuity, which are essential because they carry information about object boundary (Kajala & Jain, 2020). Therefore, the image segmentation and object identification can be drawn by detection methods based on these discontinuities. A lot of boundary-based segmentation methods have been used for the ROI segmentation of breast images. These methods can identify discontinuities or abrupt changes in a grey level image; unfortunately, there is no golden rule for determining the edge; it depends on the selected application. High pass filter and gradient filters are of the basic techniques that already have been used to detect edges (Bagchi et al., 2020). Moreover, the first and second-order derivatives can be used to detect edges; unfortunately, the first-order fails to report the edges, especially in images with noise. Meanwhile, the second-order derivative is more robust than the first-order derivative because its sensitivity is less vulnerable to noise. Besides, some researchers applied other methods to detect edges on medical images such as Speculation Filter, Butterworth high-pass filter alongside with Sobel edge detection, Sobel edge detection alone, Non-linear Polynomial Filtering, Difference of Gaussian (DoG) filter, snake-based algorithm, and Color Gradient-based Geodesic Active Contour (Bagchi et al., 2020; Kajala & Jain, 2020).

3) Region-based segmentation

Region-based segmentation is another methodology used to segment image, which also is called region-growing methods. It checks the adjacent pixels based on similarity or smoothing criteria, and then these pixels are added to the region class if the class similarity criteria are met. This operation is repeated for all surrounding pixels in the region. Therefore, this algorithm can identify similar features of the region like grey level, colour, texture. For achieving good results, different operations such as uniform blocking, merge and split can be performed alongside this algorithm. A study mentioned in (Bagchi et al., 2020) used this method to segment mammography images, while another study in (Bagchi et al., 2020) used Mean Based Region Growing Segmentation (MRGS) to segment images too. Besides, some researchers applied an automated region growing segmentation along with the threshold obtained from trained Artificial Neural Network (ANN).

Generally, this type of methodology is robust in noisy images where edges are difficult to be detected, especially when an appropriate seed is selected. Unfortunately, when a noisy seed is select, a faulty segmented area will be chosen. Moreover, some main drawbacks of this method are reported, which are stopping criteria, higher computation time, and memory usage.

4) *Template matching*

Mainly, this technique only might be used only when prior knowledge of a lesion is known, which makes it the main drawback of the technique. Template matching has been used by some researchers, especially the Sech template which applied alongside thresholding to address the suspicious regions of medical images (Kajala & Jain, 2020). Meanwhile, other researchers used template-matching with dynamic programming and local cost function for achieving a higher optimization in detecting tumour regions (Kajala & Jain, 2020).

C. Segmentation stage Feature Extraction and selection

Extracting and selecting an image feature such as colour, shape, and texture, may include contour-based and region-based methods. The contour-based method provides a shape feature based on boundary information, while the region-based method provides shape features based on the entire region (Kajala & Jain, 2020). Different features are reported as a kind of texture features such as geometric or structural, statistical, model-based, and transform-based features. Generally, large sets of features can be extracted with the hope that a subset may include the optimal set that makes them able to grade cancer (Bagchi et al., 2020). Furthermore, often the extracted feature could be redundant or irrelevant, so a feature selection stage is performed to select the essential features. Some researchers used mean and standard deviation to extract ROI segmentation to be used for cancer grading and prognosis (Veta et al., 2012). While other researchers extracted the minimum intensity value, area, intensity mean, major and minor axis, standard deviation, and minimum intensity values of each segmented region to be fed into clustering using a pre-trained binary decision tree (Petushi et al., 2004).

