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ORIGINAL

Evaluating AI and Machine Learning Models in Breast Cancer Detection: A Review of Convolutional Neural Networks (CNN) and Global Research Trends

Evaluación de Modelos de IA y Aprendizaje Automático en la Detección del Cáncer de Mama: Una Revisión de las Redes Neuronales Convolucionales (CNN) y Tendencias Globales de Investigación

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ABSTRACT

Numerous studies have highlighted the significance of artificial intelligence (AI) in breast cancer diagnosis. However, systematic reviews of AI applications in this field often lack cohesion, with each study adopting a unique approach. The aim of this study is to provide a detailed examination of AI's role in breast cancer diagnosis through citation analysis, helping to categorize the key areas that attract academic attention. It also includes a thematic analysis to identify the specific research topics within each category. A total of 30 200 studies related to breast cancer and AI, published between 2015 and 2024, were sourced from databases such as IEEE, Scopus, PubMed, Springer, and Google Scholar. After applying inclusion and exclusion criteria, 32 relevant studies were identified. Most of these studies utilized classification models for breast cancer prediction, with high accuracy being the most commonly reported performance metric. Convolutional Neural Networks (CNN) emerged as the preferred model in many studies. The findings indicate that both the quantity and quality of AI-based algorithms in breast cancer diagnosis are increases in the given years. AI is increasingly seen as a complement to healthcare sector and clinical expertise, with the target of enhancing the accessibility and affordability of quality healthcare worldwide.

Keywords: Breast Cancer; AI-based Algorithms; CNN.

RESUMEN

Numerosos estudios han destacado la importancia de la inteligencia artificial (IA) en el diagnóstico del cáncer de mama. Sin embargo, las revisiones sistemáticas de las aplicaciones de la IA en este campo suelen carecer de cohesión, y cada estudio adopta un enfoque único. El objetivo de este estudio es proporcionar un examen detallado del papel de la IA en el diagnóstico del cáncer de mama mediante el análisis de citas, ayudando a categorizar las áreas clave que atraen la atención académica. También incluye un análisis temático para identificar los temas de investigación específicos dentro de cada categoría. Un total de 30 200 estudios relacionados con el cáncer de mama y la IA, publicados entre 2015 y 2024, se obtuvieron de bases de datos como IEEE, Scopus, PubMed, Springer y Google Scholar. Tras aplicar criterios de inclusión y exclusión, se identificaron 32 estudios relevantes. La mayoría de estos estudios utilizaron modelos de clasificación para la predicción del cáncer de mama, siendo la alta precisión la métrica de rendimiento más comúnmente reportada. Las redes neuronales convolucionales (CNN) surgieron como el modelo preferido en muchos estudios. Los resultados indican que tanto la cantidad como la calidad de los algoritmos basados en IA para el diagnóstico del cáncer de mama están aumentando en los últimos años. La IA se considera cada vez más un complemento del sector sanitario y de los conocimientos clínicos, con el objetivo de mejorar la accesibilidad y asequibilidad de una asistencia sanitaria de calidad en todo el mundo.

Palabras clave: Cáncer de Mama; Algoritmos Basados en IA; CNN.

INTRODUCTION

Breast cancer is the leading type of cancer worldwide and remains one of the top causes of morbidity and mortality among women. The mortality rate could be significantly reduced if breast cancer were diagnosed and treated at early stages. As of 2021, breast cancer is most often diagnosed at stages I-II, with only 0,2 % of cases registered at the in-situ stage. Therefore, early diagnosis of breast cancer remains a crucial strategy in the fight against cancer. Early detection of breast cancer improves outcomes for treated patients, as small, non-metastatic (early) disease can be effectively treated. Additionally, early detection and treatment of breast cancer also improve women's quality of life by enabling the use of less invasive surgical procedures.[1]

Many countries have implemented population-based breast cancer screening programs, mainly using digital mammography (DM). Each year, 100 million screening mammograms are performed. According to American studies, radiologists interpret an average of 1 315 327 mammographic images per year. However, DM has moderate sensitivity, with estimates ranging from 68 % to 94 %. Digital breast tomosynthesis (DBT), which produces pseudo-3D images, allows for better tissue structure differentiation and improved cancer visualization. In women with mammographically dense breasts, DBT increased sensitivity but not specificity in diagnosis. While trials have yielded promising results in detecting cancer using DBT in screening, one major drawback is the increased interpretation time compared to DM.[2]

