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Review article

Usefulness of machine learning and deep learning approaches in screening and early detection of breast cancer

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ABSTRACT

Breast cancer (BC) is one of the most common types of cancer in women, and its prevalence is on the rise. The diagnosis of this disease in the first steps can be highly challenging. Hence, early and rapid diagnosis of this disease in its early stages increases the likelihood of a patient's recovery and survival. This study presents a systematic and detailed analysis of the various ML approaches and mechanisms employed during the BC diagnosis process. Further, this study provides a comprehensive and accurate overview of techniques, approaches, challenges, solutions, and important concepts related to this process in order to provide healthcare professionals and technologists with a deeper understanding of new screening and diagnostic tools and approaches, as well as identify new challenges and popular approaches in this field. Therefore, this study has attempted to provide a comprehensive taxonomy of applying ML techniques to BC diagnosis, focusing on the data obtained from the clinical methods diagnosis. The taxonomy presented in this study has two major components. Clinical diagnostic methods such as MRI, mammography, and hybrid methods are presented in the first part of the taxonomy. The second part involves implementing machine learning approaches such as neural networks (NN), deep learning (DL), and hybrid on the dataset in the first part. Then, the taxonomy will be analyzed based on implementing ML approaches in clinical diagnosis methods. The findings of the study demonstrated that the approaches based on NN and DL are the most accurate and widely used models for BC diagnosis compared to other diagnostic techniques, and accuracy (ACC), sensitivity (SEN), and specificity (SPE) are the most commonly used performance evaluation criteria. Additionally, factors such as the advantages and disadvantages of using machine learning techniques, as well as the objectives of each research, separately for ML technology and BC detection, as well as evaluation criteria, are discussed in this study. Lastly, this study provides an overview of open and unresolved issues related to using ML for BC diagnosis, along with a proposal to resolve each issue to assist researchers and healthcare professionals.

1. Introduction

Among all cancers, BC is one of the most common diseases among women, leading to many deaths every year. Undoubtedly, this disease is among the most difficult to diagnose, and in other words, the initial diagnosis process can also be challenging. This disease is usually detected using a variety of different methods [1]. The most important thing to note is that this disease has various types, each

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with its treatment regimen. This disease is difficult to diagnose in the early stages, and tests may need repeated several times to diagnose correctly, resulting in time-consuming diagnostic procedures [2]. Meanwhile, early diagnosis and the type of the disease can help doctors begin treatment faster, resulting in the disease being controlled as much as possible, ultimately saving the lives of those who suffer [3]. ML technology is one of the emerging technologies that can assist doctors in the early diagnosis of BC. Hence, using data from patients previously diagnosed with a disease, this technology attempts to develop models that can be utilized to diagnose diseases that are difficult to diagnose by clinical means [4]. In other words, this is a notable issue that such a possibility can quickly improve the process of diagnosing a difficult-to-diagnose disease. However, ML involves many approaches and techniques. Each of these techniques can result in a different result. Therefore, determining a technique that will present reliable results is also challenging [5]. A significant obstacle to the adoption of new technologies by the healthcare field is the lack of trust that medical practitioners have in emerging technologies like ML. Therefore, it is crucial to assess the effectiveness and performance of technologies before applying them to a sensitive area such as healthcare [6]. Therefore, a set of criteria has been developed to measure each ML technique's performance to ensure the performance of the ML methods. On the other hand, these evaluation criteria can be used as a criterion and a basis for comparing the performance of ML methods with one another [7]. It is important to note that ML techniques or algorithms will always receive data as input. Based on this input data, they will generate patterns and ultimately make predictions. Healthcare typically involves a great deal of data or parameters regarding patients [8]. Those data or parameters can significantly impact the development or occurrence of a disease. In this regard, it is essential to refine these data and parameters and select those that will have the most significant impact on the process of disease emergence [9]. There are several clinical ways to diagnose BC, and each method has its own set of effective parameters [10]. Using ML technology to diagnose diseases more quickly needs thorough consideration of the data used and the choice of the appropriate technique based on the intended outcomes. When dealing with such data, selecting techniques that can produce reliable results is essential due to a wide variety of complex parameters [11]. For instance, some techniques are well-suited to the processing of images, while others are not. Due to this, it is important to consider various factors when using ML to diagnose diseases such as BC. Therefore, a researcher must have a basic understanding of both fields, i.e., BC and ML, to use ML technology in diagnosing diseases such as BC [12]. The study of BC includes learning about different types of BC, clinical diagnosis methods, the types of data that can be obtained from these methods, and the effective parameters for determining the diagnosis. For ML technology, such information includes how it works, the approaches available, the techniques available, evaluation criteria, how to calculate them, and input data formats to ML techniques [13]. A better understanding of these items will likely result in a more efficient and effective implementation, eventually leading to results that can be trusted and cited. Therefore, conventional clinical diagnosis methods can be time-consuming for the primary diagnosis of BC due to the consideration of investigation of various factors. On the other side, these methods can be highly costly for patients and have side effects [14]. In this regard, new technologies like machine learning can provide a fast, accurate, and low-cost method of diagnosing BC disease. The process of BC diagnosing using machine learning technology can have various dimensions and methods [15]. Among these aspects are the analysis of mammograms and MRI images using ML techniques to enable a more accurate diagnosis and classification of the type of tumors in BC disease and the analysis of blood test results to determine the type of cancer present. This study systematically examines the available studies for the application of ML technology in the process of BC diagnosis and the ML techniques implemented on the data obtained from different clinical diagnosis methods, as well as the performance of these techniques based on the criteria. To ensure that a systematic and comprehensive evaluation of the selection and implementation of ML techniques is undertaken, this work evaluates the clinical parameters of cancer diagnosis to make a systematic and comprehensive assessment of the methods of cancer diagnosis. Therefore, in this case study, an attempt has been made to investigate the impact and performance of ML technology in the faster and more accurate diagnosis of BC disease based on various factors. Hence, this study draws on the most current research conducted between 2017 and 2023 in order to present a comprehensive perspective and accurate information. Presenting the influence and intended goals based on the characteristics and parameters obtained from clinical methods of cancer diagnosis along with ML technology implementation is another goal presented in this research. There are several main contributions to this study, which can be summarized as follows:

- Reviewing the published papers on the process of applying ML technology in the process of BC diagnosis, each study provides insight into the approaches and strategies of implementing ML technology on the data obtained from different clinical diagnosis methods
- Analysis of the implementation of ML technologies in the process of BC diagnosis and presentation of the implementation goals in each study related to ML technologies and BC diagnosis
- Evaluation and analysis of the latest approaches and techniques for diagnosing BC using ML technology
- Examining the current approaches and developing a classification based on the results obtained from implementations of ML techniques in the diagnosis of BC by separating clinical diagnosis methods from ML implementation methods
- Review and analysis of effective methods and clinical parameters for the diagnosis of BC
- Analysis of the implementation of ML techniques in the diagnosis of BC, as well as their evaluation criteria
- Presenting future research challenges that have not been explored or underutilized that could significantly impact BC diagnosis performance

Consequently, the rest of this article is arranged as follows: Section 2 provides a background on BC, BC types, and clinical diagnosis methods on the one hand, and on the other hand, about ML technology and its approaches. An overview of some of the relevant survey articles is provided in Section 3, along with the pros and cons of those papers. The research method utilized in this research is outlined in section 4. Section 5, the classification of BC diagnosis methods based on ML techniques implemented on them, presented a brief description of the implemented approaches and a comparison of these approaches. In Section 6, a discussion and comparison of these topics is also presented. Section 7 presents some game issues that should be paid attention to in the future. Finally, the conclusion part is presented in Section 8.

2. Background

This section briefly overviews BC and its types, ML technology, and essential and widely used techniques. In continue explained is an inventory of parameters and factors to consider when using ML techniques to diagnose and predict BC incidence.

2.1. Overview of the breast cancer

Breast tissue is composed of several different types of tissues, ranging from highly fatty to extremely dense tissues. This tissue consists of segments called lobules with milk glands inside them. It is believed that in the nipple, milk is transported from the lobesby means of tiny ducts that connect the glands. The areola, a dark region encircling the breast, contains the nipple at its center. The breast also contains lymphatic and blood vessels [16]. The blood vessels carry oxygen and nutrients to the cells while removing waste products and carbon dioxide. The lymphatic vessels, on the other hand, transport fluid away from tissues. They are connected to the lymphatic structure, which removes waste materials, and the lymph nodes [17]. The small, bean-shaped structure, known as lymph nodes, protects the body against infection. Numerous lymph nodes are located throughout the body, including the abdomen, neck, and groin. Regional lymph nodes are those located near the breast, like the underarm lymph node under the armpit. The breasts contain healthy cells that may change and grow out of control, resulting in a tumor, a mass, or a sheet of cells [18]. It is critical to note that tumors may be benign or malignant. Malignant tumors develop and spread to different parts of the body. In contrast, a benign tumor is still growing and has not yet expanded. It vital to notice that most breast tumors are benign and not cancerous (malignant) [19]. Breast tumors that are not cancerous are abnormal growths that do not extend outside the breast. There are several types of BC. The type of BC depends on the type of breast cells that develop into cancer. BC can occur in various areas of the breast [20]. Breasts have three major components: connective tissue, ducts, and lobules, as shown in (Fig. 1). Breast milk is produced by glands known as lobules that travel through passages known as ducts to the nipple. Connective tissue, composed of fatty and fibrous tissue, surrounds and holds everything together [21]. Most breast tumors begin in the breast ducts or lobules. Blood vessels and lymphatic vessels are two ways cancer spreads outside the breast [22]. If a tumor spreads to other body parts, it is metastasized. Even though BC typically spreads to near lymph nodes, it can also spread to other parts of the body via the blood vessels, which is why it is still considered a disease of the local or regional area [23].

2.2. Breast cancer types

BC can be classified as aggressive or non-invasive. BC that spreads to nearby tissues and distant organs is aggressive. Non-invasive BC does not spread beyond the breast lobules or milk ducts. BC varieties are categorized by their appearance under a microscope [24]. Therefore; there are typically two varieties of BC, invasive and benign. Each of which may include special categories. In this classification, BC types are typically examined based on the extent of their spread. Their classifications is based on the fact that some progress slowly and are considered benign, while others are invasive [25]. Due to its rapid rate of progression, this form of cancer is considered invasive. A tumor's aggressiveness is affected by various factors, such as its biological structure, size, stage, etc. Though typically speaking, BCs that are inflammatory and Angiosarcoma are typically the most aggressive [26]. At the same time, ductal carcinomas in situ, lobular carcinomas in situ, and Phyllodes tumors tend to grow more slowly. Particularly certain types of BC, including inflammatory BC and triple-negative BC, are two subtypes more possible to recur despite forceful treatment [27]. BC recurrence can be influenced by the size and hormone-receptor status of the original tumor and whether cancer has spread to the lymph nodes. The analysis provided in the following shows that various BC types will categorize as aggressive or benign, as shown in (Fig. 2). Therefore, for each of these two types of BC, there will be distinct subtypes, each of which will entail a distinct breast region, and each will have its method of diagnosis, treatment, and examination, which are not identical. In addition to affecting efforts to enhance patients, this subject can also affect the costs incurred by patients.

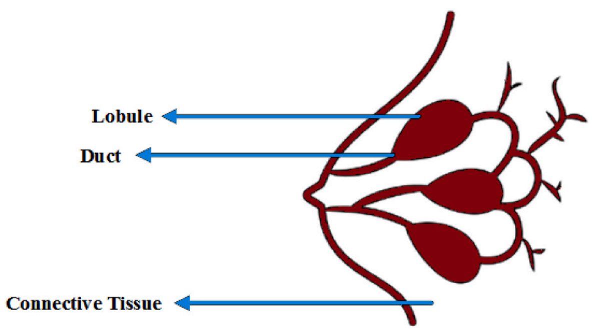

Fig. 1. Lobules, Ducts, and Connective Tissue in breast.

2.2.1. Invasive breast cancer

Most BC cases are invasive, meaning cancer spreads from the foremost site to other body areas, including adjacent breast tissue, lymph nodes, or other organs. Invasive BC cells can penetrate breast tissue's typical barriers and extend to other organs via lymph nodes and circulation. This is the overwhelming majority of BC cases [28]. A subtype of BC known as infiltrating BC is more hazardous than other subtypes. This type of BC may also be called infiltrating, depending on the circumstances. The two most common kinds of invasive BC are invasive lobular carcinoma and invasive ductal carcinoma. The two subtypes of invasive BC can metastasize to other breast areas. In the following, each subtype of aggressive BC will be dissected in minute detail [29].

2.2.1.1. Phyllodes tumors. Generally, Phyllodes tumors are extremely rare and typically develop in breast fibrous tissues. Hence, these tumors mainly occur in fibrous tissues. Although this specific type of tumor can affect individuals of any age, it tends to affect women in their forties more frequently than other women or children [30]. There is a high probability that this tumor will develop in individuals with Li-Fraumeni syndrome. This inherited condition is transmitted from generation to generation and runs in families. According to existing reports, about one-fourth of all Phyllodes masses are cancerous. However, it is important to understand that some distinctive forms of aggressive BC exist. Some examples of these uncommon types include adenosquamous carcinomas of low grade, mucinous carcinomas, tubular carcinomas, medullary carcinomas, and papillary carcinomas [31].

2.2.1.2. Angiosarcoma of the breast. According to the National Cancer Institute or NCI, Angiosarcoma is a form of BC that arises from the lining of blood vessels or lymph vessels. According to reports existing, it is one of the rarest types of sarcoma, accounting for only (1 %) to (2 %) of all instances. Angiosarcoma can affect anyone, but the majority of cases are discovered in patients over the age of 70 [32]. This is true although anyone can contract the disease. Radiation therapy to the breast is the most common cause of this disease, but symptoms may not appear until eight to ten years after the treatment has been completed. Fast-growing cancer, Angiosarcoma, is often not diagnosed until it has spread throughout the body. It is one of the most difficult types of cancer to diagnose [33].

2.2.1.3. Invasive lobular carcinoma. Invasive lobular carcinoma is women's second most common form of BC. It is estimated that between (5 and 10 %) of all BCs result from this condition. In the breast, where milk is produced, known as the lobules, invasive lobular carcinoma or ILC first develops before spreading to the breast tissue surrounding the lobules. The disease may spread similarly to invasive ductal carcinoma or IDC [34]. Unlike IDC, ILC is more difficult to detect through mammograms and other diagnostic methods. One out of five women with ILC will experience symptoms in both breasts [35].