The structural features depend on some patterns: points and edges, and their spatial arrangement in the hierarchy. While statistical features refer to the spatial distribution for the intensity values of the image pixels and they could be of first-order (i.e., variance, mean, standard deviation, skewness, entropy, and kurtosis) and second order. The first statistical order gives information about specific pixel and their related intensity, while the second-order like Gray Level Co-occurrence Matrix (GLCM) presents the relation in terms of contrast, energy, correlation, and homogeneity between specific pair of pixels with determining distance and angle (Kajala & Jain, 2020). Accordingly, selecting the distances and angles between pixels will affect the accuracy of the results. Therefore, some researchers used GLCM to efficiently calculate the geometric and texture related measures (X. Liu & Tang, 2013). While others, used Local Binary Pattern (LBP), is a method combining statistical and structural, and texture analysis methods that can show the relation between a pixel and its neighbour through binary pattern (Kajala & Jain, 2020). Generally, the first-order is sample and has a low computational cost, while the second-order gives better outcomes even though the increasing statistical order rises exponentially the computational cost (Bagchi et al., 2020).

In (Belsare et al., 2015), the authors proposed a linear discriminant analysis–based classification method. The proposed method was able to classify 70 histopathological images of the breast achieving 100% accuracy. A textural-based feature method based on the geodesic mean of region covariance descriptors was proposed for nuclear grading of breast tumours in histopathology images (A. M. Khan et al., 2015). While in (Ojansivu et al., 2013), a textural feature algorithm was proposed for automatically classifying breast cancer. In addition, a fusion method was applied in (Gardezi & Faye, 2015), is combining both curvelet sub-band features and the completed LBP (CLBP), and 96.68 % as accuracy was achieved, as well as the number of false-positive was reduced. A hybrid segmentation-based and texture-based method were implemented in (Gandomkar et al., 2019), it can extract features from histopathological slides for cancer grading. Besides, a new extracted feature method was presented in (Ganesan et al., 2014), namely, Run Difference Method (RDM) and Square Centroid Lines Gray Level Distribution Method (SCLGM).

In recent years, genetic algorithms have been used with high dimensional features which can minimize the redundancy and achieve a better accuracy (Yeh & Chan, 2017). As well as another study was presented for extracting features of breast parenchyma using a lattice-based strategy for determining breast tissues heterogeneity (Gastounioti et al., 2018), besides, the number of the used features were reduced using Convolutional Neural Network (CNN).

D. Classifications

Generally, the term classification in the images of breast cancer means that divide them into three classes: normal, malignant and benign. Two phases are implemented in the classification model: training and testing. First, an input dataset with labels (called features vectors) are provided to the classifier, which allows the classifier to train and learn from the input dataset. After that, when the classifier has already trained on the current input data set, it can be used for a testing set of samples of unknown classes. Recently, the most popular ML techniques that have been widely applied in CAD systems are Naive Bayes, decision trees, artificial neural network (ANN), k-nearest neighbour (KNN), support vector machines (SVMs), Gaussian Mixture models, random forest, SVM along with Bayes classifier, and Convolutional Neural Networks (CNN)

(Bagchi et al., 2020; Das et al., 2020; Kajala & Jain, 2020).

1) *Naïve Bayes*

Naïve Bayes is a simple and accurate classification algorithm that has been used in a wide range of applications due to its flexibility (Arar & Ayan, 2017). Moreover, some researchers implemented this algorithm to predict breast cancer (G. Kumar & others, 2019; Shaikh & Ali, 2020). In (Lemons, 2020), the authors presented a study to compare the accuracy of breast cancer diagnosis between Naïve Bayes and Random Forest. Unfortunately, the performance of random forest was more reliable than the Naïve Bayes method in terms of accuracy by getting 97.82%.

