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PAPER

Detection of Breast Cancer through the Analysis of Radiographic Images Using Machine Learning: A Systematic Review

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ABSTRACT

Breast cancer is an illness that affects many women and can cause even death; this is a case of not being detected on time, which could be due to a human error during the analysis of radiographic images or not going on time in a health center. For this, using machine learning (ML) to analyze radiographic images is proposed as a support tool for radiologists aiming to reduce false diagnostic rates. While researching information, it was detected that this technology has many benefits in the health area; however, it also has limitations or disadvantages. The importance of this paper is to demonstrate that there are not enough clinical tests nor details about the methodologies that were used; there should be more to assert that ML is defined at the moment of making a diagnosis, which generates no conclusive results regarding effectiveness and therefore creates mistrust in doctors, and some people might rather use deep learning (DL) for its application in the detection of breast cancer because DL has more practical tests and fewer limitations than machine learning.

KEYWORDS

machine learning (ML), medicine, breast cancer, detection, systematic review, cancer diagnostics, cancer prognosis, mammography

1 INTRODUCTION

Breast cancer is women's most frequently diagnosed cancer and rapidly grows [1]. It is the fifth most common cause of death [2], accounting for approximately 685,000 deaths a year [3]. One in eight women develops it in her lifetime [4]. Unfortunately, late detection of breast cancer leads to a diminished quality of life and is the primary cause of death. At least 70% of women are diagnosed with cancer in its advanced stages, negatively impacting survival rates [5].

Cancer identification outcomes rely on human interpretation, resulting in false positives or negatives. This generates anxiety and unnecessary patient concerns,

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sometimes portraying the cancer as more aggressive and rapidly progressing [6]. Overdiagnosis and excessive testing have also made patients symptomatic [7].

Given the issues above, delayed detection of this disease poses a problem, emphasizing the importance of early breast cancer diagnosis. Early detection is crucial, as disease progression complicates treatment [8]. Diagnosing it in its early stages can reduce associated mortality [9] and increase patient survival rates by 50% [1]. Early detection offers the best opportunity for effective and gentle treatments [9], making cures more achievable [10].

Specialists usually conduct inspections, or mammograms, to improve early detection. However, automated approaches are desired to provide better responses that can serve as a second opinion [5]. Image analysis enhances survival prospects [4], and AI-processed mammograms are essential for early breast cancer diagnosis [8]. Machine learning and deep learning can help identify cancer signs in mammographic images early [11].

In connection with the above, it's evident that ML facilitates cancer prediction. In this case, image analysis can aid in timely tumor detection. Notably, AI's presence in medicine is expanding, rapidly improving, and reducing human errors in detecting tumor indicators. AI contributes to both diagnosis and treatment through the interpretation of echocardiograms. It's worth highlighting that human observer-based image interpretation relies on observer knowledge or experience, whereas AI technologies produce accurate and consistent performances that provide support [12].

Based on the reviewed articles, the theme "Breast Cancer Detection through Radiographic Image Analysis Using Machine Learning" was established. This topic is of utmost importance and should be elaborated upon to inform the public about ML's impact on the healthcare sector, its findings, advantages, and disadvantages. Furthermore, employing this technology could assist radiologists in early disease diagnosis through image analysis, enhancing public health and reducing mortality rates caused by this type of cancer. Treatment can be administered when the disease is in its early stages.

The results obtained aim to empower readers to draw their own conclusions. The objective is to contribute to researchers' studies on this topic.

This research is structured as follows: The next section, methodology, presents the method used for the SLR (systematic literature review), detailing technical aspects from posed research questions to operations leading to material selection discussed in the document. Then, the results present and organize outcomes from analyzing primary works on ML usage in the healthcare sector. After that, the discussion deliberates on sources and findings, analyzing the pros and cons of ML employment in healthcare. Lastly, conclusions, key results, and limitations of this RSL study are synthesized, along with recommendations for future research.

