Abstract: Breast cancer is the most leading cancer occurring in women and is a significant factor in female mortality. Early diagnosis of breast cancer with Artificial Intelligent (AI) developments for breast cancer detection can lead to a proper treatment to affected patients as early as possible that eventually help reduce the women mortality rate. Reliability issues limit the current clinical detection techniques, such as Ultra-Sound, Mammography, and Magnetic Resonance Imaging (MRI) from screening images for precise elucidation. The capability to detect a tumor in early diagnosis, expensive, relatively long waiting time due to pandemic and painful procedure for a patient to perform. This article aims to review breast cancer screening methods and recent technological advancements systematically. In addition, this paper intends to explore the progression and challenges of AI in breast cancer detection. The next state of the art between image and signal processing will be presented, and their performance is compared. This review will facilitate the researcher to insight the view of breast cancer detection technologies advancement and its challenges.

Keywords: breast cancer detection; feature selection; feature fusion; machine learning

1. Introduction
Breast cancer is the most common cancer worldwide and leading cancer compared to other types of cancer for both sexes in Malaysia, which accounted for 8418 (17.3%) out of 48,639 total new cancer cases that recorded by World Health Organization (WHO) in 2020 [1-4]. According to the National Cancer Institute, Ministry of Health Malaysia, 7372 breast cancer deaths are expected in 2017 in Malaysia [5]. Previous researchers and experts have suggested that early breast cancer detection or early screening with proper diagnosis and treatment could increase breast cancer survival rates for the long term, as shown in Figure 1, and significantly reduce treatment costs. Cancer that detects in an early phase, before it grows and spread, is bound to be dealt with effectively [6-9]. Tables 1 and 2 show the relative survival types of cancer and selected variable period of diagnosis 2007–2011 and followed up to 2016, respectively.
Cancer is a syndrome associated with an imbalance of replication cells and cell response in the body, causing abnormal cell growth or known as a tumor [11]. The tumor is classified as non-cancerous (benign) or cancerous (malignant). Benign tumors do not invade nearby tissues or spread to other areas of the body (metastasize) [12]. On the other hand, a malignant tumor consists of cancer cells that can invade and kill surrounding tissues and can attack different parts of the body. Cancer cells can spread to other organs causing systemic complications. In most cases, breast cancer first spreads into nearby lymph nodes and can affect the lungs. Lymphoma is a malignant lymphoma that begins in
lymph tissue, however it is not the same as breast cancer. However, in the early stages of the disease, lymphoma can be difficult to identify from breast cancer. Anaplastic Large Cell Lymphomas (ALCL) are a kind of primary breast lymphoma that is extremely rare [13]. The cancer cells in the lungs are designated as breast cancer cells, as shown in Figure 2. Therefore, it is pretty apparent that early detection of the cancer cells presence is a crucial stage to cure and prevent the cell from spreading to the other part. Early detection can be done by performing a regular self-examination (once a month) and, more accurately, through early screening at nearby public and private health facilities (annually check-up) before a person experiences more severe cancer symptoms [14–18].

**2. Existing Breast Cancer Detection Techniques & Technologies**

The primary key in women’s survival from breast cancer is early detection and proper treatment [20,21]. Many existing screening and emerging technology tools are used for the detection of the early stages of breast cancer. As illustrated in Figure 3, the current breast cancer detection tools are classified into two categories: body imaging-based technology [22] and microwave imaging-based technology [23].

**Figure 2.** Common cancer incidence locations in female breast [19].

**Figure 3.** Block diagram showing the different modalities in breast cancer detection.

**2.1. Body Image-Based Technology**

Body image-based technology includes Magnetic Resonance Imaging (MRI), mammography, and ultrasound that obtain the breast structure image to be examined and evaluate the abnormality of the breast by the radiologist. These tools can be found in most clinics and hospitals. Table 3 compares the advantages and disadvantages most used breast
cancer screening techniques methods. Microwave imaging-based technology, on the other hand, has the potential to replace expensive and invasive screening methods. Furthermore, this technology is safe, robust, ionizing radiation-free, and causes lesser physical harm to users. Microwave imaging-based technology uses two approaches which are microwave tomography and radar-based imaging [24,25]. In both methods, the Ultra-Wideband (UWB) signals were used to classify breast cancer according to the dielectric properties [26–29].