2) *Decision tree*

The classified data are in the form of a tree, where a feature is presented by an internal node, while a leaf node presents a label of the classified data. Besides, the tree is traversed from root to leaf, and the leaf node contains the final result of the classification. Recently, many works have been used this method to classify breast cancer, i.e., in (Tabrizchi et al., 2020), a new ensemble learning method based on Multi-Verse Optimizer (MVO) and Gradient Boosting Decision Tree (GBDT) is implemented. The Wisconsin Diagnostic Breast Cancer and Wisconsin Breast Cancer datasets were used. The proposed method achieves 0.9876% for accuracy and 0.9764% for specificity and 0.9943% for sensitivity (Tabrizchi et al., 2020). On the other hand, the Gaussian Light Gradient Boost Decision Tree Classification (GLGBDTC) is presented in (Ezhilraman et al., 2020), which is an ensemble technique mainly used to improve breast cancer detection. C4.5 decision trees are used in this work, which is one of the most commonly used algorithms of decision trees. The writers in (Bagchi et al., 2020) mentioned that a new version of C4.5 called EC.4.5 is introduced and the performance of it was five times improved compared to the performance of C4.5. Besides, k-means and decision trees were implemented to predict breast cancer using the Wisconsin Breast Cancer dataset (Marne et al., 2020).

Another research was conducted in (Hamim et al., 2020) based on breast cancer genes, in this work, a method using C5.0 decision tree alongside with fisher-score based feature selection was investigated. Moreover, other classification methods were used such as artificial neural networks, Logistic Regression, and Support Vector Machine along with fisher-score based feature selection but the C5.0 decision tree achieved the highest accuracy than the other used classification methods with 93.28%. All experiments were implemented using a dataset of microarray breast cancer with a total of 24481 gene expressions for 97 patients.

Researchers presented a comparative study among decision tree, Naïve Bayes, KNN, SVM methods to investigate the most accurate one for classifying breast cancer, this study reveals that decision tree outperforms the rest ones (G. Kumar & others, 2019).

3) *Artificial Neural Network (ANN)*

ANN is one technique of artificial intelligence that attempts to simulate the physiological neural systems of the human brain. In general, ANN consists of interconnected nodes called artificial neurons, and it is a family of pattern recognition algorithms; therefore, it can learn using some input data (Bagchi et al., 2020). Moreover, different architectures of ANN are existed, such as the multilayer perceptron (MLP) architecture, which is one of the most commonly used. Recently, many researchers have checked the ability of this technique to detect breast cancer.

In (Syed et al., 2018), a novel system for the early detection of breast cancer from remote and underserved areas was proposed. The Mammographic Image Analysis Society (MIAS) database was used, which holds a group of mammographic images. A wavelet-based image processing was applied efficiently for preprocessing detection. Different classification algorithms are implemented, such as multi-layer perceptron neural networks, random forest, J48 decision trees, and K-Nearest Neighbor classifiers. The final results using neural network classifier outperforms the results given by using K-NN, random forest, and decision trees classifiers.

A method was proposed to help the radiologist in breast cancer diagnosis by using a fuzzy c-mean algorithm (FCM) in the detecting phase (Faisal & El Abbadi, 2020). Furthermore, discrete wavelet transformation (DWT) and principal component analysis (PCA) had been implemented to extract relevant features to be used as a data input to the ANN classifier. Mammography images extracted from MIAS database were the primary source of original images.

A comparative study was present to investigate the best results among five supervised machine learning techniques: SVM, KNN, ANNs, random forests, and logistic regression (Marcia Boraas, M.D., 2019). The dataset used in this work is Wisconsin Breast Cancer dataset, which is a dataset obtained from the UCI machine learning repository (Frank & Asuncion, 2010). This study reveals that the highest accuracy, precision, and F1 score were obtained by using the ANNs with values of 98.57%, 97.82%, and 0.9890% respectively.

4) *k-nearest neighbor (KNN)*

KNN is a supervised classification algorithm producing new data points based on the k number or the closest data points (Bagchi et al., 2020). In recent years, many researchers have been used this method for breast cancer detection and diagnosis. For example, in (Mohan & others, 2020), two classifiers were considered in this paper, support vector machine (SVM) and k-nearest neighbour (KNN) using mammography images of CBIS-DDSM dataset. A 2D median filter was used to remove noise and unwanted artefacts, and then local binary pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM) were implemented for features extracting. The final results show that KNN outperforms SVM in the term of the final accuracy, where SVM achieved 96%, while KNN acquired 100%.