2.2.1.4. Inflammatory breast cancer. There is a high probability that inflammatory BC, which occurs in the lobules or ducts, spreads more rapidly than other kinds of BC. As stated by the National Cancer Institute or NCI, this rapidly aggressive and progressing disease

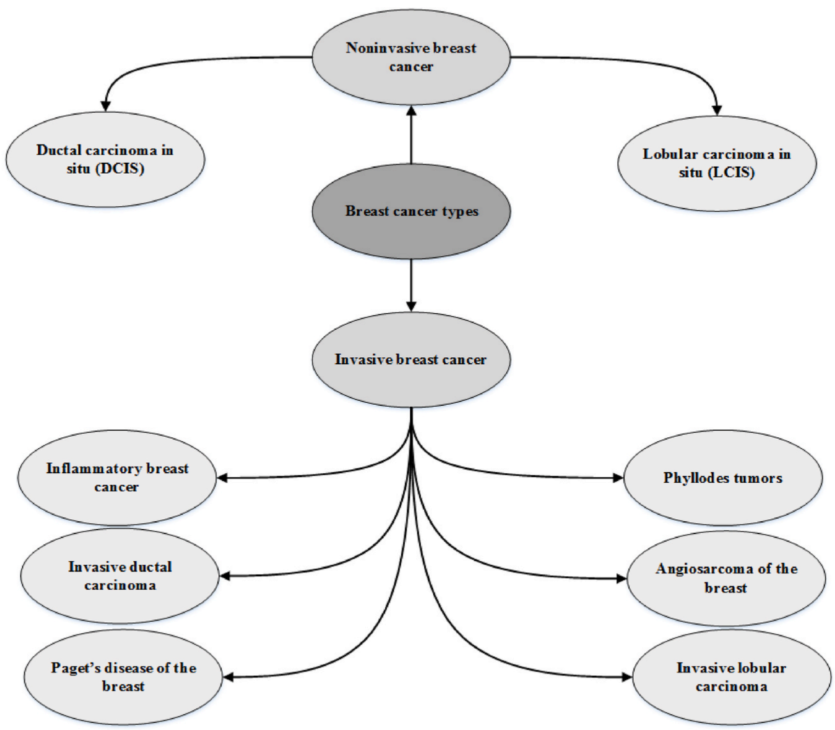

Fig. 2. Breast cancer types.

accounts for approximately (1–5 %) of BC cases in the United States [36]. The condition receives its name from the inflammatory signs it produces, generally swelling and redness on the breast's exterior. These symptoms are characteristic of inflammatory breast disease. These symptoms often lead to a mistaken diagnosis of the condition as an infection of the breast [37]. According to provided reports from accredited scientific institutions, one out of every three individuals diagnosed with this type of cancer is diagnosed at an advanced stage of the sickness when cancer has already spread to other parts of the body. The prognosis for patients diagnosed with inflammatory BC is less favorable than those with other BC [38].

2.2.1.5. Invasive ductal carcinoma. Approximately 70–80% of BC cases are invasive ductal carcinoma. It is also the most deadly form of BC. Indicative ductal carcinoma or IDC is the term used by medical community members to describe this type of BC [39]. A subtype of BC called IDC originates in the milk duct (one of the tubes in the breast that transport milk to the nipple), but it can spread to other domains of the breast as it progresses. In other words, one of the vessels in the breast that convey milk to the nipple is the milk duct, and one of the breast tubes that convey to milk the two nipple will involve. Hence, cancer spreading to other body parts is known as metastasis. Therefore, cancer may have metastasized [40].

2.2.1.6. Paget's disease of the breast. Compared to other BC subtypes, Paget's disease of the breast affects a significantly smaller percentage of patients. Paget's disease is a variant of BC. This condition is often referred to as Paget's disease of the breast in some areas, such as the nipple [41]. According to accredited scientific institutions' provided reports, this subtype of BC is estimated to affect one to four percent of patients who have already been diagnosed with another type of illness. In this condition, Paget cells are solitary tumor cells that form in the tissue of the nipple, areola, and breast [42].

2.2.2. Non-invasive breast cancer

Generally, BC cells found in situ are considered non-invasive, as they do not extend to the breast lobules, ducts, or surrounding tissues. Also, the fact that these cells have always been located in the same breast region was considered significant when they were first discovered [43]. BC that has not yet extended beyond the milk lobules or tubes is understood as in situ BC. In situ BC is more likely to develop in women. There are two kinds of in situ malignancies, called lobular carcinoma and ductal carcinoma. Both kinds are capable of growing into complete tumors [44].

2.2.2.1. Lobular carcinoma in situ. Lobular carcinoma in situ or LCIS is, in fact, not cancer but breast changes that are not cancerous. In the context of the medical industry, it is critical to establish this distinction. Thousands of smaller lobule groups are found in each breast, and by cooperating, they all help to produce breast milk [45]. These lobules provide opportunities for the growth of cells identical to cancer cells [46]. An LCIS typically does not spread to other areas and stays in place for an extended period due to the increased risk of developing invasive BC in LCIS. Hence healthcare team may want to keep an eye on patients. Doing so will allow them to take action quickly if their condition changes [47].

2.2.2.2. Ductal carcinoma in situ. According to reports from accredited scientific institutions, approximately (20 %) of cases of BC that are newly diagnosed are classified as ductal carcinoma in situ or DCIS. A tumor appears inside a milk duct as the first sign of DCIS. As a result of a DCIS, cancer has not moved to any other organs or tissues. The milk duct transports milk from the lobules, commonly referred to as glands, to the nipple [48]. With time, the likelihood that the mass will penetrate the ductal walls and spread throughout the surrounding breast tissue and the breast's fatty tissue increases. Most patients treated for DCIS have a positive prognosis, although

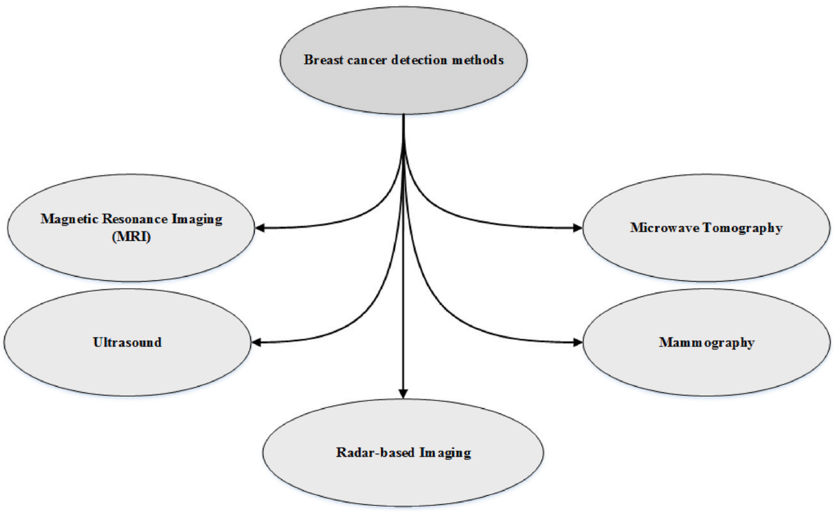

Fig. 3. Breast cancer detection methods.

it is sometimes referred to as step-first BC. The early stages of DCIS are sometimes referred to as BC [49].

2.3. Breast cancer detection methods

Early detection and appropriate BC treatment are essential for women's survival. There is a variety of screening instruments that are currently available and those that are being developed for the detection of BC in its early stages [50]. According to (Fig. 3), the current methods of detecting BC can be divided into six groups: Microwave Tomography, Mammography, Radar-based Imaging Technology, Ultrasound, and Magnetic Resonance Imaging. It is currently possible to detect BC using two approaches: body imaging-based and radio imaging-based.

- **Body imaging-based**:Ultrasound, Mammography, andmagnetic resonance imaging (MRI) are imaging methods that produce images of the breast structure for radiologists to examine and assess the breast for abnormalities. A majority of clinics and hospitals have these instruments. Hence, Microwave imaging technology may replace costly and invasive screening techniques [51].
- **Radio imaging-based:** As well as being reliable and secure, microwave imaging technology is also free of ionizing radiation and less dangerous to human health. Radar-based imaging and microwave tomography are two methods used in microwave imaging [52]. The two techniques use Ultra-Wideband or UWB signals to determine the dielectric characteristics of BC. As an alternative to X-rays and MRIs, which are inconvenient, inaccessible, high-risk, and expensive, novel technologies have focused on BC detection using microwave imaging or MI [53]. MI is a non-ionizing electromagnetic signal imaging method that utilizes frequencies ranging between 300 MHz and 30 GHz. The MI medical screening instrument facilitates tumor identification without ionization effects by providing strong contrast between tumors and healthy tissue. The most significant disadvantage of microwave imaging is the limited spatial precision of the images Radar-based imaging and microwave tomography are the two primary types of MI [54]. In the following, the methods used in BC diagnosis will be examined in detail, as shown in (Fig. 3).

2.3.1. Magnetic resonance imaging

Magnetic resonance imaging or MRI creates precise images of the soft tissues and organs of the body using radio waves and high magnetic fields. While MRI is a costly technology with a long waiting list, it can detect structural abnormalities in the body with greater precision, accuracy, and sensitivity than other imaging modalities. The painless radiology procedure known as MRI does not utilize hazardous amounts of ionizing radiation X-rays [55]. In the MRI scanner machine, the patient lay in bed and moved from the front device section to the back with the assistance of the technician or radiographer. The scanner consists of a huge horizontal tube enclosed by a circular superconducting magnet [56]. MRI generates a strong magnetic field that compels the body's protons to align with it. Patients may feel uncomfortable or have a fear of enclosed environments during this operation which is called claustrophobia. Through a radio-frequency current transmitted through the patient's body, the proton is disrupted and forced to realign 90° or 180° with the static magnetic domain. The scanner can still detect energy signals from the patient's body even when the radio is turned off [57].

2.3.2. Mammography

The mammogram, also named mastography, is a technique that uses low doses energy of radiation to create images (radiographs) of the breast. Symptomatic people (have symptoms of disease) or asymptomatic can be screened or diagnosed with mammograms. A typical radiation dose for two viewpoints of each breast is 0.4 millisieverts or 30 peak kilovolts. A 2D mammography compresses only the breast's front and side and takes images of them [57]. Tomosynthesis, also known as 3D mammography, creates X-ray images of the breast by rotating and observing in different directions across the breast. The combination of 3D and 2D mammography can greatly enhance detection accuracy when performed by a mammography specialist, also known as a mammographer. Women with denser breasts should not undergo a mammogram because the overlap of normal fibro-glandular tissues makes false alerts more probable [58].

2.3.3. Ultrasound

Unlike MRIs and mammograms, ultrasound imaging (sonograms) utilizes high-frequency sound waves or echoes to produce real-time images of the body's internal structure or detect suspect nodular forms without utilizing ionizing radiation. For patients, ultrasound is a cheap, non-invasive, and helpful manner. Medical ultrasound is often used to diagnose internal body conditions and pregnancy, which needs exceptionally high frequency. Medical ultrasound is typically characterized by a frequency range of 2–18 MHz, which is hundreds of times higher than the human ear's frequency range [57]. A transducer rubs the patient's skin across the area being examined during an ultrasound examination. Although ultrasound is frequently used to avoid invasive diagnoses, it can occasionally fail to identify smaller masses, resulting in false-negative and false-positive results. For women over 60, mammography has an increased sensitivity range, while ultrasound is a good option for women under 45 and those with dense breast tissue. Examples of ultrasound breast images are divided into three groups malignant, benign, and normal [59].

2.3.4. Radar-based imaging

In this technique, an image is created by reflecting waves from things. The breast is illuminated by a UWB pulse transmitted by a transmit or TX antenna, and the reflected waves are gathered by the receive or RX antenna. Unlike microwave tomography, this method reconstructs scattering power distributions when microwaves are delivered on the breast and the reflected waves are examined. In contrast to tomography, UWB microwave imaging requires less computational resources and has relatively straightforward and reliable signal processing, allowing for faster detection [60].

2.3.5. Microwave tomography

Microwave Tomography, or MT, is a new biomedical imaging tool that can measure tissues' dielectric properties using an inverse scattering approach. In medicine, MT is widely used for non-invasive imaging of biological structures. In this technique, the lowest frequency is 30 GHz, while the highest is 500 MHz it consists of three components: an image reconstruction algorithm, an interface, and a sensing device. An MT BC inquiry technique lowers the breast into a cylinder-shaped antenna system that completely encloses the breast, creating a dielectric contrast. In the following, microwave measurements are performed using multiple antennas acting as transmitters and receivers. The wave field becomes incredibly complex as microwaves pass through tissue and are scattered, reflected, and dispersed [61].

2.4. Overview of the ML

The field of ML as a subset of artificial intelligence allows computers to automatically learn from data and previous experiences while recognizing patterns to generate predictions with little human interference. ML techniques have enabled computers to operate independently without explicit plans. ML applications can learn from new data and grow, develop, and adapt accordingly to time and conditions [62]. By utilizing algorithms, ML extracts valuable knowledge from vast amounts of data through an iterative process of finding patterns and learning. ML algorithms use computation techniques to learn directly from data instead of relying on preconceived equations that might serve as models. By having a large number of samples to draw upon during the learning process, ML algorithms can adapt and improve their performance [63]. For example, a type of ML called DL teaches computers to mimic natural human functions, such as learning from examples. In comparison with traditional ML algorithms, it offers superior performance parameters. ML can automatically perform sophisticated mathematical operations on ever-expanding volumes and types of data [64]. As DL and ML are frequently referred to interchangeably, it is crucial to understand their differences. NNs, DL, and ML are all branches of artificial intelligence. DL is a subfield of NNs, which is a subfield of ML. Currently, ML algorithms are used everywhere. In addition, it facilitates the interaction between banks, online retailers, and social media sites [65]. It is possible to use ML technology in the critical healthcare field to identify or predict diseases rapidly. It is algorithms that drive ML. As shown in (Fig. 4), ML models can be divided into four primary groups: supervised learning, unsupervised learning, reinforcement learning, NNs, and DL. It is important to note that, as shown in (Fig. 4), the two fields of NNs and DL are considered one. The following is a detailed analysis of each field.