Table 3. Advantages and disadvantages of various imaging modalities in breast cancer screening [30–33].

| Type                  | Advantages                              | Disadvantages                      | Technique                                                                 |
|-----------------------|-----------------------------------------|------------------------------------|---------------------------------------------------------------------------|
| Ultrasound            | Inexpensive                             | Low resolution                     | This technology uses a high frequency of sound waves to produce an image of organs and structures within the body |
|                       | Suitable dense breast                   | Low sensitivity                    |                                                                           |
|                       | Quick and painless radiation            | Low specificity                    |                                                                           |
|                       | Nonionizing radiation                   | High operator dependency           |                                                                           |
|                       | Widely available                        |                                    |                                                                           |
| Mammogram             | The old standard                        | False negative                     | This imaging uses a low-dose (ionizing radiation) X-ray system to discover inside the breast |
|                       | Regular check-up                        | Not convenient                     |                                                                           |
|                       | Provide high                            | Compressed Ionizing                |                                                                           |
| MRI                   | High sensitivity                        | Long scan time                     | MRI uses magnetic fields and radio waves to create detailed images of organs and tissues in the body |
|                       | Image in any angle                      | Claustrophobia                     |                                                                           |
|                       | Painless                                | Expensive                          |                                                                           |
|                       | Nonionizing radiation                   | Less widely available              |                                                                           |
| Microwave Imaging     | Nonionizing radiation                   | Not available in clinic or hospital | This technology uses a microwave                                          |
|                       | Non-invasive                            |                                    |                                                                           |
|                       | Inexpensive                             |                                    |                                                                           |
|                       | Comfortable                             |                                    |                                                                           |

2.1.1. Ultrasound

Ultrasound imaging (sonogram) is a medical tool that uses a high frequency of sound waves (echoes) to obtain real-time images of the body’s internal structures or detect suspicious nodular formations without involving ionizing radiation compared to MRI and mammogram. Ultrasound is a low-cost and non-invasive procedure for patients. There are two significant functions of ultrasound which are for diagnostic of internal body and pregnancy. The frequency range commonly employed in medical ultrasound is 2 to 18 megahertz, hundreds of times above the human hearing range [34–36]. A transducer is a device that rubs the patient’s skin across the area being investigated during an ultrasound. Although ultrasound is often used to prevent an invasive measure for diagnosis, sometimes it may overlook detecting the smaller size of masses that will carry false-positive and false-negative results. Ultrasound is suitable for women below 45 years and women with dense breasts, while mammography has progressive sensitivity in women 60 years and above [37]. The samples of ultrasound breast images are illustrated in Figure 4 and categorized into three classes, which are normal, benign, and malignant.
2.1.2. Mammography

Mammogram, also called mastography, is a low-dose energy X-ray (ionizing radiation) procedure to produce images (radiographs) of the breast. It can be used to screen or diagnose people who are symptomatic (have symptoms of illness) or asymptomatic (have no symptoms of illness) [39]. Ordinary radiation dose around 0.4 millisieverts (mSv) or 30 peak kilovoltage (kVp) for two views of each breast [40,41]. 2D mammograms only compress the breast and catch images from the front and side. 3D mammography (or called tomosynthesis) produces X-ray images of the breast by taking various views across the breast in an arc. Previous studies reported that the detection is significantly improved when 3D mammography was used with 2D mammography [42]. A mammography expert, often known as a mammographer, performs this process. A mammographer is well-trained to take X-ray images of the breast. The radiologist specializing in reading medical imaging tests will review the mammogram to search for unusual configurations that look different from normal tissues. It can be representing a cancerous tumor, non-cancerous masses or cysts. Breasts are compressed between two firm surfaces to separate overlapping breast tissue and to reduce the thickness of the breast during the procedure. Then an X-ray produces black-and-white picture of breasts that are appear on a computer screen and examined by a radiologist that looks for signs of cancer, as shown in Figures 5 and 6. A mammogram is not suitable for women with denser breast and more likely to have false alarms due to the overlap of normal fibro-glandular tissues [43–45].