2 MATERIALS AND METHODS

Description of the systematic search strategy

For the development of the systematic search strategy, a guiding question was formulated, which is: What are the benefits of using ML in image analysis for tumor detection?

Subsequently, the identification of the components of the PICO strategy was carried out. It will be show in Table 1.

Table 1. Components of the PICO question

Population	Patients Suffering from Cancer
Intervention	Machine learning for image analysis
Comparison	Without configuration
Outcomes	Early detection
Context	Healthcare sector

After defining the components of the PICO question, keywords were identified for each component. As you will see in Table 2.

Table 2. Keywords for components of the PICO question

Population	Tumor, Cancer, Cancer Patients
Intervention	machine learning, artificial intelligence, ia, study of images with machine learning
Comparison	Without configuration
Outcomes	detection, diagnosis, analysis, medical results, cancer results, prevention, cancer prevention, early detection, study of tumors
Context	medicine, health, clinical, telemedicine, healthcare, oncology

Description of the selection logic considered (PRISMA)

Three databases were used: Scopus, Scielo, and IEEE Xplore. The following search equations were used for the searches conducted in these repositories:

- Scopus and IEEE Xplore databases

((tumor OR cancer OR "cancer patients") AND ("machine learning" OR "artificial intelligence" OR ia OR "study of images with machine learning") AND (detection OR diagnosis OR analysis OR "Medical results" OR "cancer results" prevention OR "cancer prevention" OR "early detection" OR "study of tumors") AND (medicine OR health OR clinical OR telemedicine OR healthcare OR oncology)) (1)

The same search equation was used for both repositories. In Scopus, the number of obtained records was 2,039; in IEEE Xplore, it was 36,329.

- Scielo database

(tumor OR cancer OR cancer patients) AND (Machine learning OR artificial intelligence) AND (detection OR diagnosis OR analysis OR prevention) (2)

For the SciELO database, the search equation was modified, as the one used for the other databases yielded no results in SciELO. The number of obtained records in SciELO was 14.

The total number of records obtained from the three repositories was 38,382. A series of exclusion and inclusion criteria were applied to reduce this number.

The first exclusion criterion, CE1, eliminated documents not of the type "All Open Access." This criterion was decided to be applied first due to the large number of records obtained in IEEE Xplore, making it impractical to export to an Excel file for duplicate removal (the maximum exportable data was 2,000 records). After applying this exclusion filter, 33,864 records were discarded, leaving 4,518 selected.

Next, the CE2 criterion was applied, which excludes publications before 2022 to ensure a more up-to-date study of the topic. Literature beyond 2022 was found to be based on earlier documents. After applying this criterion to the previously obtained results, the records decreased to 1,429.

Following this, the CE3 criterion eliminated duplicate records between the selected databases. This criterion could be applied up to this point because the amount of data from IEEE Xplore, after applying filters CE1 and CE2, was manageable to be exported to Excel. The number of discarded articles was 8, and the remaining number of articles after eliminating duplicates was 1,421.

Next, the CE4 exclusion criterion was applied, focusing on different publication types than original articles and reviewing articles for Scopus and Scielo. For IEEE Xplore, other document types were present; therefore, records other than IEEE journal articles and IEEE Early Access articles were excluded, as these are the article types intended for developing the SLR. Original articles, review articles, journals, and early access articles were included, while chapters from books, conference papers, books, editorials, etc., were excluded. After applying this criterion, the number of articles was reduced to 1,379 documents.

The following criterion was applied: CE5, which aimed to eliminate records published in languages other than English or Spanish, reducing the number of records to 1,378.

Subsequently, the CE6 criterion was applied, which involved reviewing the title, abstract, and keywords of the 1,379 articles from the previous step to determine which ones were relevant to the selected topic. A total of 153 documents remained.

Finally, the CE7 criterion was applied, involving a comprehensive review of the articles to be used to develop the SLR. The number of articles at this stage was 103.