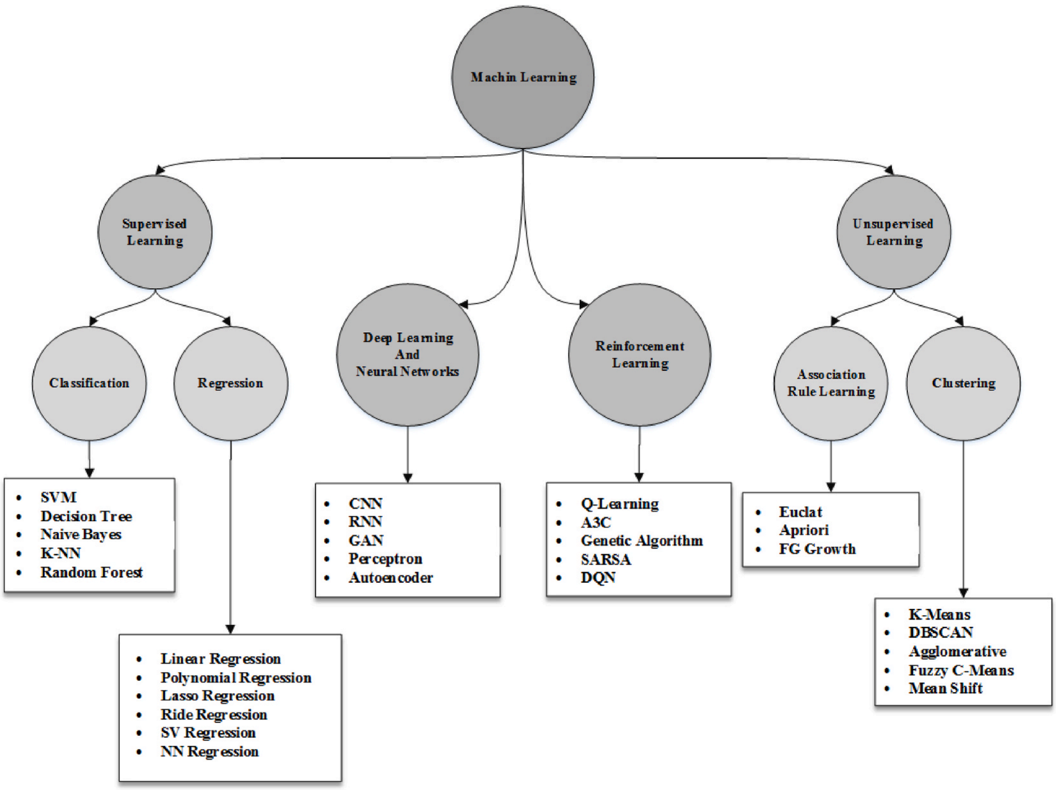

Fig. 4. Machin learning types.

2.4.1. Supervised learning

In this MLtype, algorithms are trained on labeled datasets and then allowed to make predictions based on the training data. The labeled dataset has already been mapped to some parameters of input and output. Thus, the input and output parameters are used to train the algorithm and the next step, a pattern is created to forecast the result based on the test dataset. The main objective of supervised learning is to map the input variables with the output variables [66]. The field of supervised ML can be further divided into two main categories:

- **Classification**: As the name implies, these are categorical output variables used to solve classification problems, such as no or yes, false or true, female or male, etc. Examples of this category in the real world include detecting spam and filtering messages in email. Some techniques utilized in supervised learning include Support Vector Machin (SVM), Decision tree (DT), Naive Bayes (NB), K-Nearest Neighbors (KNN) and Random Forest (RF) [67].
- **Regression**: The regression method is used to solve regression problems where the input and output variables are linearly related; these methods are well known for their ability to forecast continuous output variables. In this regard, weather forecasts are an example. Some techniques utilized in supervised learning include Linear Regression (LR), Polynomial Regression (PR), Lasso Regression (LaR), Ride Regression (RR), Support Vector Regression (SVR) and Neural Network Regression (NNR) [68].

2.4.2. Unsupervised learning

In unsupervised learning, no supervision is given to the algorithm. The algorithm is trained using an unlabeled data set and is given the ability to predict the results independently. An unsupervised learning algorithm always tries to classify the inputs based on their differences, similarities, and patterns into groups corresponding to the unordered data set. For example, the ML model is unfamiliar with the input dataset of pictures of parking lots filled with vehicles. The ML model fed the input photos into the ML model, which classifies the items in the input photos based on their characteristics, such as color, model, shape, price, and other factors [69]. Hence, with the help of a test dataset, the computer anticipates the outcome of categorization. Unsupervised ML can be further divided into two main categories:

- **Clustering**: Clustering involves grouping various objects into categories based on predetermined criteria, such as the degree to which they are similar or divergent. It is possible, for example, to classify consumers into several subgroups based on the types of goods commonly found in most items that consumers regularly add to their shopping carts. Clustering can be accomplished using a number of well-known methods, includingK-MeansDBSCAN, Agglomerative, Fuzzy C-Means and Mean Shift [70].
- **Association Rule Learning**: The association rule learning process identifies the typical relationships among the various elements within a large dataset. Analyzing the data in such an enormous dataset will assist in achieving this goal. It accomplishes this goal by identifying the relationships between the data items and mapping the related variables. A few examples of typical applications include market analysis and web mining. Some techniques used in association rule learning includeEuclat, Apriori and FG Growth [71].

2.4.3. Reinforcement learning

The basis for reinforcement learning is receiving feedback. The artificial intelligence component will assess its environment autonomously, take appropriate actions, learn from its mistakes, and improve performance using the hit-and-try technique. As a result of the component, every correct move will be rewarded. However, every erroneous motion will result in a penalty. Thus, the reinforcement learning mechanism strives to act in a way that will result in the most significant success. In contrast to supervised learning, reinforcement learning relies solely upon the agents' experiences to guide their education [72]. Supervised learning is the process of analyzing data that has been predefined and tagged. Think about video games. Specifically, the game determines the environment, and the reinforcement agent's state is determined by its activities. The player can receive feedback in the form of awards. These factors will ultimately affect the score they have accumulated throughout the game. Therefore, obtaining a high score is the essential objective for the agent. Some techniques used in reinforcement learning includeQ-Learning, A3C, Genetic Algorithm, SARSA and DQN [73].

2.4.4. DL and NNs

In NNs, also known as artificial neural networks or ANNs, the primary structural base is node layers consisting of an output layer, one or more additional hidden layers, and an input layer. A node, also called an artificial neuron, is connected to other nodes and assigned a weight and threshold value. Any node will become active and start transmitting data to the layer below it in the network if its output exceeds the value determined to be the threshold for activation. When the aggregate output of several individual nodes exceeds the threshold value determined, it is considered that the network has been activated. In case this condition is not met, the involved node will stop providing data to the network layer below [74]. In a nutshell, "deep learning" describes the enormous number of layers that make up a NN. 'DL' refers to NNs with multiple layers, as "deep learning algorithms" and "deep neural networks" refer to NNS with many layers. Consequently, there are many levels of inputs and outputs in the network. The term "deep neural network" refers to a network of more than three layers. A NN with only three layers can be considered a primary neural network. Some techniques used in NNs and DL includeCNN, RNN, GAN, Perceptron and Autoencoder [75].

2.5. Evaluate factor on ML

This section presents an overview of the evaluation criteria used in the different technique's performance evaluation. Therefore, if the result of evaluations is detected correctly, it can be classified as true positives or true negatives, and if it is detected incorrectly, it is classified as false positives or false negatives [76]. According to (Table 1), all of these cases have been shown in a confusion matrix. Hence, in Table 2 is to briefly illustrate the elements that are used in the formulas related to the evaluation criteria considered.

Accuracy, specificity, sensitivity, recall, and F-score surface are among the most prevalent assessment metrics for BC classification. One of the essential evaluation metrics is precision. Some critical evaluation criteria can be outlined as follows:

2.5.1. Accuracy

The accuracy evaluation criterion is one of the most important and widely used criteria for evaluating a model created in data mining methods. The evaluation criterion can be calculated by dividing the number of samples whose labels are correctly estimated by the total number of estimated samples by the model [77]. It represented by Equation (1).

$$ACC = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{1}$$

2.5.2. Specificity

A specificity evaluation criterion can determine the number of true negative predictions in the data set by dividing the total number of true negatives by the total number of true negatives and the total number of false positives generated in the prediction model [78]. This criterion can be calculated using Equation (2).

$$SPE = \frac{T_N}{T_N + F_P} \tag{2}$$

2.5.3. Sensitivity

By dividing the total number of true positives prediction by the total number of true positives and the total number of false negatives in the prediction model created, it can be used to determine the number of true positive predictions in the data set. This mechanism is called a sensitivity evaluation criterion [79]. Calculating this criterion can be done using Equation (3).

$$SEN = \frac{T_P}{T_P + F_N} \tag{3}$$

There is no difference between the sensitivity and recall criteria, and these two criteria may be used interchangeably.

2.5.4. Precision

A precision evaluation criterion can determine the number of true positive predictions in the data set by dividing the total number of true positives by the total number of false positives and by the total number of true positives generated in the prediction model [80]. For the calculation of this criterion, use Equation (4).

$$PRE = \frac{T_P}{T_P + F_P} \tag{4}$$

2.5.5. Area under the ROC curve (AUC)

As one of the most widely used ranking-type metrics, AUC can be utilized to develop an optimal learning model and compare learning algorithms. In contrast to the threshold or probability metrics, AUC represents a classification classifier's overall performance. Hence, for evaluating the performance of a classifier and selecting an optimal solution during classification training, the AUC is superior to the accuracy metric [81]. This criterion can be calculated using Equation (5).

$$AUC = \frac{SPE + SEN}{2} \tag{5}$$

2.5.6. F-score

The F-score evaluation criterion can be computed by multiplying recall and precision criteria by their aggregate. By using this evaluation criterion, the system's efficiency can be increased in many situations. In the context of this evaluation criterion, the F-score is directly correlated to the recall and precision evaluation criteria. High recall and precision evaluation criteria will also result in a high F-score when analyzed. It is calculated by taking the harmonic mean of the recall and precision values of the system to determine how efficiently a system estimates precision and recall [81]. This criterion can be calculated using Equation (6).

Table 1
The confusion matrix.

True Values			
		Positive (P)	Negative (N)
Predicted Values	**Positive (P)**	True Positive (TP)	False Positive (FP)
	Negative (N)	False Negative (FN)	True Negative (TN)

Table 2
The symbols used and a brief description of them.

Symbols	Brief Description
T_P	True Positive
T_N	True Negative
F_P	False Positive
F_N	False Negative
ACC	Accuracy evaluation criterion
SEN	Sensitivity evaluation criterion
FS	F-score evaluation criterion
REC	Recall evaluation criterion
SPE	Specificity evaluation criterion
PRE	Precision evaluation criterion

$$FS = \frac{2 \times Pr_{ec} \times Re_{ec}}{Pr_{ec} + Re_{ec}} \tag{6}$$

3. Related work

This section analyzes recent reviews of ML applications for BC diagnosis. We will provide an overview of each survey article's advantages and disadvantages. Thus, we will examine some of the articles reviewed in the literature in more detail.

Nasser and Yusuf (2023) [82] attempted to provide a systematic review of the use of ML in diagnosing BC in their study. Their objective in presenting this study was to provide doctors and researchers interested in this topic, i.e., using learning technology to diagnose BC, with the opportunity to become familiar with the existing approaches to this existing issues and challenges and comprehend those. Due to the wide variety of approaches available in ML technology, this study focused on a DL approach. Therefore, they examined the studies on applying DL techniques to genomic and histogenetic imaging datasets. Finally, after reviewing the studies in this field, they concluded that CNN-based techniques could provide more accurate models. In contrast, researchers tend to use this approach more to prove and correct their conclusions because of the power that it provides. It is important to note that this review study has both advantages and disadvantages, including:

- **Summary of the article's advantages**
  - Utilizing an adequate number of studies to provide a comprehensive view of the application of ML technology to BC diagnosis
  - Considering the power of DL techniques, their results are reliable and trustworthy
  - Examining the challenges that researchers in this field face
  - Assisting researchers who wish to research this area by providing a clear and precise direction
- **Summary of the article's disadvantages**
  - Concentration on using DL techniques without considering other methods of ML
  - Insufficient comparison of ML techniques based on DLwith other approaches, such as supervised learning, unsupervised learning, etc
  - Focusing only on genomic and histopathological imaging data and not considering other clinical diagnosis methods
  - Failure to compare the performance of MLmethods to images obtained from clinical diagnosis methods

Mridha et al. sought to provide a qualitative review of the use of ML technology in BC diagnosis. They have attempted to focus their work on techniques based on DLdespite the wide range of approaches and techniques used in ML. Their study is distinguished from other studies because they attempted to utilize six aspects in their work, including the architecture of BC diagnosis models, data sets and image preprocessing, BC imaging methods, performance measurement, and research directions. Hence, this can lead to the opening of the matter as much as possible. As a result, they have provided researchers interested in this field with a comprehensive view of the issue of using ML technology in the BC diagnosis process [83]. These review study have both advantages and disadvantages, including the following:

- **Summary of the article's advantages**
  - Consideration and analyzing the data obtained from different clinical imaging techniques
  - Providing appropriate solutions to upcoming challenges
  - Review of the steps involved in implementing different DLtechniques
- **Summary of the article's disadvantages**
  - Focused on DLbased ML techniques
  - Failure to use important clinical parameters in the diagnosis of BC
  - Failure to specify the intended goals for ML-based cancer diagnosis
  - Lack of clear statement of the intended goals for the application of ML technology to BC-related data

Amethiya et al. attempted to present a comprehensive case study that explored the use of ML technology in BC diagnosis. As part of their review study, they also attempted to relate biological sensors with ML technology. Hence, this distinguishes their review study from others of a similar nature. This review study examined and analyzed various ML techniques, algorithms, and data derived from various clinical imaging methods. Therefore, they presented their case study intending to influence the early and accurate diagnosis of BC using ML technology, as well as the role of biosensors in this regard [84]. There are several advantages and disadvantages to be found in this review, including the following:

- **Summary of the article's advantages**
  - Utilizing a variety of MLtechniques for analyze
  - Analyzing and applying a wide range of clinical data pertaining to BC
  - Investigating the impact of biosensors on BC diagnosis using ML
- **Summary of the article's disadvantages**
  - Lack of comparison of ML approaches, such as supervised learning, unsupervised learning, DL, and others, as well as their effectiveness and accuracy in the diagnosis of BC
  - Lack of attention paid to powerful ML approaches such as DLand NNs
  - Failure to provide a taxonomy to provide a detailed review of detection methods, ML approaches used, or the type of data used during the review

Houssein et al. conducted a review study to examine how ML technology may help detect BC. Thus, they examine the impact of ML with a DLapproach on diagnosing and classifying images obtained from different clinical methods of BC diagnosis. As a next step, they examined the details of the ML techniques used to classify tumors and non-tumor images. To complete their case study, they investigated the existing challenges and presented effective solutions to overcome them, providing a good vision [85]. In this review, there are several advantages and disadvantages to be considered, including the following:

- **Summary of the article's advantages**
  - Investigating the impact of different ML techniques using a DLapproach
  - Introduce approaches and techniques that facilitate the classification of tumors
  - Examining the effective challenges and proposing a suitable solution

Table 3
Research questions.