![Figure 4. Samples of Ultrasound breast image [38].](image1)

![Figure 5. Samples of Mammogram breast image [46].](image2)
2.1.3. Magnetic Resonance Imaging (MRI)

Magnetic Resonance Imaging (MRI) is a medical imaging technique that records changing strong magnetic fields and radio waves to produce detailed images of the organ and soft tissues of the human body [38,47,48]. MRI is the most effective imaging modality that offers precise accuracy and sensitivity in detecting structural abnormalities of the body compared to the other technique, as shown in Figure 6 [49–51]. However, MRI is an expensive technology, and a waiting list is often long. MRI is a painless radiology procedure and does not use harmful ionizing radiation of X-ray. The MRI scanner machine is a large horizontal tube surrounded by a circular superconducting magnet where one patient enters (lie down in bed) [52] and running through the magnet from front to back that assist by the technician or a radiographer. During this procedure that take around 30–45 min, some patients can experience discomfort or fear of enclosed spaces (claustrophobia). MRI creates a powerful magnetic field that forces the protons in the body to align with that field. Then, a radio-frequency current is pulsed through the patient’s body that disrupts the proton and forces it into 90-degree or 180-degree realignment with the static magnetic field. The scanner can identify the energy signal from the patient’s body when the radio frequency is switched off. On the computer screen, these impulses were used to create visual images [53] as shown in Figure 7. Combining mammography, MRI, and certain clinical techniques yielded the best sensitivity 94.4%. The highest level of accuracy attained was 75.6%, implying that one out of every four diagnoses is incorrect [46]. The comparison of diagnostic performance of different breast tumor detection techniques is present in Table 4.

Figure 6. Conventional mammogram of breast cancer [46].

Figure 7. Typical finding of MRI-detected breast cancer (arrow) [50].
Table 4. Comparison of diagnostic performance of different breast tumor detection techniques [46,54,55].

| Modality                        | Sensitivity | Specificity | Accuracy | Advantage       | Limitations                  |
|---------------------------------|-------------|-------------|----------|-----------------|-----------------------------|
| Mammogram                       | 67.8%       | 75%         | 70.2%    | Low cost        | False positive and negative |
|                                 | (120/177)   | (61/81)     | (181/258)|                 |                             |
| Mammogram and clinical examination | 77.4%       | 72%         | 75.6%    | Low cost        | Lower accuracy              |
|                                 | (137/177)   | (58/81)     | (195/258)|                 |                             |
| Clinical examination            | 50.3%       | 92%         | 63.6%    | Easy process    | A small tumor cant detect   |
|                                 | (89/177)    | (75/81)     | (164/258)|                 |                             |
| Ultrasound                      | 83%         | 34%         | 67.8%    | Better than X-ray | Difficult to detect solid tumor |
|                                 | (147/177)   | (28/81)     | (175/258)|                 |                             |
| Mammogram and ultrasound        | 91.5%       | 23%         | 70.2%    | Cost effective  | Unwanted compression        |
|                                 | (162/177)   | (19/81)     | (181/258)|                 |                             |
| Mammogram, ultrasound, and clinical | 93.2%       | 22%         | 70.9%    | Good detection  | Complex signal processing   |
|                                 | (165/177)   | (18/81)     | (183/258)|                 |                             |
| MRI                             | 94.4%       | 26%         | 72.9%    | Provide high resolution | Higher cost time consuming |
|                                 | (167/177)   | (21/81)     | (188/258)|                 |                             |
| Mammogram, clinical exam, and MRI | 99.4%       | 7%          | 70.5%    | Best solution ever found | Complex , expensive, and time |
|                                 | (176/177)   | (6/81)      | (182/258)|                 |                             |

2.2. Microwave Imaging-Based Technology

Alternative technology has focused on breast cancer detection research involving Microwave Imaging (MI) in the recent decade to overcome the inconvenience, accessibility, high risk, and cost associated with X-rays and MRI [56–59]. MI is a nonionizing electromagnetic signals imaging technology that uses frequencies ranging from 300 MHz to 30 GHz [60]. MI provides higher and stronger contrast between healthy tissue and tumors, contributing to tumor identification without the risk of ionization effects (safe medical screening tool) [61,62]. As illustrated in Figure 8, a MI architecture consists of two main components: (i) hardware (antenna) for transmitting and collecting microwave signals that reflect from the breast phantom using Vector Network Analyzer (VNA) or any proper electromagnetic transceiver; (ii) software to rebuild the signals received and stored in a computational tool that contains detection algorithm [63]. The latter uses the power distribution of scattered waves to distinguish between healthy and tumor-containing tissues. MI is a cost-effective procedure since the equipment is often a fraction of the cost of equipment for other diagnostic approaches [64]. The most significant problem is that microwave imaging produces an image with limited spatial resolution [65–67]. Microwave tomography and radar-based imaging are the two main types of microwave imaging [68,69].