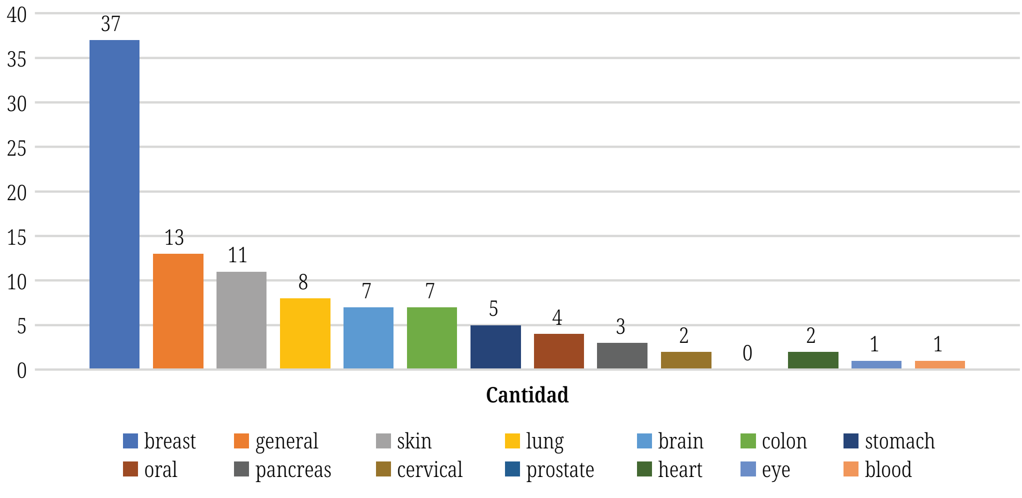

Fig. 1. Types of cancer discussed in the articles

The obtained documents were analyzed at this point, revealing their significant number. Consequently, a decision was made to focus on a specific type of cancer, and graphs were generated to aid decision-making.

Figure 1 shows that the predominant type of cancer in the obtained articles is breast cancer, with 37 records. The second type of cancer, with 13 papers, is general cancer, which contains information about cancer in general without focusing on any specific type of cancer. Considering this, our population would shift to individuals who have breast cancer.

Therefore, another filter, CE8, was applied to eliminate articles with information different from breast or general cancer. The articles remaining after using this filter were 50. To further reduce this number, filter CE9 was applied, which aimed to eliminate articles not mentioning the technology of ML. In total, 26 articles remained.

Finally, the number of articles was reduced to 26, which will be used to develop the systematic literature review.