Index	Questions	Descriptions
TQ1	What classification is employed to apply ML technology to BC diagnosis?	The systematic classification of applying ML approaches in the BC diagnosis process can include: •BC detection by NNs and DL approaches in MRI •BC detection by Hybrid approaches in MRI •BC detection by NNs and DL approaches in Mammography •BC detection by Hybrid approaches in Mammography •BC detection by NNs and DL approaches in Hybrid •BC detection by Hybrid approaches in Hybrid The demonstration of this systematic classification enables adequate coverage of unconsidered areas. This question is discussed in section 6.
TQ2	What evaluation criteria are usually used to evaluate the performance of ML techniques in the process of BC diagnosis?	The studied articles consider different criteria to evaluate the performance of ML techniques in the BC diagnosis process. The most important criteria to evaluate are Accuracy, Sensitivity, Specificity, Recall, F-score, and Area under the ROC Curve (AUC). Applying these criteria allows researchers to cite their results and accurately evaluate their research. This question is answered in section. 6.
TQ3	What clinical parameters are usually used to diagnose BC using ML techniques?	The studied articles consider various clinical parameters in diagnosing BC using ML techniques. The most clinical parameters are the Benign and malignant, Tumor grade, Tumor size, Gender, Age, and Number of tumors. Using these clinical parameters, researchers can evaluate the results of their BC diagnosis research. The answer to this inquiry is provided in Section 6.
TQ4	What ML techniques are usually used in the BC diagnosis process?	The articles studied use a variety of ML techniques to diagnose BC. ML techniques frequently used include CNN, SVM, Random Forest, Decision Tree, Logistic Regression, DNN, ANN, Naive Bayes, K-Nearest Neighbor, DBN, DAL, and K-means. Researchers always strive to select the best ML technique by applying different techniques. This question is answered in section. 6.
TQ5	What methods are typically used to diagnose BC clinically?	The articles studied use various clinical diagnosis methods in this study. Therefore, the clinical diagnosis methods data were gathered using various clinical techniques. Some of the critical methods include MRI, Mammography, Histopathological, Clinical pathology, Ultrasound, Microwave Tomography, and Radar-base. Thus, researchers continuously try to use methods that produce accurate results with the least possible consequences. This question is answered in section. 6.
TQ6	What are the future research directions and open perspectives for using ML technology in the BC diagnosis process?	This question aims to describe different orientations that can assist researchers in clarifying their focus areas and applying them to their research. This question is answered in Sect. 7.

- Present a wide range of data derived from clinical BC diagnosis methods
- **Summary of the article's disadvantages**
  - Failure to specify the intended goals for ML-based BC diagnosis
  - Lack of comparisons between supervised learning, unsupervised learning, DL, etc., and analyzing their effectiveness and accuracy in the context of BC diagnosis
  - Failure to provide a detailed taxonomy review of detection methods, ML approaches used, or the type of data used during the review

4. Research methodology

This section provides guidelines for reviewing relevant articles on the use of ML technology in the BC diagnosis process. Searching, collecting, organizing, and analyzing relevant articles are the first steps to creating an excellent review of knowledge. Conducting a systematic technique that includes narrowing the criteria of topics and collecting and evaluating those specific topics will be available to researchers. This study focuses on explaining the mechanism of discovery of important topics in related fields.

4.1. Question formalization

This research aims to investigate the important factors and techniques in the articles studied at a particular time, along with the primary issues and challenges related to the application of ML technology in BC diagnosis. This survey aims to provide a comprehensive review of approaches to utilizing ML technology in BC diagnosis and highlight related open issues. It is, therefore, necessary for several related questions to be answered to focus on relevant issues, as shown in (Table 3).

4.2. Data analyzing and papers choices

The systematic running structure of opting for and analyzing articles is outlined as follows:

- Published articles associated with The process of applying ML technology to detect BC between 2017 and 2023

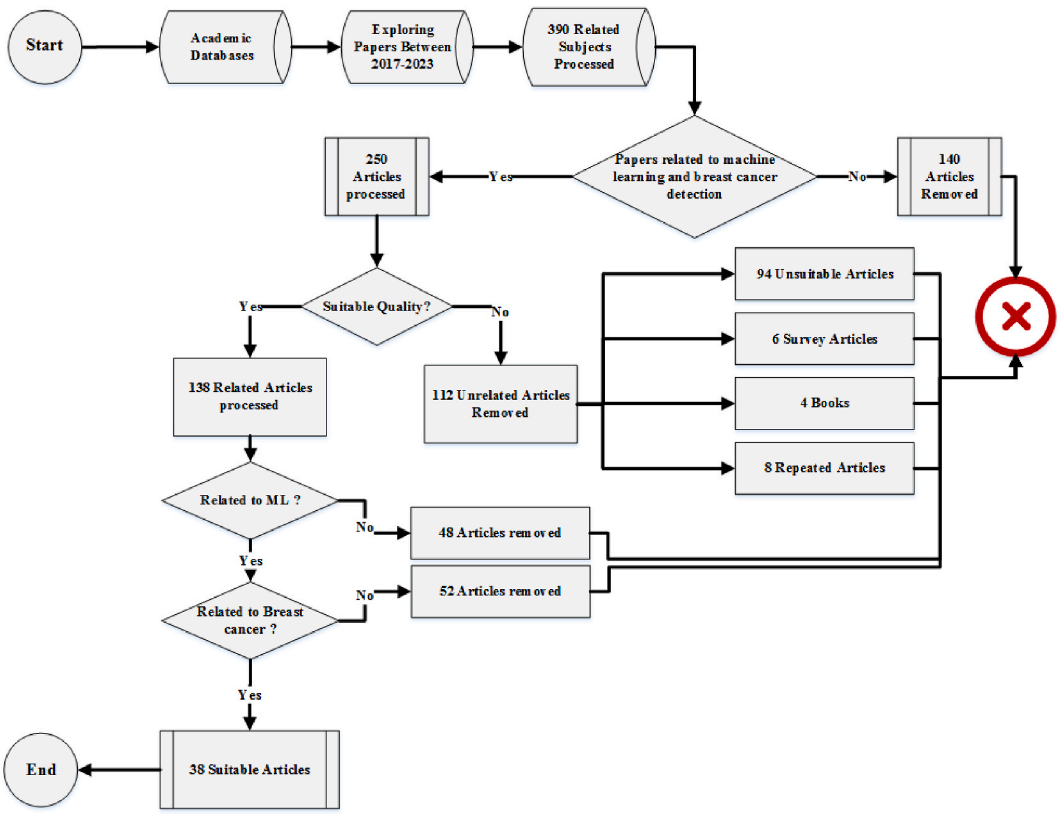

Fig. 5. Framework for evaluating and selecting appropriate articles based on applied filters.

- To recognize significant keywords and synonyms for The process of applying ML technology to detect BC can involve the following targeted keywords:
  - ("Breast Cancer" OR "Magnetic Resonance Image" OR "MRI" OR "Mammography" OR "Ultrasound" OR "Radar-based Imaging" OR "Microwave Tomography" OR "Hybrid") AND ("Machine Learning" OR "Deep Learning" OR "Neural Network" OR "Hybrid") OR ("Supervised Learning") OR ("Reinforcement Learning") OR ("Unsupervised Learning") OR ("Classification") OR ("Regression").
- Searches were conducted in April 2023 using restrictions about the time range from 2017 to 2023. The final results indicated 390 articles. Hence, the process was also continued, by studying some important sections of papers, such as the Abstract, Objectives, Contributions, and Conclusions; finally, at the beginning of this process and in the first step, 140 articles irrelevant to the research topic were determined and eliminated. In the following stage, because of the existing unsuitable articles with inferior content, we tried to consider other sections of papers, such as study system models, strategies, research results, implementation methods, and resolutions supplied for the future, in the remaining papers. Hence, in continuation of the review at the start, 94 papers have been detected as unsuitable for this project; also, six papers were surveyed, eight articles were repeated, and four books were eliminated from this process. Consequently, 252 articles have been removed according to the filters applied. As a result, 138 articles related to the study sample remain marked. Of these, 52 articles are devoted to the application of ML for cancer diagnosis without focusing on BC, which has been saturated and removed from the study sample. Further, 48 articles were watered down and removed after selecting the relevant articles since they dealt with the BC diagnosis process without utilizing ML technology. In the end, the survey included 38 articles that discussed using ML technology to diagnose BC.

A presentation of a flowchart for eliminating and incorporating alternatives based on the filters applied is shown in (Fig. 5).

As shown in (Table 4), relevant articles related to the application of the ML process for BC diagnosis have been studied in valid scientific databases.

The thorough distribution of these 38 selected articles between 2017 and July 2023 is depicted in (Fig. 6). During this period, the highest percentage of articles published occurred in 2019. Therefore, this shows that in 2019, the process of using ML techniques to diagnose BC has had high momentum. As shown in (Fig. 7), an attempt has also been made to compare the selected articles based on the number of articles published and publishers' titles each year. From 2017 to 2023, Elsevier was ranked highest among all other publishers. On the other hand, the section named under the title others includes various publications categorized as others.

5. Detection of breast cancer based on ML

As ML has become increasingly popular in the healthcare field for early diagnosis of diseases that have been difficult to diagnose in the past few years, its use has increased significantly. In diagnosing complex diseases, using ML technologies can result in fundamental changes in the detection process for infection patients [86]. Hence, to facilitate the treatment process, the diagnostic process must focus on specific and more accurate factors, which can reduce diagnosis time. The process is usually recommended for diseases where the issue of diagnosis time is highly critical [87]. One such illness is cancer, which has been regarded as challenging to diagnose. Considering the fast and silent growth of cancer inside the body, diagnosing it as soon as possible can make the treatment process start in a shorter period and the recovery process of the affected patient continue at a faster rate, ultimately resulting in the patient's life being saved. BC is one of the diseases that affects many women and is generally difficult to diagnose in its early stages [88]. Therefore, the need for rapid diagnosis of women infected with this disease will be important. ML can provide early diagnosis of these diseases by leveraging the power of artificial intelligence. There are various clinical ways to diagnose BC; however, the most common method is through breast imaging. Therefore, using its powerful algorithms, ML technology can recognize and classify images of new patients with high accuracy if presented based on examples of existing images from previous patients. Since the photos of new patients are in the early stages of their disease, it can be very important because determining which type of BC the patient is likely to be involved with can, in turn, guide the testing process and lead to a suitable path, which can lead to a faster diagnosis of the disease [89]. As a result, the process of treatment or preventing the development of the disease can be done more quickly. Thus, this section aims to examine and propose a taxonomy of ML methods applied to BC datasets for analysis. Hence, using the presented taxonomy, three main parts of clinical diagnostic methods have been divided into three groups: MRI, mammography, and combinations of other methods referred to as hybrids. On the other hand, the MLapproaches used in this section are divided into two parts: using NNs and DL and other approaches in a Hybrid format. In this division, the application rate of these approaches is considered. This taxonomy is shown in (Fig. 8). Therefore, the final goal of this section is to examine the type of MLapproaches used in the process of disease diagnosis based on the use

Table 4
Involved credible scholarly databases.

Database	Links related to databases
Elsevier	https://www.elsevier.com
Nature	https://www.nature.com
Springer	http://link.springer.com
IEEE explorer	http://ieeexplore.ieee.org
ACM	http://www.acm.org
Wiley	http://onlinelibrary.wiley.com
MDPI	https://www.mdpi.com

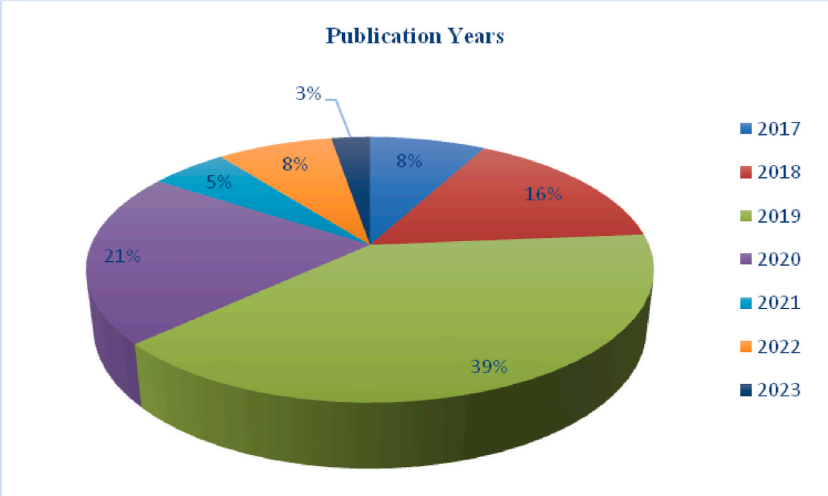

Fig. 6. The percentage of the diversity of selected papers according to the publishing years.

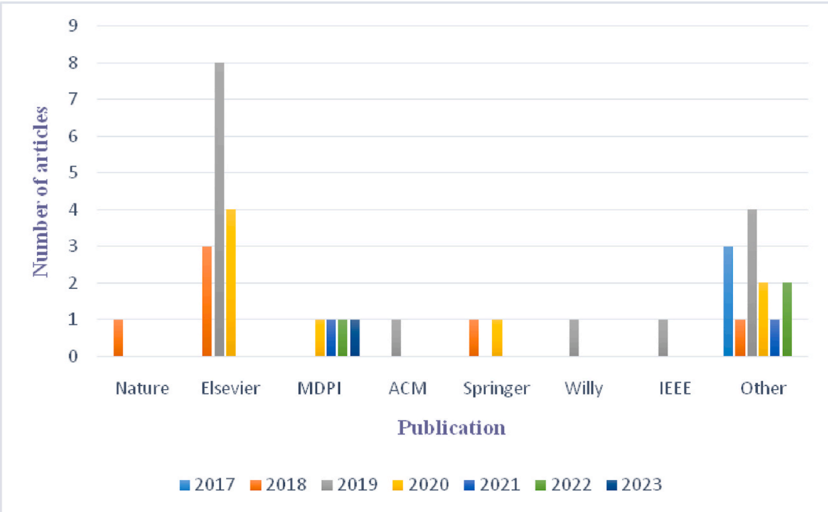

Fig. 7. The percentage of the diversity of selected papers according to the publishing year and database of publication.

of obtained data from widely used clinical diagnostic methods. Therefore, in this section, we compare the performance of various ML algorithms based on images obtained from conventional methods.