A study was presented to assess two machine learning: k-nearest neighbour (KNN) and artificial neural network on a group of mammography images extracted from the Wisconsin Breast Cancer Database (O'Shea, 2020). The accuracy of KNN and ANN was 100% and 95.24% respectively.

Subspace KNN algorithm, together with Stacked autoencoder (SAE), used for the diagnosis of disease on the breast cancer microarray dataset at the first stage (Adem, 2020). And then, such hybrid approaches were applied to a group of images taken from the Kent Ridge-2 database. Such hybrid approaches can deal with high-dimensional and uncertainty datasets and 91.24% of accuracy was achieved.

A survey was presented in (Pharswan & Singh, 2020) to investigate the best classifiers between SVM, KNN. GLCM had been used to extract the essential features. This study reveals that SVM achieved higher accuracy with a value equal to 94%; moreover, it got a better recall and F1 score than KNN.

5) Gaussian Mixture models

The Gaussian mixture model is a classification that can cluster similar points predicting an unseen point from training data. The authors of (Ezhilraman et al., 2020) used this classifier for breast cancer-detecting. In another study, the Gaussian mixture model (GMM)–based classifier was developed based on mRNA expression data to predict the molecular characteristics of tumours (Prabakaran et al., 2019).

6) Random Forest

Random forest is an ensemble learning method that has been used for classification. Some recently proposed methods are investigated for breast cancer detection using computer vision and machine learning techniques by (Y. Lu et al., 2018). The detection performance of different methods on mammography images and histological images are compared and analyzed. For enhancing the diagnosis of breast cancer, three imaging modalities are used: histological imaging, x-ray (mammography) imaging, and ultrasound imaging. Different datasets already exist for each type of modality. This paper shows that deep learning-based methods have achieved good results for breast cancer detection using histological imaging or mammography imaging. The ScanNet method has achieved the highest accuracy on histological images. Besides, an impressive result could be achieved using Adaboost with a random forest classifier on mammography images.

Random Forest method was implemented using three datasets: the Wisconsin Diagnostic Breast Cancer (WDBC) dataset, Wisconsin Original Breast Cancer (WOBC) dataset, and Surveillance, Epidemiology, and End Results (SEER) breast cancer dataset (S. Wang et al., 2020). This method achieved high accuracy, but the reasons behind the diagnosis results are unable to be explained. Therefore, an improved random forest (RF)-based rule extraction (IRFRE) method is proposed for getting a higher accuracy and interpretable classification for breast cancer diagnosis. IRFRE contains two parts: random forest-based rule generation and multi-objective evolutionary algorithm (MOEA)-based rule extraction.

Random Forest and Extreme Gradient Boosting (XGBoost) were applied for breast cancer prediction (Kabiraj et al., 2020). The main goal of this paper was to classify recurrence and no-recurrence events accurately, and it achieved 74.73% and 73.63% of accuracy. The UCI Machine Learning Repository was used as an input data (Frank & Asuncion, 2010), while for data pre-processing, trimmed mean and mode had been used.

7) Support Vector Machines (SVMs)

Support Vector Machine (SVM) is a learning classifier method that can separate data into categories (Bagchi et al., 2020). Many researchers have been using this method to classify breast cancer.

A comparison study based on the confusion matrix and accuracy for breast cancer diagnosis among different supervised learning classification algorithms was conducted: SVM, logistic regression, KNN classifier, Naïve Bayes, and decision trees (A. Kumar & Poonkodi, 2019). The suggested algorithm, namely, Kernel SVM with PCA outperformed the rest used classifiers by achieving 98.24% of accuracy.