The tissue-dependent dielectric contrast to reconstruct signals and pictures using tomographic or radar-based imaging techniques is the physical foundation of medical microwave imaging. Relative permittivity and conductivity are used to describe the dielectric characteristics of various tissues [70]. Furthermore, if tumorous, tissue of the same kind will have differing dielectric characteristics. Because of this variation, the interaction of EM signals in various tissues will be different [71]. Varied reconstruction techniques may use this to create an image, in 2D or 3D, that displays additional tissue dielectric characteristics or a tumor’s location within the body [72].

For creating the dielectric characteristics of the breast, the tomography method is frequently conducted iteratively and may be represented as a nonlinear inverse problem.
that demands enormous processing resources. Inverse scattering methods estimate the constitutive characteristics of the breast tissues by analyzing the absorbed and reflected microwave signals, allowing imaging of the breast tissues to be generated from the recovered microwave data file. An external microwave source is used to illuminate the breast tissues with Ultra-WideBand (UWB) waves in radar-based techniques. Breast tumors are detected using backscattered signals from the breast [57].

Figure 8. A schematic diagram showing the components of the microwave imaging system [57].

2.2.1. Microwave Tomography Technique

Microwave Tomography (MT) is an emerging biomedical imaging technique to determine the dielectric characteristics of the tissue under investigation using the inverse scattering approach [73,74]. MT is extensively used in medical for non-invasive biological imaging. 500 MHz and 30 GHz are the lowest and highest frequencies utilized in clinical MT, respectively, [75–78]. It can be divided into three main components; sensing system, interfacing, and image reconstruction algorithm [79,80]. This gives a dielectric contrast to it. Through inversion scattering, it generates a chart of permittivity and conductivity. The breast is lowered into a cylinder-shaped antenna system that completely covers the breast in a microwave tomography breast cancer investigation system, as illustrated in Figure 9. Microwave measurements are then conducted using as many antennas as possible, functioning as both a transmitter and a receiver. The wave field gets extremely intricate as microwaves penetrate tissue and are dispersed and reflected. The vast amount of data created by the big wave field is examined using a radical image reconstruction technique that creates a picture of the whole-body part’s internal dielectric characteristics (the tissue under examination). The dielectric characteristics of malignant tissue, such as permittivity, conductivity, and electrical parameters, are critical in this detection methodology. These features were found to be vastly different from those of normal breast tissue.
2.2.2. Radar-Based Technique

UWB microwave radar-based imaging technique (known as beamformers) rebuilds the image using the reflected wave from objects [82]. The radar system uses a UWB pulse from a transmit (TX) antenna to illuminate the breast, and the resulting reflections that are created at dielectrically differing tissue boundaries are collected by the receive (RX) components [83,84]. This technique, unlike microwave tomography, reconstructs the scattering power distribution when microwaves are emitted on the breast, and their reflected waves are analyzed. Compared to tomography, UWB microwave imaging leads to faster detection due to the lower computational power needed, relatively simple and robust signal processing [85,86]. The setup is shown in Figure 10. It works very much like a ground-penetrating radar (GPR). The origin dates to 2001 by Hagness and Xu Li in Wisconsin University, USA. Therefore, it becomes imperative to understand the behavior of human tissues as a channel to propagate the UWB-emitted waves in this context.

The MARIA® system is a novel technology that utilizes dielectric value to distinguish between tissue types within the female breast. Radiowave radar-based imaging is well-researched, and the unique physiological characteristics of the breast have made it an important research area for radio-wave technology [87]. As seen in Figure 11, this research
area divided into two categories: image processing and signal processing. Most researchers using an available dataset that can get through Wisconsin Breast Cancer Dataset (WBCD) will focus on image processing. In contrast, for signal processing, the researcher will start from data collection until processing the result.