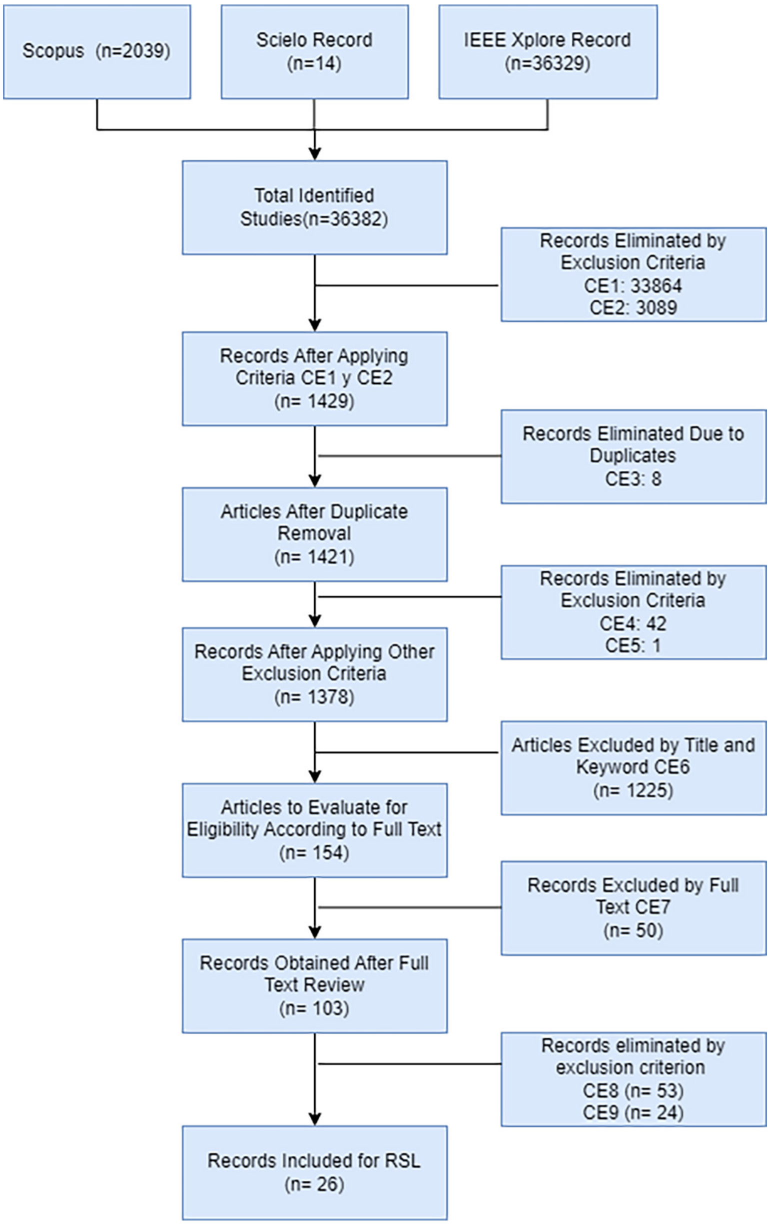

Fig. 2. PRISMA diagram

3 RESULTS

After conducting the literature search and applying different exclusion criteria, as shown in Figure 2, 26 articles were obtained to develop the current systematic literature review.

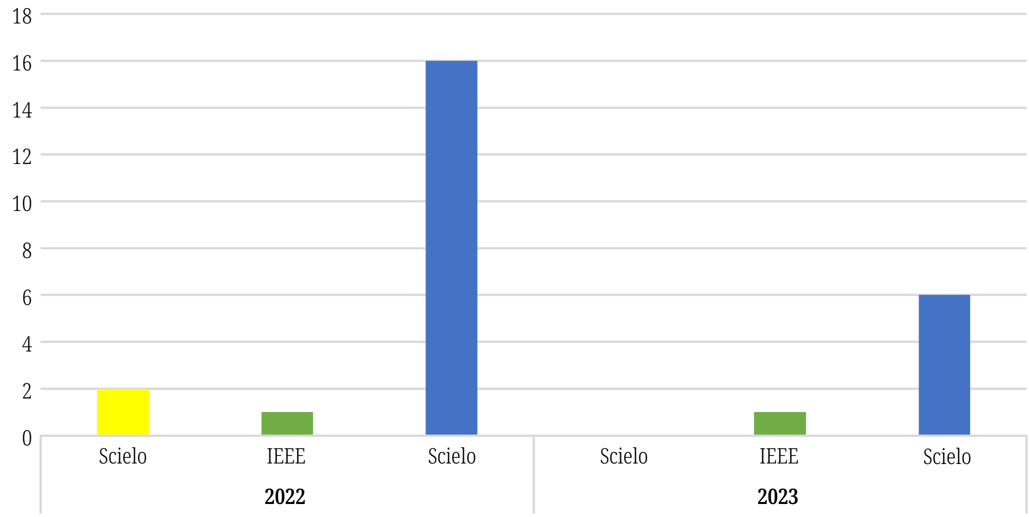

Fig. 3. Number of articles per year

From the different databases, eight articles published during the year 2023 were identified [1], [3], [4], [6], [11], [13], [14], along with eight articles from the year 2022 [2], [5], [7–10], [15–29], all of which met the filters established in the methodology, and that is why they were selected. The will above aids in conducting the review with data from up-to-date research grounded in knowledge from subsequent years. See Figure 3 for details.