The thermograph technology was investigated to be a better alternative to the standard mammography, which is being a painful procedure and exposure of the body to harmful X-rays (A. A. Khan & Arora, 2018). Some of the thermogram images are taken from DMR-Database which is a database for Mastology Research (A. A. Khan & Arora, 2018). Gabor filters are used to extract the texture features of the left and right breasts, while support vector machine (SVM) is used to classify breast lesions based on the textural asymmetry between the breasts. The proposed methodology attained 84.5% of accuracy; therefore, thermography might be able to detect early breast cancer.

A histopathology-based feature method has been considered in breast cancer detection and classification (Singh & Kumar, 2020). The BreakHis dataset was used as input data, while K-Nearest neighbour (KNN), Random Forest, and about six flavours of SVM have been investigated. The final outcomes show that the proposed cubic SVM classifier achieved 92.3% accuracy as maximum.

In (J. Liu et al., 2020), the researchers presented a study to develop a rapid, effective, and economical screening tool for breast cancer using Fourier-transform infrared (FT-IR) spectroscopy data collected from the Affiliated Tumor Hospital of Xinjiang Medical University. The used modality name in this work is VERTEX 70 infrared spectrometer from Germany BRUKER, and a total of 229 serum samples were collected. PCA was used to reduce the number of extracted features of samples, while SVM was used as a classifier, as well as the linear, polynomial, and RBF kernels were implemented to verify the diagnosis results of SVM. The final results show that the best performance has been given under the polynomial kernel and SVM.

The authors in (Gong et al., 2020) proposed a novel multi-view deep neural network support vector machine (MDNNSVM) to diagnose breast cancer using bi-modal ultrasound.

Gene expression microarray data was collected from the GSE76275 dataset, which contains 265 samples (Chen et al., 2020). SVM and KNN algorithms are tested, and recursive feature elimination (RFE) was used to find the optimal feature subset. The suggested SVM-RFE-SVM method worked effectively compared to other used classifiers such as SVM, KNN, KNN-PCA, SVM-PCA, SVM-RFE-SVM, and SVM-RFE-KNN.

A study was presented in (Vrigazova, 2020) to propose a modification of the SVMs that can reach a high accuracy in detecting malignant tumours to 99.6% using the Wisconsin breast cancer dataset. Moreover, a small error rate was reported compared to some of the mentioned methods in (Vrigazova, 2020).

The authors in (Hamouda et al., 2020) showed a study to predict breast cancer using blood analysis data collected in Coimbra Dataset. A Support vector machine (SVM) was used as a classier and Grid Search Algorithm implemented to optimize the SVM classifier.

At another study, Median filter and adaptive histogram equalization were used as pre-processing, and then the Gabor algorithm and the mean and standard deviation implemented to extract features, finally SVM classifier was applied to classify a group of mammography images in Mini-MIAS dataset (Thakare et al., n.d.).

Classifying breast cancer using three modalities, namely, Mammogram, Ultrasound, and Magnetic Resonance Imaging, has been investigated in (Venkata & Lingamgunta, 2020). The proposed work applied SVM to categorize the common phenotype features of different medical images issued by the three modalities. The final results show that the SVM classifier in detecting lesion is more accurate in MRI images than Mammography and Ultrasound images.

The Boruta feature selection was implemented for getting the most important features (Aroef et al., 2020). Furthermore, the SVM and random forest were the machine learning model used, with accuracies of 95% and 90% respectively.

8) Convolutional Neural Networks (CNN)

CNN is a multilayered neural network for recognizing complex features in data (Bagchi et al., 2020). Recently, many researchers have been using this classifier to detect and diagnose breast. For example, the authors of (H.-C. Lu et al., 2019) used deep learning techniques; namely, CNN to detect and diagnose breast cancer using 9000 mammograms collected from a teaching hospital in Taiwan. The preprocessing techniques, median filter, contrast-limited adaptive histogram equalization, and data augmentation were applied. The final outcomes show that the model with preprocessed images achieves higher accuracy than the model without preprocessed images. 70% of the dataset is chosen as training data, 10% of the dataset is selected as validation data, and the rest of the dataset works as testing data. The overall specificity, sensitivity, and F1 score achieved by the proposed model with preprocessed images were 0.57, 0.91, 0.88, while they were 0, 0.79, 0.88, using the proposed model without reprocessed images.