In this review, the results have been analyzed and reviewed in two areas of cancer diagnosis, using existing clinical methods and utilizing ML techniques with different approaches. Therefore, related research has been reviewed, and the most important findings have been extracted. These findings include the following:

- Approach
- Targets for ML
- Targets for BC
- ML Advantages
- Advantages of the BC approach
- Disadvantages of the BC approach
- Evaluation criteria

Depending on the taxonomy in which the desired articles are organized, pertinent information is extracted and presented in table format. Hence, in the end, an attempt has been made to provide a summary and conclusion separately for each relevant category regarding the application of ML technology to diagnose BC. The point that can be mentioned here is to provide an overview of the

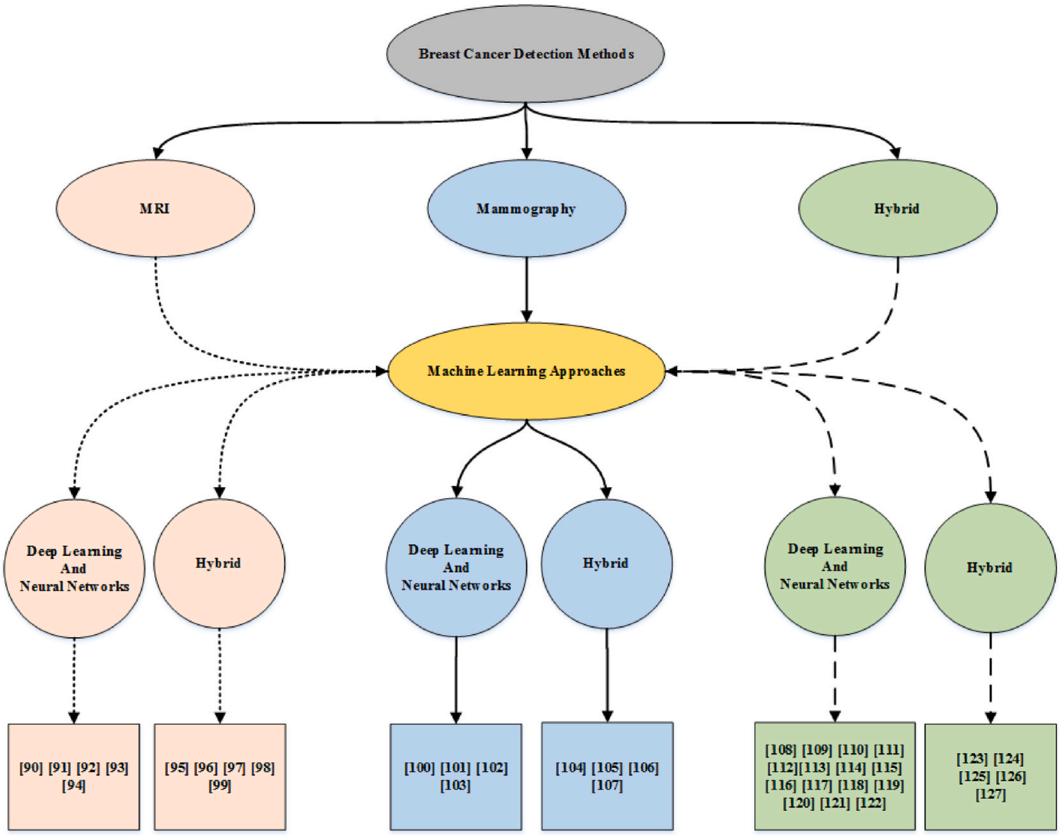

Fig. 8. Proposed taxonomy of ML-based detection of cancer in the breast.

evaluation criteria. Hence, the following are considered: AUC, ACC, SPE, SEN, Recall, and F-Score. As a result of the extraction of the mentioned items from the related articles grouped within the same category and in the taxonomy, they are displayed in the tables corresponding to each section.

5.1. Breast cancer detection by DL and NN approaches in MRI

A conventional approach that researchers usually attempt to use is to combine ML techniques with approaches NN and DL to diagnose BC from the data obtained from the MRI method. In BC diagnosis, MRI imaging is considered one of the most widely used methods, so it has always been considered to utilize databases created in this method of clinical detection or, to put it another way, to use images taken using this method. By using images obtained using the MRI method, researchers are attempting to teach ML techniques with a DL approach and NN and use these techniques to recognize new images. Specifically, their goal is to provide a detailed classification of newly received images based on previous images so that they can continue the cancer diagnosis process more quickly (Table 5). presents extracted items from articles related to this category.

5.1.1. Summary of the discussion regarding detection plans in MRI using DL and NN

The review and analysis of articles about the application of techniques based on NNs and DL, which are applied to clinical diagnosis data obtained by MRI, indicates that, among the various approaches and techniques available in the field of ML, the CNN approach has been most commonly used. The purpose of the techniques used in this classification is to provide an approach that can perform the separation and classification process with the desired level of quality on the data obtained through the MRI clinical diagnosis method. In BC diagnosis, the main goal of these articles is to achieve a precise classification of images. Based on this classification, they can perform the process of a BC diagnosis with high accuracy and quality. The advantages usually considered in the section on ML are typically related to increasing the classification quality. In the BC diagnosis field, they consider advantages such as helping doctors and specialists diagnose BC early, which can improve the treatment process for patients. However, most of these articles and approaches suffer from the weakness that the proposed approaches have only been implemented on a limited number of datasets, despite multiple clinical diagnosis methods for this approach; hence, the models should be generalizable and applicable to other datasets. Additionally, due to the availability of effective clinical parameters, they have generally used some of these parameters, and as a consequence using other parameters would have resulted in more accurate results. Additionally, some criteria are used more frequently than others to

Table 5
Analysis of BC diagnosis based on DL and NN approaches in MRI using information from reviewed articles.

Reference	Approach	Targets for ML	Targets for BC	Advantages of the ML approach	Advantages of the BC approach	Disadvantages	Evaluation criteria					
							AUC	ACC	SPE	SEN	Recall	F-Score
[90]	CNN	•Proposing an improved diagnostic approach to MRI images classification	•Enhancing the performance of the classification process	•Assisting in the accurate diagnosis of BC	• Enhanced performance across the BC classifier	• Failure to utilize clinical characteristics and effective parameters when diagnosing • Lack of evaluation of the proposed approach on other datasets	✔	✘	✔	✔	✘	✘
[91]	CNN	• Presenting an approach for achieving competitive performance in image classification	• Obtaining reliable results in the classification of images	• Assisting in the process of classification by improving its quality	• Providing more assistance in the diagnosis of BC • The proposed approach is more effective than single detection-based image classification methods	• The incapability of the proposed approach to deal with data obtained from other diagnostic methods • Failure to use powerful techniques to predict results	✔	✔	✔	✔	✘	✘
[92]	CNN	• Presenting a novel approach to accurately detecting tumor-containing axial slices	• Finding an optimal classification using tumor-containing axial slices	• Reducing the learning time of the proposed algorithm to recognize new samples from the created patterns better	• Facilitating the accurate identification of tumors • Reducing the time it takes to diagnose tumors	• Lack using of a considerable lot of samples for investigation performance proposed method • Failure to use critical clinical features in the process diagnosis	✔	✔	✔	✔	✘	✘
[93]	CNN	• Propose a novel method to evaluate the efficacy of 3D deep convolutional neural network for diagnosing BC	• Achieving high accuracy and quality in the classification of images	• Present a high accuracy for diagnosing BC	• Aid to radiologists in BC diagnosis. • Assisting in the classification of images in an optimal manner	• Ignoring the influence of other factors • Incompatibility with other clinical diagnosis methods	✔	✔	✔	✔	✘	✘
[94]	CNN	• Proposing an algorithm to evaluate the complete pathological response (pCR) to chemotherapy	• Achieving rapid and accurate detection of BC	• Improving PCR status prediction with MRI images in neoadjuvant therapy	• Aiding patients in maximizing their chances of survival • Assisting in improving the quality of treatment	• Insufficient use of important clinical parameters • A lack of implementation of the proposed approach in large datasets	✔	✘	✔	✔	✘	✘

Table 6
Analysis of BC diagnosis based Hybrid approaches in MRI using information from reviewed articles.

References	Approach	Targets for ML	Targets for BC	Advantages of the ML approach	Advantages of the BC approach	Disadvantages	Evaluation criteria					
							AUC	ACC	SPE	SEN	Recall	F-Score
[95]	RF	• Presenting an approach based on graph theory to classify images	• Obtaining an accurate prediction to reduce the time required for diagnosis	• Optimization of the image recognition and classification process	• Enhancing the chances of recovery for people at risk • Assisting in the reduction of the decision-making time for initiating high-impact treatments	• Lack of reliability of the obtained results as a result of using weak techniques • A lack of ability to apply the proposed method to large-scale real-world datasets	✘	✔	✔	✔	✘	✘
[96]	SVM	• Proposing a new approach based on Gaussian support vector machines	• Finding a mechanism to improve the detection of BC	• Assisting with the accurate diagnosis of suspected breast tumors	• Facilitating the diagnosis of BC • Assisting in reducing unnecessary benign breast biopsies	• Insufficient use of clinical features critical to the diagnosis of BC • Lack of reliable methods for predicting outcomes	✔	✔	✔	✔	✘	✘
[97]	SVM	• Proposing a new approach to improve the diagnostic performance of created models using reinforcement classification	• Achieving a high degree of precision in the diagnosis of BC lesions in order to improve classification	• Providing assistance in improving the accuracy of BC diagnosis	• Assisting doctors in reducing their subjective interpretation errors • Assisting in the accurate differentiation of benign and malignant breast lesions	• Failure to use critical clinical features in the process of BC diagnosis • Failure to use powerful classification techniques in the evaluation process	✔	✔	✔	✔	✘	✘
[98]	• SVM • LR • RF • DT	• A comparative study of several algorithms in BC detection	• Provide valuable predictive information to guide treatment decisions	• Prediction of survival outcomes in BC patients with high accuracy	• Assisting in the early prediction of chemotherapeutic response • Assisting patients in maximizing their chances of survival	• Failure to use powerful ML techniques with deep learning approaches and NNs to ensure the results obtained • Failure to check the data obtained from other available clinical diagnosis methods	✔	✘	✘	✘	✘	✘
[99]	SVM	• Presenting a method of detecting the presence or absence of tumors	• Achieving high-accuracy BC detection	• Assisting in the reduction of the time needed for predicting the results	• Assisting patients with BC in maximizing their chances of survival • Aiding in the early detection of BC	• Failure to compare the results obtained from the technique used with other techniques	✔	✔	✔	✔	✘	✘

Table 7
Analysis of BC diagnosis based on DL and NN approaches in mammography using information from reviewed articles.

References	Approach	Targets for ML	Targets for BC	Advantages of the ML approach	Advantages of the BC approach	Disadvantages	Evaluation criteria					
							AUC	ACC	SPE	SEN	Recall	F-Score
[100]	CNN	• Proposing an approach based on NNs to recognize images with high accuracy	• Presenting a model of classification and accuracy that is close to that of a human performance	• Detects and classifies benign or malignant lesions on mammograms without human intervention	• Exceptional success in the classification of images • Assisting radiologists in mammography images analysis	• Inapplicability of the presented approach to large datasets	✔	✘	✘	✘	✘	✘
[101]	CNN	• Proposed a system to improve the diagnostic performance of breast lesions using an integrated detection and classification method	• Finding a mechanism to improve classification accuracy	• Increasing accuracy in the process of identifying BC lesions	• Assisting professionals in accurately diagnosing breast lesions • Achieve promising breast lesion diagnostic performance.	• A lack of effective clinical parameters for diagnosis	✘	✔	✘	✘	✘	✔
[102]	CNN	• Proposing a neural network-based method for extracting high-level semantic features	• Optimizing classification performance through the use of selected features	• The proposed approach is superior to other CNN models and obtains presenting better performance in classification	• Improvements in the classification of images • Enhancements to the extraction process of high-level semantic features	• Limiting the extraction of features only from mammograms • Inability to use newly developed imaging features as well as more clinical characteristics to diagnose BC grades.	✔	✔	✘	✘	✘	✘
[103]	DAL	• Proposed a novel mass detection methodology with DAL	• Improve the accuracy of the classification process	• Minimizing the annotation efforts in detecting of BC • Compared to its counterparts, the proposed learning framework is more effective at detecting BC	• Breast mass accurate detection in mammogram • Reduces the requirement of the annotated samples in detection.	• Failure to perform more measurements in sample selection criteria. • Failure to use the proposed approach in various imaging types, such as pathology and MRI	✘	✘	✘	✔	✘	✘

evaluate the performance of ML techniques. These criteria include the AUC, the SEN, and the SPE.

5.2. Breast cancer detection by hybrid approaches in MRI

In ML, various techniques and approaches are available, which has led researchers to choose suitable approaches and techniques based on their research goals. Hence, the researchers always strive to select techniques assured in obtained results when implementing ML techniques on BC data. Therefore, considering the power of ML techniques with DL approaches and NNs, researchers tend to use more techniques related to these approaches in their research process. For this purpose, in the proposed taxonomy has tried to generally divide the approaches used in the ML process into two categories, including NNs and DL, and considered other existing approaches as hybrid ML approaches. Therefore, this section has attempted to examine ML techniques combined with a hybrid approach to diagnose BC using MRI data. Based on the research examined in this classification, researchers are constantly trying to teach the techniques used in the Hybrid category using the images obtained using the MRI method to recognize new images. They aim to provide a detailed classification of newly received images based on previous images to expedite the cancer diagnosis (Table 6). presents extracted items from articles related to this category.

5.2.1. Summary of the discussion regarding detection plans in MRI using hybrid

Based on the articles' analysis related to ML techniques, except those based on NN and DL implemented on the data obtained from the MRI clinical diagnosis method, the SVM approach is the most widely utilized. On the other hand, the techniques implemented in this category aim to provide an approach that can be used to diagnose BC with high accuracy based on the data obtained from an MRI clinical diagnosis. Although the primary objectives of these articles in the field of BC diagnosis are to reduce the duration of a BC diagnosis as much as possible and to develop mechanisms to increase the accuracy of diagnosis, they can process BC diagnosis as quickly as possible and as accurately as possible based on this classification. The advantages of implementing ML techniques are focused on optimizing and improving the methods' accuracy. In the field of BC diagnosis, considered advantages such as helping doctors and specialists detect BC early and increasing the chance of survival for patients. However, one of the weaknesses of these articles and approaches is that implementing the proposed approaches has been limited to just one dataset. Hence, the results should be generalizable and applicable to other datasets. On the other hand, researchers can use more powerful techniques and compare the results obtained to be more reliable. The performance of ML techniques is also evaluated using various criteria, some more commonly used than others. These criteria include the AUC, SEN, and SPE.