**Figure 11.** Research area in breast cancer detection using image processing and signal processing.

### 3. Emerging Breast Cancer Detection Technique

#### 3.1. Artificial Intelligence in Breast Cancer Detection—The Progression

AI has placed the benchmark of human civilization in the development of technologies that influence various areas to evolve over the past decade [88]. There are subfields under AI technology include Machine Learning (ML), Deep Learning (DL), and computer vision, as shown in Table 5. Medical image and signal processing, medical resources management, medical workflow optimization, medical education, and other applications have all seen significant improvement as AI has become more incorporated into regular medical practice. In terms of the medical image processing in breast cancer detection, radiologists can benefit from AI clinical decision-making and improved patient care [89, 90]. The workflow of radiologists has transformed because of advances in medical imaging and the algorithms can improve care beyond the current boundaries of human performance. In terms of image interpretation, AI can assist the radiologist in identifying and classifying disease patterns from images, as well as helping the radiologist to suggest appropriate care pathways for a patient in consultation with other physicians involved in the patient’s care [91–93].

Recent studies conducted by the Korean Academic Hospital and Lunit show that radiologists breast cancer detection accuracy significantly improved by using AI. According to this study, only AI showed a sensitivity of 88.8% in breast cancer detection. In comparison, only radiologists showed a sensitivity of 75.3%. When AI-assisted radiologists, the accuracy increased by 9.5% to 84.8%. One of the main findings also showed that compared with radiologists, AI showed higher sensitivity in detecting tumors (90% vs. 78%) and aberrations or asymmetry (90% vs. 50%). AI performs better in detecting T1 cancers, which are classified as early invasive cancers. AI detected 91% of T1 cancers and 87% of lymph
node-negative cancers. In comparison, the radiologist reader group detected 74% of both cancers [94,95].

Table 5. Subfields of Artificial Intelligence [89].

| Artificial Intelligence: technique enables computers to mimic human behavior |
|---------------------------------------------------------------------------|
| Machine Learning (ML): the subset of AI technique; pattern identification and analysis; machines can improve with experience from provided data sets |
| Deep Learning (DL): the subset of ML technique; composed of multi-layer neural networks |

Based on the features retrieved from medical imaging, many machine learning methods are utilized to identify, categorize, and diagnose breast cancer. The most recent review paper has just been published in 2020 [96], providing a comprehensive review of the AI technique for breast cancer detection. As a result, this paper is not to offer another general review of microwave imaging as current research, but rather to focus on body image-based technology. Figure 12 shows a chart of the various machine learning techniques addressed in this study for breast cancer detection. The following section goes through the procedures for detecting breast cancer using different modalities in breast cancer detection: mammography, ultrasound, MRI, and microwave imaging.

![Figure 12. Machine learning technique used in breast cancer detection discussed in this review.](image)

3.2. Bias and Challenges of Artificial Intelligence in Breast Cancer Detection

AI is quickly gaining traction in the medical field, with applications ranging from automating tedious and regular medical practice activities to patient and resource management. Although AI has seemingly limitless possible benefits, the inherent challenges of machine learning algorithms, the imperfection of data availability access, bias, and inequality have all hindered the development of AI.

There are many algorithms proposed by researchers used to implement AI nowadays. The most obvious concern is that AI systems are sometimes incorrect, posing a risk to patients or causing other medical problems. False-positive interpretations of breast cancer screening can cause cancer to spread to other organs unknowingly. New social and AI issues occur as algorithms trained and learned to execute a task may eventually take off to the point where humans lose control, resulting in unforeseen problems and ramifications. It refers to AI’s capacity to follow its path after being programmed with the required algorithms and rejecting orders from a human controller [97,98].

One of the key barriers for AI to achieve maximum accuracy and reduce error is data scarcity. Large datasets from reliable sources are required to train AI systems, and the lack of a proper data infrastructure is a key barrier to applying AI to existing applications. However, health data might be difficult to obtain. Data privacy also limits researchers’ ability to access appropriate data in the medical field [99].
An abnormality in the output of machine learning algorithms is AI bias. It might be due to biases in the training data or biased assumptions made during the algorithm building phase. Bias may infiltrate algorithms in a variety of ways. Even when sensitive factors like gender, ethnicity, or sexual orientation are excluded, AI systems learn to judge based on training data, which might contain biased human decisions or reflect historical or societal injustices. AI systems learn from the data that have been given and can include biases from that data. For every data project, it’s critical to be aware of the potential biases in machine learning. It is better to detect it before it becomes an issue or responds to it when it arises by putting the proper processes in place early and staying on top of data gathering, labeling, and implementation [100–102].