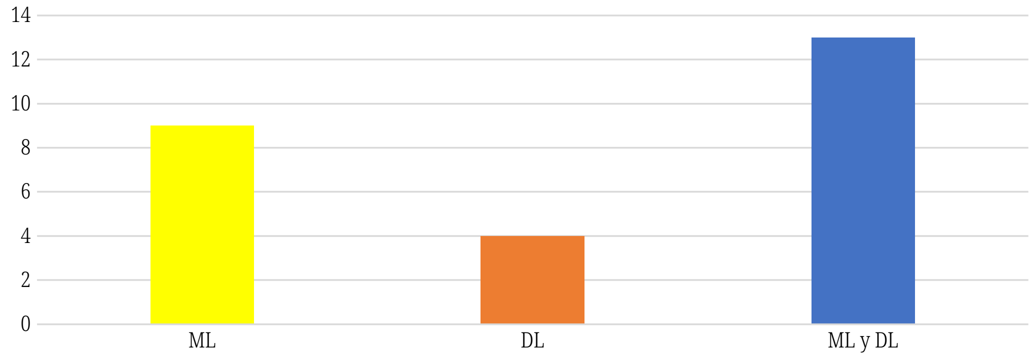

Fig. 4. Technologies referred to in articles

3.1 Results of machine learning applied to breast cancer detection

In the analyzed ML articles, it is observed that four of them conducted tests with the analysis of mammographic images in hospitals, which were grouped according to the results in terms of accuracy, specificity, and sensitivity.

Accuracy is a parameter related to effectiveness by evaluating the proportion of correct predictions from the total examined cases [4]. In Table 3, it can be seen that the accuracy of the analyzed studies [3], [4], [8] ranges from 95% to 90%.

Table 3. Precision by intervals

Precision by Intervals	References
[95–90>	[3], [4], [8]

Specificity is the portion of true positives that were correctly identified [4]. Table 4 shows that the articles' specificity [4], [17] varies between 95% and 90% of correctly identified cases. No results belonging to other intervals were found.

Table 4. Specificity by intervals

Specificity by Intervals	References
[95–90>	[4], [17]

In the case of sensitivity, it is defined as the number of true negatives correctly identified [4]. In Table 5, it can be observed that the results of the articles [3], [4], and [17] fall within the range of 95% to 80%, with more significant variability than that detected in specificity and accuracy results. This demonstrates that ML is more likely to have failures in terms of sensitivity or the detection of true negatives; false positives are still inevitable [3]. However, as seen in Tables 3 and 4, the results are high.

Table 5. Sensitivity by intervals

Sensitivity by Intervals	References
[95–90>	[3], [4]
[85–80>	[17]

It can be observed that in Tables 3, 4, and 5, there are empty intervals that were not included. This is because no ML tests with results fall within those intervals. It is noted that there are only four articles in which ML tests were conducted. In these articles, the ML methodology is not mentioned; only the name of the software employed is referenced.

3.2 Advantages of machine learning in breast cancer detection

Furthermore, in Figure 5, the identified advantages in the articles [1–3], [5–7], [11], [17], [18], [20–24], [29] were grouped. These studies found five advantages, with ML as a support for radiologists being the most mentioned and, therefore, the most significant advantage found.