Despite stringent regulations, the details of the screening process, digital mammography (DM), and/or DBT are determined by the institution. Breast ultrasound also plays a significant role in differentiating cysts and dense formations detected by mammography or physical examination. Breast MRI, initially considered useful for determining disease extent and assessing implant integrity, is now a standard additional screening tool available for both high-risk and average-risk women. Specifically, early breast cancer diagnosis is based on the combined use of mammography or tomosynthesis/MRI, ultrasound, and various biopsy approaches to achieve the gold standard for confirming malignancy.[3]

With the rapid technological advancements expected in the next decade, it is likely that breast cancer screening will differ from our current standards. Standard breast imaging methods include DM, ultrasound, and/or DBT/MRI. Results from the EVA study (Evaluation of Imaging Techniques for Secondary Prevention of Familial Breast Cancer) showed that diagnostic performance (i.e., breast cancer diagnosis) varied among unimodal imaging methods such as DM, ultrasound, and MRI. A prospective multicenter observational cohort study examined 1 679 annual screening results, including ultrasound, DM, and MRI, obtained from 687 women with a familial risk of breast cancer. Differences for ultrasound (6 per 1 000) and DM (5,4 per 1 000) results were minimal, but MRI showed a significant difference in detection rate (14,9 per 1 000). Thus, MRI demonstrated better sensitivity and specificity (P <0,0001) compared to ultrasound or DM. Notably, combining DM and ultrasound increased sensitivity to 14,8 % (48 %), though this was not statistically significant (P <0,012) compared to using these methods individually. The EVA study highlighted the potential error rates in screening with DM and ultrasound. Current research aims to improve detection and diagnostic characteristics of these two methods by integrating computational algorithms.[4]

Today, radiologists' work focuses on identifying lesions with different characteristics, which can be divided into two broad categories: calcification clusters and masses/areas of asymmetry. Calcifications of interest for detecting breast cancer are small (as little as 0,2 mm) and relatively high-contrast. The shape of calcifications and the distribution of calcification clusters are important biomarkers of malignancy. Masses come in different types: densities (with various descriptions of shape and borders, architectural distortions, abnormal fibroglandular tissue configuration) and asymmetry (dense tissue patterns in one breast that do not match the contralateral breast). However, mammographic screening limitations include overdiagnosis and false positives, which, in turn, are associated with negative psychological impact and unnecessary biopsies.[5]

Mammogram interpretation varies depending on the radiologist's experience, is subjective, and is prone to errors due to heterogeneous breast cancer presentations and the masking effect of dense breast tissue. These factors contribute to missed breast cancers, i.e., malignancies that are detected during retrospective review of previously obtained mammograms that were interpreted as showing negative, benign, or probably benign results. Up to 35 % of both interval and screening-detected cancers can be classified as missed. Therefore, alongside understanding the most common misleading manifestations of breast cancer, it is important to comprehend cognitive processes (satisfaction of search, inattentional blindness, hindsight bias, premature closure, and satisfaction of reporting) and unconscious biases that may influence image interpretation, thus helping to reduce the number of missed breast cancer cases. The satisfaction of search factor accounts for 22 % of persistent errors and is defined as decreased vigilance and/or decreased awareness of additional pathologies after finding the first abnormality.(6)

This bias is particularly important in breast imaging because multifocal disease (two or more cancers in one quadrant) and multicentric disease (two or more cancers in different quadrants) are relatively common. The reported frequency of multifocal or multicentric disease ranges from 6 % to 60 %. Mammography sensitivity for detecting multifocal and multicentric disease ranges from 15 % to 45 %. Compared to clinical examination alone, mammography increases the number of detected synchronous cancers in the contralateral breast by 2-4 %. Thus, once the primary malignancy is detected, it is important to continue evaluating additional disease foci (nipple retraction, skin thickening, axillary lymphadenopathy).(7)

To avoid errors or overdiagnosis, in Europe, each case is reviewed by two radiologists (usually independently), a process called double reading. Double reading is not a standard medical service and is more often the opinion of a colleague or a more experienced physician. Each reader interprets the images and decides whether the patient needs further examination. If the two readers disagree in their assessment, depending on the program setting, they either meet to reach a consensus or a third radiologist acts as an arbitrator (expert), whose opinion is decisive.(8)