5.3. Breast cancer detection by DL and NN approaches in mammography

Transpired research in this section has been conducted by employing NN and DL techniques to detect BC based on data obtained from mammography. The imaging method known as mammography is one of the most frequently used clinical methods in the process of diagnosing BC, and the images obtained through this method are very beneficial in the implementation of ML techniques process. Researchers in this classification aim to use a collection of mammography images to teach DLtechniques and NNs and use them to recognize new images. Their goal is to provide an accurate classification mechanism based on which it is possible to use newly acquired images to make more accurate cancer diagnoses(Table 7). presents extracted items from articles related to this category.

5.3.1. Summary of the discussion regarding detection plans in mammography using DL and NN

Upon reviewing and analyzing the articles related implementation of NN and DL techniques to diagnose BC based on data obtained from the clinical diagnosis method of mammography, it can be concluded that among the various approaches and techniques available in the field of ML, CNN has been most widely used. Furthermore, the purpose of techniques used in this category is mainly to provide a methodology that can be used to separate and classify images obtained from clinical diagnosis methods such as mammography with the desired quality. Although the primary objectives of these articles in the field of BC diagnosis are to provide a precise classification of images with benign and malignant lesions, using this classification, they will be able to diagnose the process of BC more effectively. The advantages of implementing ML techniques are typically emphasized to increase the accuracy and improve the performance in classifying the presented images. There are several advantages to using this approach in BC diagnosis, including improving radiologists' ability to diagnose masses more accurately. It is important to note that most of these articles and approaches have faced some shortcomings because the methods used to implement the proposed approaches have been only applied to a single data set. Despite various clinical diagnosis methods, the proposed method should be generalizable and applicable to other datasets. Due to the presence of significant clinical features in the used images, they have generally used some of these features. The use of other features could have brought more accurate results. As part of the evaluation process, ML techniques are also evaluated according to various criteria, some of which are more commonly used than others. These criteria include the AUC and ACC.

5.4. Breast cancer detection by hybrid approaches in mammography

In this section examine the application of ML techniques in hybrid classification to analyze and diagnose BC utilizing data obtained from the mammogram method. In this classification, researchers are always looking for ways to use images obtained from the mammography method to teach the Hybrid category techniques and apply them to new images obtained from the mammography method for accurate classification in detecting cancer breasts. In fact, their objective is to provide a detailed classification of newly received images based on previous images to accelerate the cancer diagnosis process (Table 8). presents extracted items from articles

Table 8
Analysis of BC diagnosis based on Hybrid approaches in mammography using information from reviewed articles.

References	Approach	Targets for ML	Targets for BC	Advantages of the ML approach	Advantages of the BC approach	Disadvantages	Evaluation criteria					
							AUC	ACC	SPE	SEN	Recall	F-Score
[104]	RF	• Presenting a novel approach to detection of high-risk breast lesions	• Providing the opportunity to detect BC-causing lesions at an early stage	• Increasing the accuracy of early detection of BC-causing lesions.	• Identification and diagnosis of high-risk lesions and their surgery • Identifying and diagnosing lesions with a low risk level and monitoring people	• Lack of use of powerful algorithms in order to obtain accurate and reliable results • Lack of ability to apply the proposed approach to large and real-world datasets	✘	✔	✘	✘	✘	✘
[105]	• KNN • DT • RF	• Present an analysis of several algorithms' performance	• Detection and classification of tumors in images using automated methods	• Analyzes, detects, and preprocesses images efficiently using wavelets.	• Better and more accurate detection, • Enhancing mammographic image resolution.	• Lack of selection of effective clinical parameters in the process of BC diagnosis	✘	✔	✔	✔	✘	✘
[106]	• SVM • K-mean	• Proposed a novel approach based on a combination of pre-processing and feature extraction	• Providing radiologists with the possibility to diagnose images accurately	• Enhancing the accuracy of the proposed automatic method compared to other methods • Enhances the accuracy of outcome predictions	• Preventing disease progression by providing early diagnosis • Assisting in the reduction of BC-related death rates	• Lack of selection of effective clinical parameters in the process of BC diagnosis • Failure to utilize powerful techniques for predicting outcomes	✘	✔	✔	✔	✘	✘
[107]	SVM	• Developing an automatic system for accurately detecting BC	• The ability to detect BC at an early stage	• Provide accurate classification of benign and malignant images	• Enhancing efficiency and diagnostic abilities • Providing assistance in reducing health problems that result in the death of women	• Inability to apply the proposed approach to other datasets • Lack of comparison of results obtained with more powerful techniques	✘	✔	✔	✔	✘	✘

Table 9
Analysis of BC diagnosis based on DL and NN approaches in Hybrid using information from reviewed articles.

References	Approach	Targets for ML	Targets for BC	Advantages of the ML approach	Advantages of the BC approach	Disadvantages	Evaluation criteria					
							AUC	ACC	SPE	SEN	Recall	F-Score
[108]	DBN	• Algorithm optimization	• Optimization of BC classification	• Assists in optimizing decisions • Assists in the removal of noise	• Decrease noise • Better performance • Automated analysis of images	• A lack of use of clinical biomarker databases	✘	✔	✔	✔	✘	✔
[109]	CNN	• Present a deep learning-based approach to image analysis	• Improvement of BC classification	• Assisting the optimizer in making predictions	• Assisting the experts in reducing genomic tests	• A lack of multiclass classification • Failure to use effective clinical parameters	✘	✔	✔	✔	✘	✘
[110]	CNN	• Present a novel approach to detection and classification based on deep learning	• Improve the early detection and classification	• Enhance the effectiveness of diagnosis and classification	• Achieving a more accurate diagnosis and classification	• Insufficient use of effective clinical parameters	✘	✔	✘	✔	✔	✔
[111]	ANN	• Proposed a CAD system based on meta-heuristic algorithm for tuning the parameters of the neural network	• Identifying the type of BC	• Improve the detection and classification processes • Reduce the cost of computing	• Increasing the potential and accuracy of diagnosis and classification	• Inability to implement the proposed approach on large and real clinical datasets	✘	✔	✔	✔	✘	✘
[112]	CNN	• Developing a deep learning model for training and regulating models	• Improved accuracy in the classification of BC	• Improved accuracy and reduced time of image recognition and classification	• Increased efficiency in diagnostics • Reduction in the cost of diagnosis	• Lack of selection of effective clinical parameters in the process of BC diagnosis • Lack of comparison between the proposed approach and existing powerful techniques	✘	✔	✘	✘	✘	✘
[113]	ANN	• Presenting a comparative process between two neural network-based algorithm	• Finding factors associated with de novo metastases in invasive BC	• Introduction of ANN as a reliable model in the process of identifying new metastases in invasive BC compared to the traditional model	• Improved detection of new metastases of BC	• Unreliability of results due to the comparison between only two techniques	✔	✔	✔	✔	✘	✘
[114]	CNN	• Propose an approach for combining deep learning, transfer learning, and generative adversarial network to improve classification performance	• Effectively classifying BC	• Optimizing image classification performance	• Reducing noises caused by GAN images • Enhancing classification accuracy based on a limited training dataset.	• Ineffective selection of clinical parameters during the diagnostic process	✘	✔	✘	✘	✘	✘
[115]	CNN	• Propose an automated method for the binary classification of BC tumors as either malignant or benign	• Enhancing the classification mechanism in the diagnosis process	• Improving classification performance and accuracy based on new models	• Assisting in the accurate identification of dangerous malignant tumors from	• Inability to create effective classification models using updated CNN models • Inability to implement the proposed	✘	✔	✔	✔	✘	✔

(continued on next page)

Table 9 (*continued*)

References	Approach	Targets for ML	Targets for BC	Advantages of the ML approach	Advantages of the BC approach	Disadvantages	Evaluation criteria					
							AUC	ACC	SPE	SEN	Recall	F-Score
					harmless benign tumors • Providing assistance to doctors in low-resource environments	approach when confronted with large and real datasets						
[116]	DNN	• Developing a new method based on DNN that can be used to detect BC	• Achieve high-quality and efficient image classification	• Provide very accurate and effective results compared to similar methods	• Accurate diagnosis of BC using the proposed approach • Early detection of BC using the proposed approach	• Inadequate use of powerful prediction and comparison techniques	✘	✔	✔	✘	✔	✘
[117]	CNN	• Presenting a novel deep learning model to achieve enhanced classification.	• Automating the classification of BC	• Improve the speed of diagnosis • Enhance the accuracy of diagnosis	• Ability to accurately detect and classify images using automatic classification approach	• Inability to use the proposed approach on other datasets • Lack of application of the proposed approach to actual datasets	✘	✔	✔	✔	✘	✔
[118]	CNN	• Presenting a hybrid approach for accurate classification of breast images	• Enhancing the accuracy of image classification	• Improve classification performance in interactive cross task extreme learning machine.	• Providing an efficient tool for BC classification in clinical settings • Accurate classification performance of remarkable quality	• A lack of consideration for images that cause noise to reduce the accuracy of classification • Failure to test the proposed approach in different environments	✘	✔	✔	✔	✘	✘
[119]	CNN	• Propose a modified architecture for extracting images' features efficiently	• Incorporating effective features into BC classification	• Enhancing image classification accuracy through automatic classification models	• Assist to classify breast lesions as benign and malignant • Increasing diagnostic reliability	• Failure to use CADx systems to extract lesion characteristics and robust classification of BC effectively • Failure to evaluate the proposed approach with specific algorithms for detecting lesions more accurately	✔	✘	✔	✔	✘	✘
[120]	DNN	• Propose a novel hybrid convolutional and recurrent deep neural network for image classification.	• Achieve an effective classification system for BC	• Using an automated method for analyzing images accurately	• Alleviate the problem of relatively low classification accuracy of benign images	• No direct use of low-resolution images as an input • Failure to apply the proposed approach to	✘	✔	✘	✔	✘	✘

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Table 9 (*continued*)

References	Approach	Targets for ML	Targets for BC	Advantages of the ML approach	Advantages of the BC approach	Disadvantages	Evaluation criteria					
							AUC	ACC	SPE	SEN	Recall	F-Score
					• The possibility of more authentic and finer recognition in classifying classes	all available images in datasets						
[121]	DNN	• Propose a deep learning-based approach to breast mass classification in sonography	• Finding a mechanism to improve the accuracy of image classification	• Improve the overall performance of the transfer learning techniques using DNN • Improved classification accuracy by using pre-trained DNN	• Providing assistance to radiologists in the classification of breast masses • Efficacy of the proposed approach as a clinical tool for diagnosis	• Failure to determine the effectiveness of the presented approach in the other datasets • Failure to compare the proposed approach with other algorithms for accurate diagnosis	✔	✔	✔	✔	✘	✘
[122]	DNN	• Developing an automated BC detection model based on images classification	• Implementing a strategy aimed at improving image classification	• Resolving the shortcomings caused by image classification in existing methods	• Detects BC masses with a high degree of accuracy • Provided a performance comparable to human sonographers in image classification.	• Failure to use the proposed approach in large data sets and real-world scenarios • Lack of use of the technique of combining different image methods to improve accuracy	✘	✔	✔	✔	✘	✔

Table 10
Analysis of BC diagnosis based on Hybrid approaches in Hybrid using information from reviewed articles.

References	Approach	Targets for ML	Targets for BC	Advantages of the ML approach	Advantages of the BC approach	Disadvantages	Evaluation criteria					
							AUC	ACC	SPE	SEN	Recall	F-Score
[123]	SVM	• Developing a novel method for classifying breast biopsy images	• Increasing the classification accuracy of stained breast biopsy images	• Efforts to reduce costs • Achieving greater efficiency	• Optimizing the performance of the proposed approach on histological images • Enhance the accuracy and speed of image classification	• Inability to apply the proposed approach to different datasets • Lack of comparison of results obtained with more powerful techniques	✗	✓	✗	✓	✗	✗
[124]	• SVM • LR • KNN	• Present an analysis of several algorithms' performance	• Achieving a pattern for increases classification accuracy	• Introducing an algorithm that is more accurate	• Providing a satisfactory classification based on the quantitative features	• A lack of use of CV techniques, such as k-fold cross-validation, to verify the results • Failure to utilize bias parameters	✗	✓	✓	✓	✗	✗
[125]	• SVM	• Presenting a mechanism to determine the factors influencing patient survival accurately	• Achieving prognostic indicators affecting patients' survival	• Accurately identifying influencing factors and parameters	• Enhancing a patient's chances of survival • Improving the effectiveness of selected factors	• A lack of utilizing powerful techniques for predicting outcomes • A lack of accuracy in clinical parameter selection	✓	✓	✓	✓	✗	✗
[126]	• LR • RF	• Presenting a comparative approach to the performance of two algorithms	• Achieving an accurate prognosis immediately after surgery without the need for further interaction with the physician	• Introducing an algorithm with higher accuracy • Assist in increasing the accuracy of the results obtained	• Predicting the level of anxiety, type of surgery, and level of acute pain during movement • Achieving an accurate prognosis for postoperative neuropathic pain	• Inaccurate selection of the parameters that are most influential • A lack of certainty regarding the results	✗	✗	✓	✓	✗	✗
[127]	• LR • SVM • NB • RF	• Presenting a comparative approach to the performance of several algorithms	• Increasing the possibility of longer survival in patients with metastatic disease	• Providing an accurate prediction of patient survival	• Early diagnosis of metastasis among patients • Enhancing patient survival by providing a detailed pre-awareness process	• Failure to use large and real data sets • Lack of use of existing powerful forecasting techniques to increase confidence in the results obtained	✗	✓	✓	✓	✗	✗

related to this category.