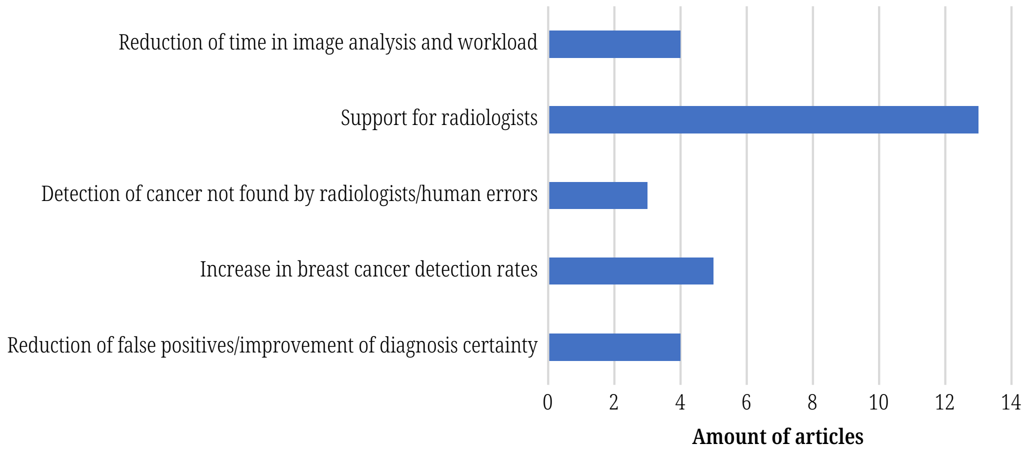

Fig. 5. Advantages based on references in articles

When analyzing the articles, an advantage identified in the studies [6], [7], [17], [23] was the reduction of false positives; ML helps to reduce false positives and minimize the anxiety generated in patients by these results [7]. Additionally, it is considered the main positive impact because it increases survival rates for breast cancer patients [23]. It was also observed that there is an increase in breast cancer detection rates, as referenced in five articles [1], [5], [6], [11], [17]. It is demonstrated that the implementation of ML in oncology improves the accuracy and efficiency of cancer management, helps to detect cancer signs early, and improves certainty for diagnosis [11]. Furthermore, another advantage is that AI detects cancers not found by radiologists, as indicated in three articles [6], [11], [24], demonstrating a significant number of such cases. Research has proven that ML can address the challenges faced by doctors, who often encounter errors directly related to their experience, blurry images, and similar appearances during reviews [1]. Given this, it is deduced that ML is a reliable network for detecting cancer that was not detected by the initial reader [17]. It was also observed that ML provides support for radiologists, according to several articles [1–3], [6], [7], [11], [17], [18], [20–23], [29], so it is deduced to be the main advantage since it is the most mentioned in the reviewed articles. ML would help doctors build a comprehensive and personalized view of each patient and assist in making judgments and decisions [11]. Finally, studies [1–3], [17] mention that ML and the use of AI, in general, reduce the workload of radiologists [17] and minimize human effort, reducing the mortality rate from 30% to 70% [1].

3.3 Disadvantages of machine learning for breast cancer detection

In Figure 6, the disadvantages observed in 15 articles [1], [3–9], [11], [15–17], [23], [25], [26], [29] were grouped, and eight disadvantages were found in these studies.