4. Summary of Previous Research on Breast Cancer Detection

4.1. Image Processing

AI may be used to overcome the constraints of screening mammography in a variety of ways, including as a detection tool with a human reader. Human-like or superhuman performance has been shown in studies employing different algorithms under circumstances that are sometimes very realistic [103]. Vaka AR [104] using a dataset taken from M.G Cancer Hospital and Research Institute, Visakhapatnam, India. There are 8009 histopathological picture samples from over 683 patients in the collection, with different magnification levels. This researcher proposed novel technique called Deep Neural Network with Support Value (DNNS) is used to improve picture quality and correct other performance factors. The experimental results are presented in Figure 13, the proposed segmentation is illustrated as shown in Figure 14.

![Figure 13. The experimental result. Segmented images of proposed DNNS method [104].](image1)

![Figure 14. Comparison of result by segmentation and proposed segmentation [104].](image2)

Y. Ouyang [105] developed a novel technique for classifying benign and malignant breast cancers based on H-scan ultrasound imaging to overcome common problem of ultrasound such as limited spatial resolution and speckle noise. In H-scan ultrasound images, benign breast tumors had more red components, whereas malignant breast tumors had more blue components, according to this researcher experimental findings as shown in Figure 15. The RGB channels of H-scan ultrasound images of benign and malignant breast tumors showed substantial variations. Y. Ouyang and team find that H-scan ultrasound imaging may be utilized to categorize benign and malignant breast cancers in a novel way.

M. Elter, R. Schulz-Wendtland, and T. Wittenberg supplied A. Shirazi [106] with a dataset including 822 cases. A hybrid computational intelligence model based on unsupervised and supervised learning methods is proposed by this researcher. The patient’s attributes were then applied to a complex-valued neural network and dealt with in the sec-
ond step to identify breast cancer severity for each cluster (benign or malignant). The health and diseases breast cancer detection rates were 94 and 95 percent, respectively, throughout the testing phase.

Figure 15. Ultrasound images of benign breast tumors and H-scan images [105].

4.2. Signal Processing

S. Yuvarani [107] developed a wearable clinical prototype with a patient interface for microwave breast cancer detection in this project. This researcher looks at how NN may be used to speed up signal processing for diagnosis. Various situations were used, including homogeneous and heterogeneous breast models with varying densities, as well as ideal and realistic signal analysis techniques. This researcher proposed Signal Calibration Using Neural Network Technique (SCNN) shown in Figure 16 and gave accuracy 95.6%.

The researcher [108] presented the first clinical demonstration and comparison of a microwave UWB device enhanced by machine learning with patients having traditional breast screening at the same time. Nearest neighbor, Multi-Layer Perceptron (MLP) neural network, and SVM were used to create an intelligent classification system and their best performance is SVM with 98% accuracy.

Figure 16. Proposed SCNN technique block diagram [107].

In addition, Table 6 summarize and provides several studies related on breast cancer detection using image and signal processing technique. Based on the review, Figure 12 shows the most frequently used ML methods with different modalities. The the most popular classifiers use is: support vector machine, convolutional neural network, logistic regression and k-nearest neighbour.
Table 6. Summary comparative table on machine learning in breast cancer detection.