5.4.1. Summary of the discussion regarding detection plans in mammography using hybrid

The analysis of the articles relating to ML techniques implementation, except NN and DL that have been applied to the clinical diagnosis method of mammography, revealed RF and SVMs are the widest implementation approaches in ML among all the various approaches and techniques available. However, most of the techniques in this category are designed to provide an approach capable of extracting the most important and accurate features of a BC diagnosis with a high degree of accuracy from the data obtained on the mammogram as a clinical diagnosis method. On the side, the most important goals of these articles in BC diagnosis are to diagnose BC as early as possible and perform the diagnosis process with the highest accuracy possible. On the other hand, the advantages considered for the section related to implementing ML techniques focus on increasing the prediction accuracy of the techniques used. Among its advantages in BC diagnosis are the early detection of high-risk lesions and the prevention of disease progression. Researchers can use more powerful techniques and compare the results to be more reliable. The results should be generalizable and applied to other datasets. The evaluation of ML techniques also involves the consideration of various criteria, some of which are more commonly used than others. These criteria include the AUC, SEN, and SPE.

5.5. Breast cancer detection by DL and NN approaches in hybrid

Various processes and methods exist for diagnosing BC clinically. Some are widely used, while others are less widely used in the medical community for various reasons. Therefore, in this research, a systematic approach has been taken to categorize the taxonomy along with the two most widely used methods used by researchers in using ML techniques to diagnose BC, such as MRI and mammography. Data obtained from other methods have been used in clinical diagnosis, and they should be categorized in a hybrid format to facilitate access to more articles. Therefore, this part of the research will examine the implementation of NN and DL techniques using the hybrid classification dataset in the ML process. As a result, the data set and images obtained from the Hybrid category can be utilized to diagnose BC. As part of this classification, information regarding clinical trials is also considered in addition to the available images. Therefore, among the goals of researchers in this taxonomy is to use data sets and images obtained from different clinical methods to improve the process of BC by using ML techniques utilizing NNs and DL (Table 9). presents extracted items from articles related to this category.

5.5.1. Summary of the discussion regarding detection plans in hybrid using DL and NN

Based on the review and analysis of articles related to implementing techniques on NNs and DL, based on clinical diagnosis data other than MRI and mammography data, it has been determined that the CNN approach is the most frequently applied ML approach. However, the purpose of the techniques used in this classification is to provide a method for performing the separation and classification process with the desired quality on the data obtained by other clinical diagnosis methods, except MRI and mammography with the desired quality. These articles have also highlighted the most important goal in BC diagnosis, namely improving the classification of BC, identifying its type, and achieving high accuracy in classification. However, it is usually emphasized that the benefits of increasing the effectiveness of classification for diagnosis, reducing computational costs, and improving the speed of diagnosis are also considered. It has several advantages in the field of BC diagnosis, including assisting in the accurate and rapid diagnosis of malignant tumors and increasing the speed and efficiency of diagnosis. The problem with most of these articles and approaches is that implementing the proposed approaches has been carried out only on one dataset. The approach should also apply to other data sets and be generalizable. Another challenge associated with these approaches is the lack of practical implementation and combination with other approaches to enhance the results obtained. It is also essential to consider various criteria when evaluating ML techniques; some are used more frequently than others. These criteria include the AUC, and ACC.

5.6. Breast cancer detection by hybrid approaches in hybrid

Using ML techniques from the Hybrid category to analyze data obtained from clinical diagnostic methods belonging to the Hybrid category has not been extensively researched in diagnosing BC. Despite the dispersion of techniques utilized in this approach to diagnose cancer derived from rarely utilized methods, this does not imply that the results of this approach are invalid (Table 10). presents extracted items from articles related to this category.

5.6.1. Summary of the discussion regarding detection plans in hybrid using hybrid

A review of the articles related to the Hybrid classification of taxonomy based on clinical diagnosis Hybrid methods revealed that two approaches, LR and SVM, are the most commonly used approaches and techniques in ML. The techniques employed in this category are, on the other hand, primarily aimed at providing an approach through which significant and accurate BC diagnostic characteristics can be derived from the obtained data from Hybrid classification with a high degree of accuracy. Hence, to perform a combined clinical diagnosis method, researchers have generally attempted to use comparative methods of comparing the techniques to achieve this goal. During these articles, the most critical goal they strive to achieve in the field of BC diagnosis is to carry out the diagnosis process with as much accuracy as possible to increase patient survival times as much as possible by using it. Generally, the advantages of implementing ML techniques emphasize the reduction of time and the improvement of prediction accuracy of the techniques used to achieve optimal performance. It is important to note that there are significant weaknesses in implementing the majority of these articles and approaches, including the fact that the proposed approaches have only been tested on one data set and the incorrect selection of the parameters that have the least significant impact on the results. In addition, when evaluating ML techniques, it is vital to consider various criteria; some techniques are used more frequently than others. These criteria include ACC, SEN, and SPE.

6. Discussion

This section discusses and evaluates the application of ML technology to diagnose BC. These analyses are presented from the perspective of ML technology and BC detection. The logical analysis and reports based on the TQs in Section 4 are presented as follows:

- **TQ1**: What classification is employed to apply ML technology to BC diagnosis?

Based on the suggested taxonomy, a statistical comparison founded on BC detection methods and the approach used to implement the ML process with the objective of cancer detection is presented in (Fig. 9). The taxonomy presented for diagnosing BC using ML technology has been considered in six cases. Hence, this systematic taxonomy includes the following:

- BC detection by NNs and DL approaches in MRI (Deep learning-based MRI or DMRI)
- BC detection by Hybrid approaches in MRI(Hybrid-based MRI or HMRL)
- BC detection by NNs and DLapproaches in Mammography (Deep learning-based Mammography or DMammography)
- BC detection by Hybrid approaches in Mammography (Hybrid-based Mammography or HMammography)
- BC detection by NNs and DLapproaches in Hybrid (Deep learning-based Hybrid or DH)
- BC detection by Hybrid approaches in Hybrid (Hybrid-based Hybrid or HH)

Consequently, the presented taxonomy of BC clinical detection methods and the implementation of ML technologies in the selected articles cover only (22 %) of the selected articles covered the clinical diagnosis method of mammography and the data set obtained from it. However, among the researchers who used data from this method, an equal number of researchers employed DL techniques, NNs, and other ML techniques. This amount for both of these approaches is equal to (11 %). Meanwhile, (26 %) of the researchers have used information obtained from the MRI method. Researchers who used data from this method employed DL techniques, NNs, and other ML techniques equally. Hence, for both approaches, this amount equals (13 %). Finally, (52 %) of researchers have used data obtained from methods other than mammography and MRI. Of researchers who used data from these methods, 39 % used approaches based on NNs and DL while the remaining (13 %) employed other ML techniques.

- **TQ2**: What evaluation criteria are usually used to evaluate the performance of ML techniques in the process of BC diagnosis?

As evaluation criteria for the performance of ML techniques in the BC diagnosis process, some important parameters, as shown in (Fig. 10), may be used. Some of these evaluation criteria may appear in multiple articles, as some research articles have used several criteria to evaluate their work. It is evident from the analysis of these evaluation criteria that accuracy is the most commonly used criterion in evaluating the performance of ML techniques to detect BC, with (27 %), followed by sensitivity at (26 %). There are four

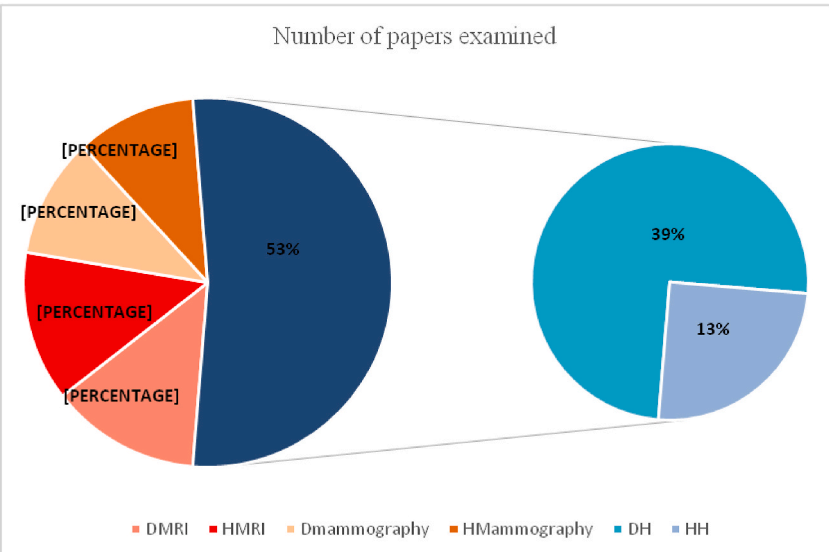

Fig. 9. The number of the utilized issue studies related to ML technology to diagnose of BC.

next ranks on the chart, namely specificity, AUC, F-score, and recall, rated (23 %), (15 %), (6 %), and (3 %), respectively, settling the next positions on the chart.

- **TQ3**: What clinical parameters are usually used to diagnose BC using ML techniques?

In BC diagnosis, researchers consider various parameters and clinical features. Therefore, some of the clinical parameters used in the cancer diagnosis process used in the articles have been analyzed to answer this question. The result of this analysis is shown in (Fig. 11). Some of these parameters and clinical features may appear in multiple articles, as some research articles have used multiple clinical parameters to diagnose BC. From the analysis of these clinical parameters, it is clear that the Benign and malignant parameter, with (41 %), is the most common clinical parameter used in BC diagnosis, followed by the Tumor grade parameter, with (16 %). There are four next ranks in the graph, namely, Tumor size, Gender, Age, and Number of tumors, with ranks of (15, 14, 10, and 4 %), respectively, representing the next positions in the graph.

- **TQ4**: What ML techniques are usually used in the BC diagnosis process?

In the process of applying ML technology, researchers use different techniques according to their goals. Therefore, some ML techniques used in the cancer diagnosis process are analyzed in the literature. The result of this analysis is shown in (Fig. 12). It is important to note that some reviewed articles have used more than one technique to conduct their research, so the number of ML techniques reviewed can be greater than the number of reviewed articles. From the analysis of the ML techniques used, it is clear that the CNN technique is the most used ML technique, with (31 %) in the process of BC diagnosis, followed by the SVM technique with (16 %). The next ten ranks on the chart are Random Forest, Decision Tree, Logistic Regression, DNN, ANN, Naive Bayes, K-Nearest Neighbor, DBN, DAL, and K-means, with ranks (15,7,7,5,4,4,4,2,2 and 2 %) representing the next positions on the chart.

- **TQ5**: What methods are typically used to diagnose BC clinically?

The process of diagnosing BC is performed clinically with different methods. Therefore, to answer this question, it has been tried to analyze some of the methods of clinical diagnosis of BC that researchers have used in their realizations from the obtained data from these methods. These results are shown in (Fig. 13) it has been shown. From the analysis of BC clinical diagnosis methods, it is clear that the MRI method is the most used clinical diagnosis method, with (26 %) in the process of BC diagnosis, followed by the Mammography method with (21 %). The next five ranks in the graph are histopathological, Clinical pathology, Ultrasound, Microwave Tomography, and Radar-base, with ranks of (18, 16, 13, 3, and 3 %) representing the next positions in the graph.

7. Open issue

This section discusses some open issues concerning the application of ML technology to diagnosing BC. In the following, we will discuss the challenges related to this field and attempt to provide solutions. The challenges are divided into two parts in this section. The first part of the report discusses the challenges researchers face in the healthcare field. The second part discusses the challenges associated with ML technology implementation. Ultimately, we provide solutions to all the challenges discussed.

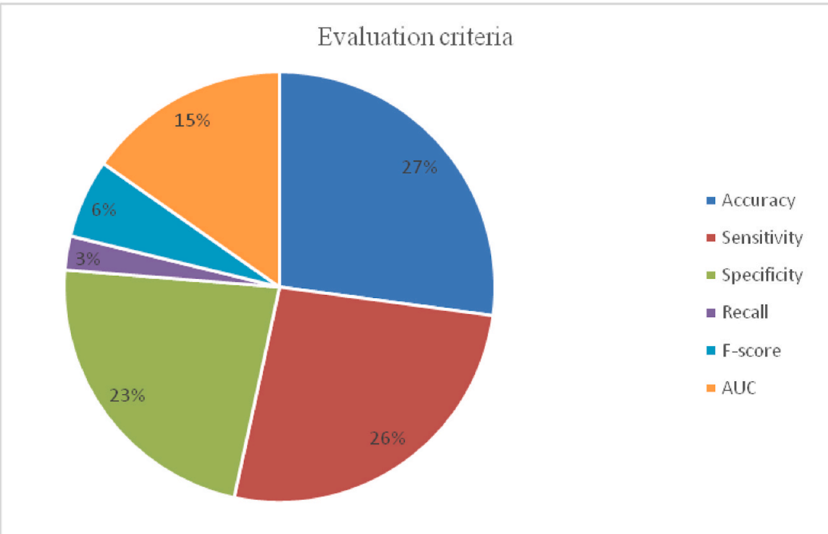

Fig. 10. The evaluation criteria for ML techniques used in the diagnosis of BC.

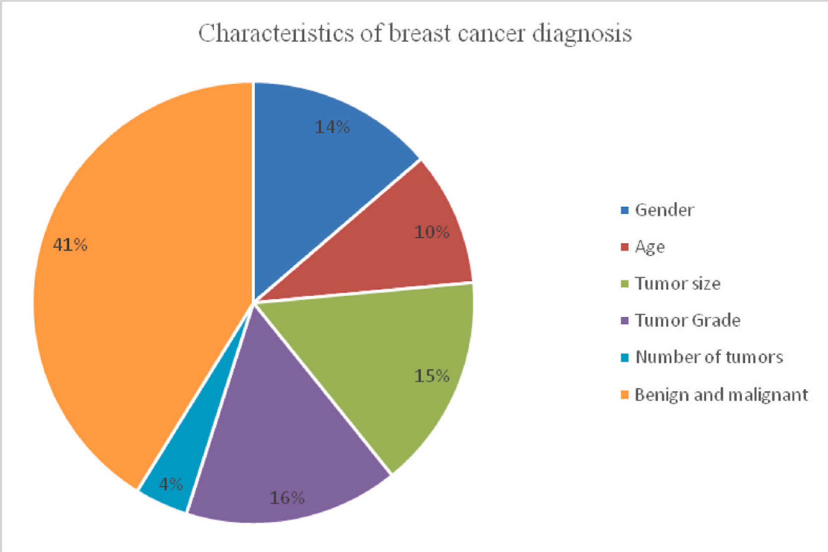

Fig. 11. The characteristics used in the diagnosis of BC.