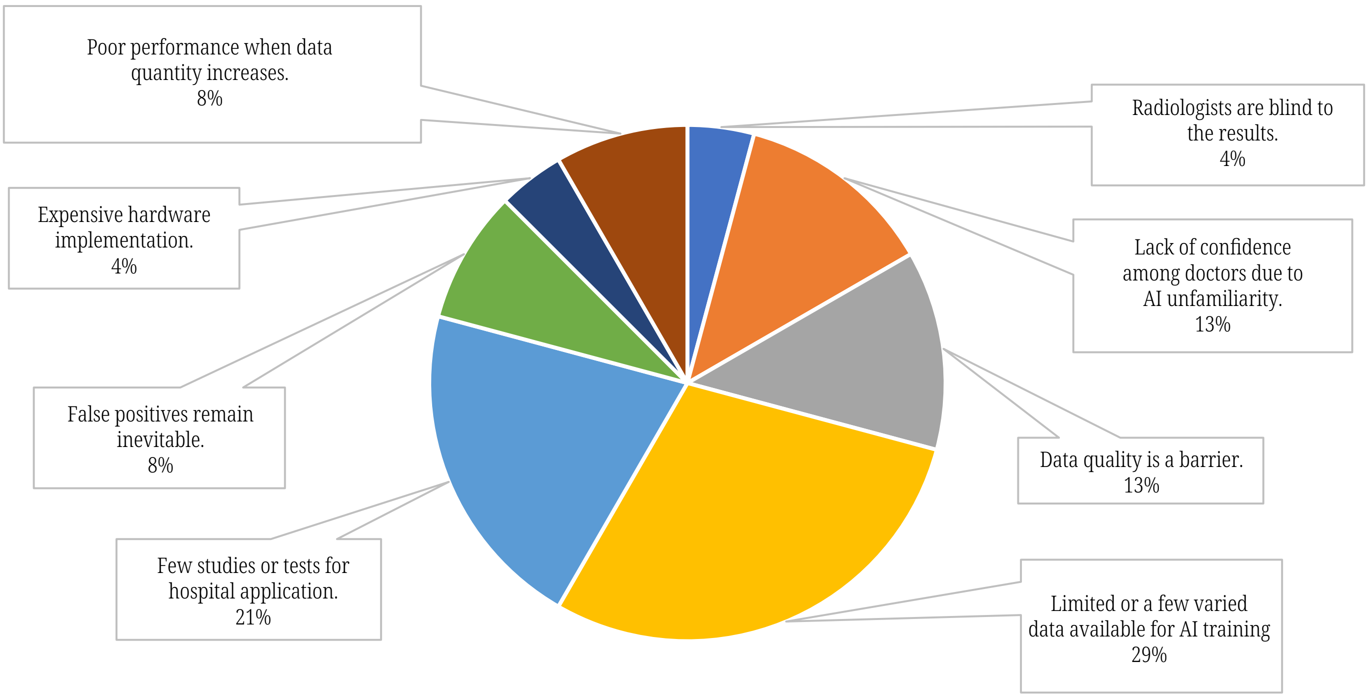

Fig. 6. Disadvantages based on references in articles

Among the identified disadvantages, it is noted that radiologists are blind to the results of AI. According to the article [6], cancer detection could be increased if radiologists were not blind to AI results. Additionally, another disadvantage of AI is that doctors need more confidence in it [5]; more tests in clinical practice and awareness of both the advantages and weaknesses of ML are required to build trust [11]. Unfortunately, even though their performance is promising, they are not yet reliable enough to be considered clinical tools [25]. It was also identified in articles [5], [11], [25] that the quality of the data used to train AI is a significant barrier to the implementation of ML in oncology, as it requires the data used to be of good quality [11]. The performance of ML depends on how accurate the extracted features are, which is different from DL. An increase of 5% in diagnostic accuracy is observed when images are improved [1]. Another disadvantage, according to studies [3], [4], [8], [11], [15], [16], [23], is the limited variety of data for AI training. Training AI with more data is recommended, considering parameters such as breast fat and density [3]. Likewise, a limitation is the quantity of images used, and the probability of obtaining better results with more data is highlighted [4].

Furthermore, according to the analysis performed, only four out of 26 reviewed articles conducted tests with ML in breast cancer detection through image analysis. The limited number of tests conducted with ML in the healthcare sector is considered a disadvantage in articles [3], [7], [15], [17], [23]. [3] recommends conducting more prospective studies to demonstrate comparisons and applicability in healthcare [15]. Another disadvantage identified in studies [1], [3] is that false positives are still inevitable [3]. ML is prone to providing incorrect diagnoses directly related to incorrect training [1]. Unfortunately, another limitation identified is that in rural areas such as India, where there is a lack of knowledge, limited accessibility to mammographic captures, technological limitations, and outdated systems, it is challenging to implement ML [5].

Another limitation of ML, according to studies [2], [7], [9], [11], [13], [14], [21–29], is related to data. When the amount of data increases for ML-based systems, it becomes evident that the algorithm faces issues that prevent it from functioning correctly [1]; the performance of ML-based algorithms is considered conventional [9]. It is also observed that in cases where the machine makes an error that cannot be anticipated or explained, difficulties arise in applying joint law liability to human healthcare professionals [26–29].

An important point to highlight is that many authors prefer technologies such as DL instead of using ML [1], [2], [7], [9], [11], [13], [14], [21–29].