Another study was conducted in (Z. Wang et al., 2019), where the authors firstly had suggested a CNN and unsupervised extreme learning machine (US-ELM) for feature extraction and clustering. Secondly, a fusion deep feature set had built by using an 8-layer CNN architecture for obtaining twenty in-depth features to integrate them with extra five shape features, five texture features, and seven density features of the tumour. Finally, the created fusion deep feature set of each mammogram was used as an input to an extreme learning machine (ELM) classifier to directly indicate whether a benign or a malignant breast tumour exists. The number of mammography images used in this work is 400 mammograms.

A pre-trained CNN was used for segmentation (Wahab et al., 2019), while Hybrid-CNN (with Weights Transfer and custom layers) used for classification of histopathological images into cancer or not. Besides, the dataset used in this work was collected from (Medical Image Analysis Group Eindhoven, 2020).

9) Logistic Regression (LR)

LR is one of the most commonly used classification algorithms in machine learning. Some researchers have used this method for extracting the essential features, while others use it in the classification process.

The authors in (Khandezamin et al., 2020) proposed a method consisting of two steps: extract important features by implementing logistic regression, while the Group Method Data Handling (GMDH) neural network was used to differentiate malignant from benign cases. Three datasets Wisconsin Breast Cancer Database (WBCD), Wisconsin Diagnostic Breast Cancer (WDBC), and Wisconsin Prognostic Breast Cancer (WPBC), are investigated in this work. The proposed method shows that the accuracy obtained using WBCD, WDBC, and WPBC dataset was 99.4%, 99.6%, and 96.9% respectively.

A new logistic regression-based model was introduced by (Zhou et al., 2020), which was used to classify breast cancer tumour samples based on microarray expression data without reducing the microarray data matrix. Three datasets were downloaded from the National Center for Biotechnology Information (NCBI): GSE65194 178, GSE20711 90, and GSE25055 310 samples. The minimum performance achieved of the proposed method was 80%.

A comparative study was conducted in (MurtiRawat et al., 2020) for breast cancer diagnosis by implementing Logistic Regression (LR), K-Nearest Neighbors (KNN), and Ensemble Learning with Principal Component Analysis (PCA). Wisconsin breast cancer diagnosis had been used. In terms of accuracy, the Ensemble Learning classifier outperformed the rest by achieving 99.30%, while 98.60% was obtained by using K-Nearest Neighbors, and 97.90% of accuracy was acquired by using Logistic Regression.

XIII. Learned Feature-Based Algorithms

As mention before that handcrafted feature means that the data scientist manually engineers a group of features. In other words, a set of features include edge detection, corner detection, histograms, are defined and then extract them. On the contrary, these features can be extracted automatically by train a machine learning model to identify and extract the relevant features. One of the most ML algorithms used for extracting essential features is CNN (Araújo et al., 2017).

XIV. Dimension Reduction

Basically, the feature extraction process generates a large dimensional feature vector, where many of the extracted features could be irrelevant or redundant. The more extracted features, the more time and high computational cost it will be to classify these features (Bagchi et al., 2020). Also, feature vectors with large dimensions cause another problem especially when the training data is little, which leads to overfitting the training dataset and the invisible images might not be recognized by the ML model (Bagchi et al., 2020). Therefore, dimension reduction is a fundamental process to enhance the performance of a system when classifying a group of images with a large dimensional feature. Furthermore, the authors in (Bagchi et al., 2020) mentioned two ways to reduce the dimension: selecting the essential features or creating new dimensions. Firstly, some researchers have been used some heuristic methods for selecting essential features such as sequential forward selection and sequential backward selection. Moreover, other selection methods have been used, including genetic algorithm, simulated annealing, boosting, grafting, and particle swarm optimization. Secondly, some methods have been used to create new dimensions like principal component analysis, linear discriminant analysis, independent component analysis, and manifold learning (Bagchi et al., 2020).