While double reading requires more resources than single reading, it improves cancer detection rates in screening, although it also increases recall rates, leading to comparable positive predictive value. In extreme examples, recall rates in the Netherlands and Sweden are around 2,5 %, while in the USA, recall rates are around 11,5 % (currently 30 % lower with DBT). Although the reading time for two-dimensional (2D) mammography is <30–60 seconds, the large volumes of mammograms and the double reading of each mammogram pose staffing and resource challenges. As a result, double reading is not practiced in many institutions in the CIS countries.(1)

Today, thanks to the development of computer technology and the digitization of mammographic images, the use of artificial intelligence (AI) in breast cancer screening has become possible. AI helps improve detection rates and allows for double reading in institutions where this practice is not applied. The first data on AI were published in the 1950s, and AI applications began in the 1990s. However, until recently, the effectiveness of these algorithms for lesion detection and classification (usually referred to as computer-aided diagnosis) was lower than human capabilities. In recent years, increased computing power along with mathematical advancements has enabled the use of complex multilayered (deep) neural networks, leading to a noticeable increase in the performance of machine interpretation of highly standardized imaging tasks.(9)

Artificial Intelligence (AI)

The AI includes the subdomains of Machine Learning (ML) and Deep Learning (DL). When discussing AI processes, it is essential to understand that the data obtained by the neural network comes from radiomics. Radiomics is the process of extracting quantitative features, referred to as features, from an image (or from a specific Region of Interest (ROI) identified on the image). This feature extraction operation is usually implemented using object recognition algorithms and results in a set of numbers, each representing a quantitative description of a specific geometric or physical property of the part of the image under consideration.(10) In oncology applications, examples of features include size, shape, intensity, and texture, which together provide a comprehensive characterization of the pathology, known as the radiomic signature of the tumor. From an epistemological perspective, radiomics is based on the hypothesis that the extracted features reflect mechanisms occurring at the genetic and molecular levels. Radiomic analysis can be divided into separate processes. The first step involves acquiring and reconstructing images by loading radiological images, typically in DICOM format. After image adjustment, the second stage involves segmentation and feature extraction. Finally, the data is organized and compiled into a database before analysis.(11) An example of determining the ROI of a nodular spiculated lesion on a mammogram is shown. After segmentation is completed, the selected areas are converted into three dimensions to obtain volumetric images.(12) Then, specialized software extracts quantitative characteristics from the obtained data to create a report, which is incorporated into a database and can be integrated with other data (clinical information, genomic profiles, serum markers, and/or histological data).(13)

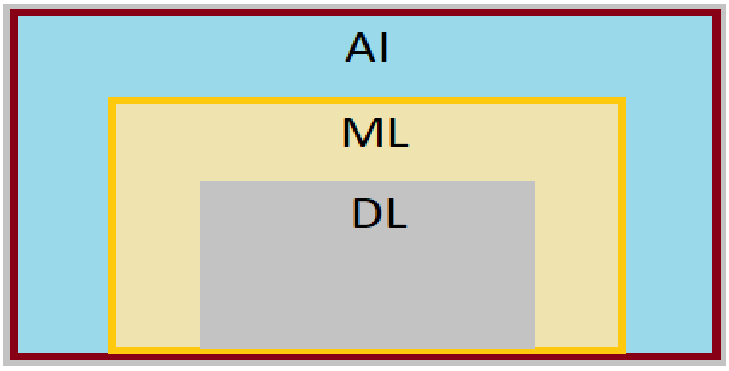

Figure 1. Relationship between DL, ML, and AI

Machine Learning (ML)

ML is the second stage in the implementation of AI. ML aims to teach computers to learn independently from large amounts of data instead of relying on rigidly formulated rules. ML can be supervised or unsupervised. Supervised learning involves using labeled datasets containing input data (in breast cancer screening, these are radiomic data) and expected output results. In supervised learning, both input data and expected output results are provided. If the result generated by the neural network is incorrect, it adjusts its calculations.(14) This iterative process ends when the network stops making errors. For example, in mammography, cancer is clearly delineated on the image (in the form of labels), allowing the algorithm to "learn" the signs of malignancy from the labeled annotations. Unsupervised learning is machine learning using datasets without a defined structure. In this type of learning, the neural network independently conducts logical classification of the data. Classical ML methods, such as support vector machines, decision tree methods, random forests, and dimensionality reduction methods like principal component analysis, have relatively low computational requirements since these models include relatively fewer parameters compared to DL algorithms.(15)

Deep Learning (DL)