Finally, it can be observed that the most frequently mentioned disadvantage in the articles is the limited variety of data for AI training [3], [4], [8], [11], [15], [16], [23]. Unfortunately, some limitations in ML lead authors to prefer using DL [1].

4 DISCUSSION

This study observed many advantages to using ML in the healthcare sector. These include reduced time in image analysis, detection of cancers not identified by radiologists, reduction in false positives and negatives, and increased breast cancer detection rates. However, it is considered that these advantages are general and inherent to the type of AI used for image analysis.

While ML is used for detection, there are much better-developed tools within AI, such as DL, which have more convincing studies indicating that results are more encouraging when using DL instead of ML. ML-based systems exhibit algorithmic flaws when data increases, and their performance is considered conventional. In contrast, DL can handle more significant amounts of data without encountering slowdown issues. It is also mentioned that ML's performance depends on how accurate the extracted features are, which differs from DL [1].

Therefore, using another technology, such as DL, can provide the same advantages and even reduce the limitations present in ML. This is detailed and verified by several authors who prefer to use DL for implementation tests [1], [2], [7], [9], [11], [13], [14], [21–26], opting for this technology over machine learning.

Another drawback of ML, which might influence authors to favor DL for their tests, is the insufficient evidence of ML applications in healthcare. Only four analyzed articles conducted tests using this technology, but the ML methodologies need to be more detailed, making it challenging to draw conclusive results [15]. Therefore, studies mention that for the time being, ML can only serve as a supporting technology for radiologists [1–3], [6], [7], [11], [17], [18], [20–23], [26–29]. The limited amount of evidence and results endorsing the use of ML for breast cancer detection applications is evident in Tables 3, 4, and 5, which group the results obtained from tests conducted by authors [3], [4], [8], [17]. Since there isn't a large amount of data or specific details about the ML methodology, there is no precise conclusion regarding its impact on the healthcare sector. However, these articles achieved precision values ranging from 95% to 90%, considered high values. Still, researchers may be more attracted to DL since there is more practical evidence in the healthcare sector with this technology.

Of all the identified disadvantages, it is considered that those mentioned above could influence researchers' decisions, leading them to choose to exclude ML and opt for deep learning.

Furthermore, it is considered that the disadvantages shown in Figure 6, excluding those mentioned in the previous paragraphs, are not exclusive to ML but apply to any AI. However, action should be taken to mitigate the remarkably manageable disadvantages, such as data quality as a barrier and the need for more confidence among doctors due to their unfamiliarity with artificial intelligence.

5 CONCLUSION

This research identified that ML significantly impacts early breast cancer detection, as shown in Tables 3, 4, and 5. However, the specific ML methods were not mentioned; only references to different software tools were made. There is insufficient practical evidence in the healthcare sector to support these findings and provide a conclusive result to affirm that ML is a promising tool. With more practical tests detailing the ML methodologies used and after analyzing the results, a better conclusion regarding its effectiveness in implementation could be reached.

The advantages of using ML shown in Figure 5 were also identified, demonstrating that its use provides benefits such as support for radiologists, reduced working time, reduced false positives, and more. Unfortunately, confidence in ML is currently low due to the insufficient number of tests conducted with this technology. However, other AIs, such as DL, are much more efficient and accurate for detecting the same pathology.

Additionally, the disadvantages of this technology were identified and represented in Figure 6. These disadvantages could lead researchers to prefer DL for analyzing breast cancer images. Furthermore, using a greater variety and quantity of high-quality data for AI tests to improve their performance and reduce the identified disadvantages is recommended. It is believed that, by doing so, better results can be achieved in the early detection of breast cancer.

Finally, based on the analyzed information, it is considered that ML is not the best technology to use in the healthcare sector for the analysis of breast cancer images due to the exact uncertainty regarding its effectiveness, stemming from the limited number of tests, lack of detailed information about the ML methodologies used, and other identified limitations. Therefore, the recommendation is to use DL, as it has more tests, good results, and improvements over some rules present in ML. It is hoped that the information presented can serve as support for future research.

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