| Year   | Author and Year               | Dataset                  | Method                          | Processing | Parameter | Result (%)          |
|--------|-------------------------------|--------------------------|---------------------------------|------------|-----------|---------------------|
| 2009   | S.A. Alshehri, et al.         | Breast phantom           | FFBPNN                          | Signal     | Location  | Presence = 100      |
|        |                               |                          |                                 |            |           | Location = 94.4     |
| 2011   | S.A. Alshehri, et al.         | Breast phantom           | Homogenous and Heterogeneous    | Signal     | Location  | Homogenous:         |
|        |                               |                          | Neural Network module           |            |           | Existence = 100     |
|        |                               |                          |                                 |            |           | Size = 95.8         |
|        |                               |                          |                                 |            |           | Location = 94.3     |
|        |                               |                          |                                 |            |           | Heterogeneous:      |
|        |                               |                          |                                 |            |           | Existence = 100     |
|        |                               |                          |                                 |            |           | Size = 93.1         |
|        |                               |                          |                                 |            |           | Location = 93.1     |
| 2014   | K. J. Reza, et al.            | Breast phantom           | FFBPNN                          | Signal     | Size      | Existence = 100     |
|        |                               |                          |                                 |            |           | Location = 80.43    |
|        |                               |                          |                                 |            |           | Size = 85.86        |
| 2015   | V. Vijayasivaraswari, et al.  | Breast phantom           | FFBPNN                          | Signal     | Size      | BPNN = 93.00        |
| 2016   | Moh'd Rasoul Al-Hadidi et al. | Mammography              | Back Propagation Neural Network (BPNN) and the Logistic Regression (LR) | Image | 240 Feature | GA+RBF SVM ensembles = 98.28 |
|        |                               |                          |                                 |            |           | GA+Poly SVM ensembles = 99.50 |
| 2016   | Hiba Asri, et al.             | Breast Cancer Dataset    | SVM, NB, KNN, C4.5              | Image      |           | SVM = 97.13         |
| 2017   | Y. Zhao et al.                | First Affiliated Hospital of China Medical University | LDA, KNN Logistic Regression | Image |           | LDA = 92.60, KNN = 96.30, Logistic Regression = 85.19 |
| 2017   | Min-Wei Huang et al.          | UCI machine learning repository | SVM, GA | Image | Small scale dataset, Large scale dataset | GA+RBF SVM ensembles = 98.28, GA+Poly SVM ensembles = 99.50 |
| 2017   | AZ. Shirazi et al.            | Mammographic image analysis | Hybrid between Self-Organizing Map (SOM) and Complex-Valued Neural Network (CVNN) | Image |           | Breast mass, shape, margin, density, age, breast imaging and data system |
|        |                               |                          |                                 |            |           | Health = 94.00 Disease = 95 |
| 2017   | V. Vijayasivaraswari, et al.  | Breast phantom           | Neural network                  | Signal     | Location  | Forward scattered signal = 84.17 |
|        |                               |                          |                                 |            |           | Backward scattered signal = 87.55 |
| 2017   | V. Vijayasivaraswari, et al.  | Breast phantom 125 data sample | FFBPNN K-fold cross validation (KFFBPNN) | Signal | Location  | FBPNN = 85.43, KFBPNN = 90.23 |
| 2018   | Vikas Chaurasia, et al.       | Wisconsin Breast Cancer Database | NB RBF Network J48 | Image |           | Benign and malignant |
|        |                               |                          |                                 |            |           | NB = 97.36, RBF = 96.77, J48 = 93.41 |
| 2018   | A. Agarap et al.              | Wisconsin Diagnostic Breast Cancer (WDDBC) | GRU-SVM, Linear regression, MLP, NN, SR and SVM | Image |           | Breast mass, benign and malignant |
|        |                               |                          |                                 |            |           | MLP = 99.04         |
| 2019   | Ch. Shravya, et al.           | UCI Repository ML database | LR *KNN SVM *Image |           |           | Breast mass, benign and malignant |
|        |                               |                          |                                 |            |           | LR = 92.10, KNN = 92.23, SVM = 92.78 |