Generally, the reduction dimensions enhance the performance but over reduction leads to the loss of some of the critical features; therefore, some researchers use dropout (Hinton et al., 2012) or regularization (Ng, 2004) methods to solve the overfitting problem in deep learning. Moreover, PCA also is used for reduction dimensions (Siregar et al., 2020). Besides, another study used PCA and Linear Discriminant Analysis (LDA) to reduce dimensions (Obaid et al., 2019).

XV. Measure of Performance

The measure of performance is a way to sure that the outcomes are accurate; therefore, to achieve a high performance of machine learning methods, some performance measures should be fulfilled. The following measures are the most popular ones used as benchmarks for performance checking (Saxena & Gyanchandani, 2020)..

A. Accuracy and area under curve:

The accuracy of the machine learning method can be calculated using a value between 0 and 1, or in percentage, and it can be calculated by (1). Where TP (True-Positive) refers that the disease is correctly classified as positive by a method, while FN (False-Negative) means that the disease is incorrectly classified as negative by a method. TN(True-Negative) denotes that the disease is correctly classified as negative by a method. Finally, FP(False-Positive) reveals that the disease is incorrectly classified as positive by a method.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

B. Sensitivity or Recall:

The sensitivity shows how well a method can correctly detect people with breast cancer, and it can be given by (2).

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

C. Specificity:

It exhibits the likelihood of the cases which are mistakenly determined as false Positive (FP), and it can be calculated by (3).

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

D. Precision:

It displays how well a method is to correctly classify cases, and it can be given by (4).

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

E. F measure:

It is the harmonic average that combines both precision and sensitivity into one single measure, is given by (5).

$$F_{Measure_{Metric}} = \frac{2*Precision*Sensitivity}{Precision+Sensitivity} \quad (5)$$

F. ROC (Receiver Operating Characteristic curve):

ROC is a graph that represents the relation between two parameters: true-positive rate (TPR) and false-positive rate (FPR). True-positive rate (TPR) is known as sensitivity or probability of detection, and it is drawn on the y-axis. In contrast, the false-positive rate (FPR) is known as specificity or a false alarm and is drawn on the x-axis. In general, the generated graph must be closer to the top and left borders in which help to get as accurate results as possible (Saxena & Gyanchandani, 2020).

CONCLUSION

Breast cancer is still one of the most widespread diseases causing death among women worldwide. The structure of this disease is various, which makes the process of detection and diagnosis is more complicated for researchers. Many hardware and software have been created to help in analyzing and classifying breast cancer. This survey has been devoted to conducting a comprehensive review of the most recent techniques used for breast cancer detection and diagnosis based on machine learning. A group of medical modalities is mentioned with its strengths and limitations such as mammography, MRI, US. Moreover, a set of commercial and non-commercial CAD system have summarized with its advantages and disadvantages. CAD system stages for analyzing and classifying breast cancer are also mentioned in detail. Five CAD system stages based on machine learning have been implemented: pre-processing, segmentation, feature extraction and selection, and classification. The most used methods in each stage are presented. Besides, a set of breast cancer datasets that collect either medical images or extracted features are presented. Generally, this survey systematically compares the recent approaches of machine learning in medical images. It shows how advances in machine learning methods give promising results that can aid radiologists or physicians for breast cancer detection and diagnosis.

This study reveals that many techniques have been raised to help for breast cancer detection and diagnosis, however, there is no perfect modality that can detect and diagnose breast cancer alone. Moreover, a complete system that can deal with different modalities and give 100% accuracy still a challenge, since the diverse structure of breast cancer and the different modalities have been used. Such limitations necessitate conducting extra improvement to keep up with the rising risk and protect patients from this deadly disease.

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