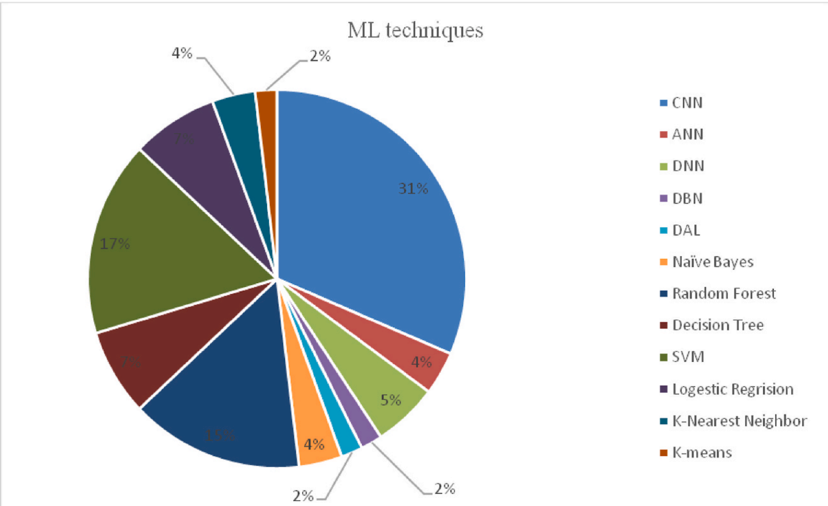

Fig. 12. The ML techniques used in BC diagnosis.

7.1. Future research prospects

The purpose of this section is to provide a technical and implementable response to the following question:

Hence, this section presents a new perspective and emphasizes the need for experts and researchers to explore the topic in greater depth. Regarding TQ6, we discuss new information challenges as well as open issues. Based on further guidelines (Fig. 14), presents the main challenges of applying ML technology to BC diagnosis. As stated in shown as (Fig. 14), the challenges are considered as follows below:

- **TQ6:** What are the future research directions and open perspectives for using ML technology in the BC diagnosis process?

While implementing ML technology on healthcare field data, researchers always face some challenges. Generally, these challenges are related to the implementation stages, which include the challenge of choosing a ML technique for implementation, the challenge of choosing the appropriate evaluation criteria to measure and check the performance of ML techniques, the challenges of data refinement stages, etc. The challenges outlined above have been examined in detail in previous research, and researchers have also attempted to solve these problems. The objective of this section is to examine several new challenges that remain unresolved for

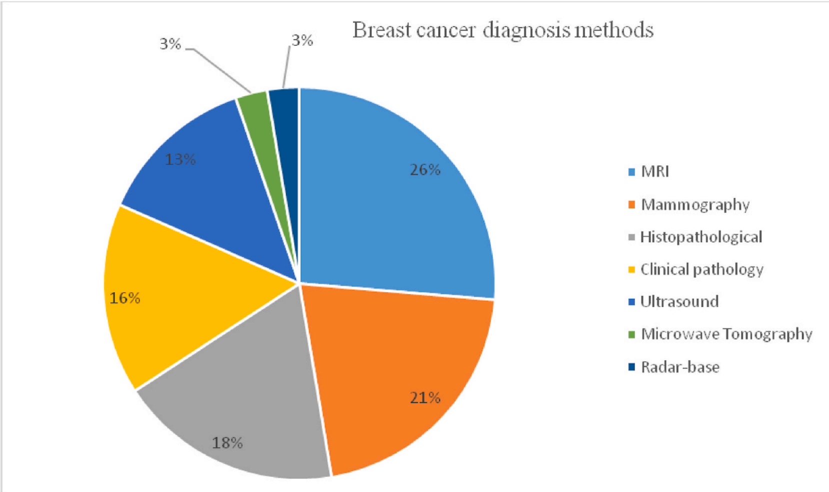

Fig. 13. The BC diagnosis clinical methods used in ML techniques.

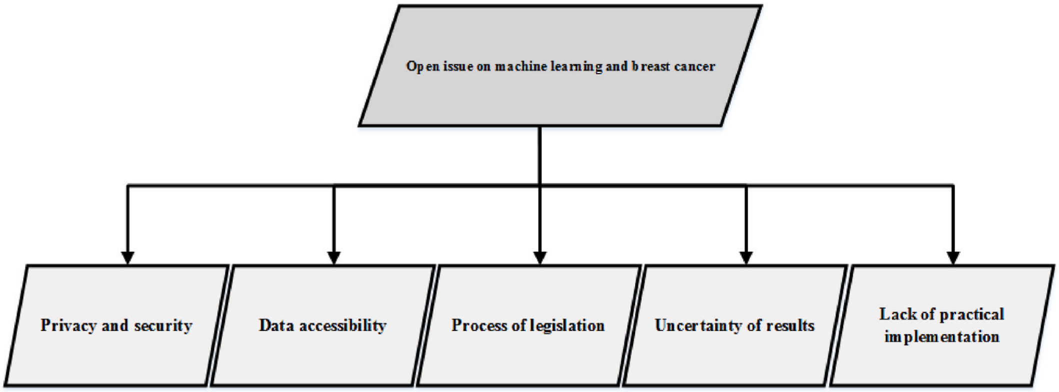

Fig. 14. Open issues related to the use of ML for the diagnosis of BC.

researchers both in the field of ML and in the field of health care. In the following sections, we will discuss these challenges in detail, and at the end, we will propose a comprehensive solution for them. Several challenges related to the healthcare field are examined in this section. These include:

- **Privacy and security: Healthcare** field-related data are high-sensitivity, as they can always be misused. Hence, people with a disease will not want to provide their information to others due to the possibility of misuse of their information. Consequently, one of the reasons why the healthcare field is always rigorous in utilizing emerging technologies is related to the issue of privacy and security protection. Therefore, providing a mechanism that can solve the privacy challenge can justify the use of emerging technologies, particularly those such as ML, in the medical field. There are two aspects to the issue of privacy. First, patients may wish to refrain from sharing their data with others because they may have an illness they would like others to be unaware of. Second, patient data is considered clinical data; thus, making it available to individuals or companies could lead to misuse of this information. As a result, the proposed solutions to the privacy and security challenges should address both of these concerns at the same time. Generally, researchers who intend to use technologies such as ML in diagnosing diseases such as BC always face the challenge of obtaining patient-related data.
- **Data accessibility**: Due to the importance of data in the healthcare field, healthcare centers that have such data generally refuse to provide it to researchers who wish to use it. Given this, researchers who plan to use healthcare data for ML processes will likely need many permissions to access such data, which is a significant challenge for them. Therefore, research efficiency depends on the accessibility of necessary data, which is a critical aspect of starting research for a researcher. Hence, the accessibility of necessary data for a researcher can increase patients' chances of survival by accelerating the diagnosis and treatment process for many diseases. However, it can present a challenge to them when they are required to access this information within certain conditions, within a specific timeframe, and with the option of accessing a certain level of data.

- **Process of legislation**: The rate at which legislation is established is much slower than the speed at which technological advances are made. Since the world is expanding rapidly, establishing rules for utilizing these technologies will require considerable time. For this reason, the legislative process is prolonged compared to the speed of technological progress. Consequently, researchers will need help applying these technologies in sensitive fields such as healthcare. All medical care centers follow the guidelines communicated by the upstream organizations and institutions. Therefore, it can be said that no comprehensive law has been established for using emerging technologies such as ML to diagnose diseases such as BC. The availability of patient data kept in healthcare facilities would be very easy for researchers if such a law existed. One of the reasons why there is no such law may be due to concerns regarding the privacy of patients and preventing their information from being published or misused.

There are several challenges that must be addressed before ML technology can be implemented. These challenges include:

- **Uncertainty of results**: Medical professionals cannot generally communicate rapidly and effectively with emerging technologies. Consequently, doctors and specialists in healthcare are cautious regarding emerging technologies due to the sensitive nature of the field and because it involves human life and health. The difficulty in using ML technology in diagnosing diseases such as BC is that doctors cannot fully trust the results of this technology. Because from the point of view of doctors, many parameters must be considered to examine, diagnose and treat disease. The incompleteness of the data can lead to the incomplete performance of techniques or algorithms in the process of implementing ML, which can lead to the creation of incomplete results. Finally, this makes the results obtained untrusted. Not trusting these results is entirely logical. Therefore, when the experts in the field of healthcare are sure that the results of the implementation of ML techniques have met the basic requirements, they may change their opinion concerning the use of emerging technologies. For this purpose, it is essential that the data be available with all of the basic parameters and that privacy and data security are maintained.
- **Lack of practical implementation**: The fact is that most of the research done in the field of using ML in diagnosing diseases, especially BC, and has only a research aspect. As a result, when this possibility is available, it will only be available to a few patients due to its limitations and difficulties existing. Therefore, researchers aim to achieve a specific goal in research and academics. Therefore, one of the critical challenges related to this field is providing this possibility for a large part of the patient community and, of course, the healthcare field. Because in this case, by using more such processes on large and real data sets, it will be possible for more people to use these services, and as a result, the results obtained will be more reliable due to the use of large datasets community, and, of course, these processes must not violate two primary subjects, namely privacy and data security.

7.2. Proposed solutions to challenges

The challenges presented are all critical and have been largely unanswered. Thus, there can be provided solutions to overcome the challenges ahead. Still, it is essential to consider that these solutions have an operational aspect and can be implemented. The ever-increasing spread of science and the emergence of new technologies are always considered an opportunity to resolve challenges and problems in other fields. A new technology that has gained significant attention in recent years is blockchain. Blockchain structures have excellent security mechanisms and are highly secure. In other words, because blockchain has powerful cryptographic algorithms, it can provide a structure that makes it impossible for abusive people to break into it, or the cost of such activity is high. The technology behind blockchain may also serve as a solution to the problem of maintaining data security and protecting people's privacy. On the other hand, blockchain can be considered a distributed database. In addition to bringing many benefits to the healthcare system, this technology can solve numerous problems in this area. Hence, the solutions provided include the following:

- Blockchain technology has powerful encryption capabilities, one of its most essential features. Due to this feature, all transactions and data stored in the blockchain are encrypted by powerful algorithms, which prevents anyone without permission from accessing this information. In fields such as healthcare, which contain sensitive data, it is possible to utilize this technology to solve the challenges associated with maintaining data security. Therefore, this technology can be viewed as a means of ensuring data security and related interactions.
- Maintaining privacy has always been considered one of the most critical challenges. There is a possibility in the healthcare field that patients would be willing to provide information to researchers to conduct research; however, what prevents them from doing so is that they wish to keep their identities private from researchers. The blockchain structure has made it possible for the identity of people to remain completely anonymous by providing mechanisms. Hence, people who wish to remain anonymous can easily share their data anonymously using this technology.
- One of the reasons legislators are not always willing to pass legislation allowing healthcare centers and individuals to cooperate with researchers is that they are concerned about protecting patients' privacy and preventing data misuse of patients is mentioned. Therefore, implementing and utilizing emerging technology such as blockchain, which can guarantee privacy protection and data security, can be the basis for solving this challenge and persuading legislators to protect patients' privacy while ensuring patient data security.
- With blockchain technology, healthcare centers will be encouraged to put their patients' data into the blockchain database with the consent of their patients while providing the safety of data and preserving privacy. Consequently, researchers can access more data, allowing them to implement ML techniques on large data sets and, of course, to analyze the complete set to identify patterns. Consequently, this method can address the challenges associated with not trusting results due to the lack of data.

- Due to existing constraints and challenges, it is only possible to implement a few of the research studies conducted by researchers on a practical or industrial basis. Therefore, using ML technology to diagnose diseases such as BC cannot be implemented from an industrial and commercial perspective. Therefore, this is even though diagnosing diseases such as BC uses clinical methods. Hence, to identify BC with ML technology, the technology can be applied from the point of view of industry and business. However, the process has the potential to bring many benefits as well. Of course, with attention to the existing limitations and high costs, this product will only be available to a limited number of users. It is, therefore, possible to overcome such a challenge by utilizing other emerging technologies, such as the Internet of Things. By designing portable gadgets, different people can collect clinical data by preparing these gadgets. They can transfer the data to the data processing center in order to use ML technology. Emerging technologies such as the Internet of Things and Blockchain provide the possibility of practically implementing the conducted research while providing the opportunity to provide benefits to a broader range of people or patients, and all of these steps are implemented. Hence, maintaining patient privacy and securing patient data simultaneously is also being considered.

8. Conclusion

The incidence of BC among women is widespread worldwide, and it is the second leading cause of death among women. Therefore, early detection of BC can significantly affect BC mortality and decrease mortality rates in women. Using new technologies to diagnose abnormalities allows healthcare professionals to make more accurate diagnoses. Healthcare data are sources of information related to various diseases and abnormalities that can be used in diagnosis. This study presents a systematic and comprehensive review of applying ML technology in BC diagnosis. Based on the results of this study, the CNN approach is the most accurate and widely used method for diagnosis among the approaches related to NNs and DL. On the other hand, this approach based on ML is the most widely used among the data obtained from hybrid diagnostic methods. In other side, despite the widespread existence of clinical diagnostic methods, such as MRI and Mammography, researchers have tended to use data obtained from other methods. Meanwhile, researchers have utilized the SVM technique for approaches other than those based on NNs and DL. Hence, decreasing the period of the illness and, consequently, the efficient performance of speeding up the treatment process has been considered by researchers. In this study, one of the primary challenges is the inability to apply the proposed approaches in ML to large and real datasets, as well as the absence of effective clinical parameters in the process of BC diagnosis. Consequently, among the wide ML approaches examined in this study, the approaches based on NN and DL provide the most accurate and widely used models for diagnosing BC. On the other hand, researchers tend to use clinical information and other information not directly related to the analysis of images. Also, this study show among the criteria for performance evaluation three criteria ACC, SEN, and SPE are very popular. The final step of this research was to examine the factors known as open issues, identified as the main barriers to the practical implementation and commercialization of using ML technology to diagnose BC. Therefore, practical and implementable solutions have been presented to overcome these obstacles, and in addition to solving the concerns, it will pave the way for commercialization in this field.

In future, In the future, using machine learning technology in conjunction with other technologies like the Internet of Things can make diagnosing this disease much more efficient and cost-effective. For example, when breast cancer occurs, certain blood markers may increase in concentration, including CA 15-3 and CA 27–29. Therefore, it is possible to develop kits to detect the amount and volume of markers in blood and then transmit the obtained information to centers equipped with ML technology using IoT devices. By using this process, patients can easily, at low cost, and in the shortest possible time perform diagnostic tests for BC in the early stages so that they may consult a doctor if their results are suspicious.

Data availability statement

Data will not be required for this article.

CRediT authorship contribution statement

Mohsen Ghorbian: Methodology, Formal analysis, Data curation, Conceptualization. **Saeid Ghorbian:** Writing – review & editing, Visualization, Validation, Supervision.

Declaration of competing interest

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

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