| 2019   | S. Rana, et al.               | Real patient as a subject | Nearest Neighbour Multilayer Perceptron SVM | Signal |           | Healthy breast and breast with lesion |
|        |                               |                          |                                 |            |           | SVM = 98           |
| 2019   | D. Ragab et al.               | Curated Breast Imaging Subset of DDSM (CBIS-DDSM) | Deep Convolutional Neural Network (DCNN) | Image |           | Benign and malignant masses |
|        |                               |                          |                                 |            |           | DCNN-SVM = 87.2     |
| 2019   | R. Chithrakkannan et al.      | Mammogram                | ANN, SVM, KNN and DNN            | Image     |           | Existence |
|        |                               |                          |                                 |            |           | DNN = 92           |
| Year | Author and Year | Dataset | Method | Processing | Parameter | Result (%) |
|------|----------------|---------|--------|------------|-----------|------------|
| 2019 | H. Dhahri et al. [123] | Wisconsin Breast Cancer Dataset | Genetic Programming (GP) | Image | Breast mass; benign and malignant | GP = 98.24 |
| 2019 | L. Shen, et al. [124] | Digital Database for Screening Mammography (CRIS-DDSM) | Convolutional network method | Image | Benign and malignant masses | AUC = 0.98 |
| 2020 | S Kesavan, et al. [125] | Mammogram database picture | KNN classifier Convolutional Neural Network | Image | - | Proposed CAD framework |
| 2020 | Muktevi Srivenkatesh, et al. [126] | Wisconsin Breast Cancer Dataset | SVM, LR, Naive Bayes, Random Forest | Image | ID, diagnosis, radius mean, texture mean, and perimeter mean | KNN = 64, SVM = 75.32, LR = 47.36, Naive Bayes = 52.63, RF = 98.24 |
| 2020 | Sami Ekici et al. [19] | Thermal image | Using CNN and optimized by Bayes Optimization | Image | - | 98.95 |
| 2020 | V. Vijayasarveswari, et al. [127] | Breast phantom | Data Normalize 4 stages of Multi Stage Feature Selection (MSFS) | Signal | Existence Location Size | 8-HybridFeature NB = 91.98, SVM = 90.44, PNN = 80.05 |
| 2020 | BS. Bari et al. [128] | Breast phantom | Feedforward back propagation Neural Network (FFBPNN) with feed forward net | Signal | Existence Location Size | Existence = 100, Size = 92.43, Location = 91.31 |
| 2020 | S. Nrea et al. [129] | Mammogram from different hospital | Convolutional Neural Network with Regen Proposed Network and Regen of Interest model proposed R-CNN | Image | Benign or malignant abnormality | R-CNN = 91.86 |
| 2020 | P. Agrawal et al. [130] | Breast Cancer Wisconsin Diagnostic Dataset | SVM, Decision Tree, Logistic Regression, Random Forest and Naive Bayes | Image | Breast mass; benign and malignant | Random forest with stratified K-Fold = 96.05 |
| 2020 | J. Abdollahi et al. [131] | Wisconsin Breast Cancer Dataset | Logistic Regression, K-Nearest Neighbours, Discrete Cosine Transform, Random Forest, SVM, Ensemble and Multilayer Perceptron combined with Genetic Algorithm (MLP-GA) | Image | Breast mass; benign and malignant | MLP-GA = 98 |
| 2020 | K. Kousalya et al. [132] | Wisconsin Breast Cancer Dataset | Linear Regression, Naive bayes and Random Forest | Image | Breast mass; benign and malignant | Random Forest = 95.7, Naive Bayes = 94.4, Linear Regression = 95.1 |
| 2020 | B. Kharthikeyan et al. [133] | UCI Machine Learning Repository Dataset | Logistic Regression, Random Forest and Decision Tree | Image | Benign and malignant | Logistic Regression = 99.3, Random Forest = 96.5, Decision Tree = 93.7 |
| 2020 | M. Islam et al. [134] | Wisconsin Breast Cancer Dataset | SVM, K-Nearest Neighbors, Random Forests, Artificial Neural Networks (ANNs) and Logistic Regression (LR) | Image | Benign and malignant | ANNs = 98.57, LR = 95.7 |
| 2021 | S. Alanazi et al. [90] | Kaggle 162 H&E - Invasive Ductal Carcinoma (IDC) Segmentation | Convolutional Neural Network (CNN) | Image | IDC positive and IDC negative | CNN = 87 |
| 2021 | M. Jabbar et al. [135] | Wisconsin Breast Cancer Dataset | Bayesian Network Radial Basis Function | Image | Breast mass; benign and malignant | RBF+BN = 97 |
5. Conclusions

Different breast screening techniques and an alternative imaging technique called microwave imaging to predict breast cancer have been studied and developed over the years with new features and improved classification performance in this review. This paper also focuses on recent studies relevant to breast cancer detection using image and signal processing through predictive models using machine learning methods and classification algorithms to predict breast cancer. Therefore, image and signal processing play an imperative role in maximizing breast cancer detection.

Even though numerous studies conducted offered a good report that microwave imaging has a high potential for early breast cancer detection, improvement needs to be explicitly discovered for predictive model construction, including feature selection and classification. Nevertheless, the model itself needs to be validated in clinical implementation. Thus, it is proposed to have various open-source data in microwave imaging, enabling other researchers to contribute their prediction model in this area.

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