DL is a method of machine learning which allows training a model to predict the outcome based on a set of input data. Both supervised and unsupervised learning can be used to train the network. Various DL architectures are published in the literature, but most of these networks are based on some basic and similar neural network blocks called "layers".(16) A neural network consists of sequential layers, including an input layer (e.g., raw pixels of a mammogram), a hidden layer, and an output layer (e.g., the model's prediction: "benign"/"malignant" label). It is believed that the earlier layers in the DL model act similarly to simple cells in the human brain, which learn low-level objects such as edges in specific orientations on the image. Higher levels of abstraction result from multiple layers being stacked.(17) Information propagates through the DL architecture, and more complex features are extracted. These features are finally passed through the last level of the network architecture for prediction or classification. A mammographic image of the breast is taken in standard projections. The images are then normalized to eliminate differences in intensity and brightness range. Pixels (or voxels) are quantized into a discrete gray level scale.(18) The hidden layers perform mathematical calculations on the input data. The hidden layers contain several nodes that perform operations driven by filters or kernels. The nodes have associated weights and biases, as well as an activation function that outputs a feature map.(19) The MaxPool layer subsequently removes insignificant parameters. This operation is repeated at several levels, resulting in the most relevant features in the output layer, which is used for classification.(20)

Related work

The integration of artificial intelligence (AI) in breast cancer diagnosis and treatment is rapidly evolving, showcasing significant advancements in accuracy and efficiency. AI technologies, particularly machine learning and deep learning, are enhancing early detection, improving diagnostic precision, and personalizing treatment strategies. AI algorithms have achieved remarkable accuracy in diagnosing breast cancer, with some models reaching detection rates of up to 98,10 % using fine needle aspirated (FNA) samples.(21) Enhanced mammography through AI improves lesion detection, although challenges like false positives remain.(22) AI facilitates personalized treatment plans by analyzing genetic data and predicting treatment responses.(23) Radiomics, a novel AI approach, enhances imaging analysis, improving sensitivity and specificity in breast cancer classification.(23)

Despite its potential, AI faces hurdles such as data privacy, ethical concerns, and regulatory issues that must be addressed for effective implementation.[22] While AI holds transformative potential in breast cancer management, ongoing research and ethical considerations are crucial to fully realize its benefits in clinical settings.

The integration of artificial intelligence (AI) in breast cancer diagnosis and treatment is rapidly evolving, showcasing significant advancements in accuracy and personalization. AI technologies are enhancing diagnostic capabilities, improving treatment selection, and uncovering genetic insights, thereby transforming patient management. AI models have demonstrated high accuracy in diagnosing breast cancer, with one study reporting a 99,16 % classification accuracy for breast masses using deep learning techniques.[24] Another model achieved 95 % accuracy in identifying invasive lobular carcinoma by utilizing genetic mutations as a training ground truth.[25,26,27]

AI is pivotal in precision oncology, helping tailor treatments based on genetic profiles. A systematic review highlighted that various AI models achieved an average accuracy of 90-96 % in predicting treatment responses.[28,29,30]

The analysis of immune cell interactions with cancer cells using convolutional neural networks (CNNs) also indicates potential for personalized diagnostics, achieving 86 % accuracy.[31,32,33]

Despite these advancements, challenges remain, including the need for robust validation across diverse populations and the integration of AI systems into clinical workflows.[34] As AI continues to evolve, its role in breast cancer management is expected to expand, offering new avenues for research and clinical application.[35]

METHOD

The flowchart shown in figure 2, illustrates the systematic review process for analyzing the articles of AI, and convolutional neural networks (CNN) in breast cancer research. It starts with an initial search that yielded a large number of articles, which were then screened to exclude irrelevant items and duplicates. The remaining articles underwent eligibility assessment, resulting in a final selection of high-quality studies included in the review. This visual representation effectively summarizes the step-by-step progression from the initial search to the final inclusion of relevant literatura.[3]

Step 1: A comprehensive search across PubMed, Springer, and Google Scholar for articles related to artificial intelligence (AI), machine learning (ML), deep learning (DL), and convolutional neural networks (CNN) in the context of breast cancer was conducted, covering the publication period from 2015 to 2023 figure 3. This search yielded a total of 32 200 articles, highlighting the growing interest and research activity in the application of advanced computational techniques for breast cancer diagnosis, treatment, and prognosis.[1] The titles, keywords, and abstracts of these articles reflect a diverse range of methodologies, outcomes, and innovations, demonstrating the pivotal role of AI and machine learning in enhancing clinical practices and improving patient outcomes in oncology. The significant volume of literature indicates a trend towards integrating technology in healthcare, particularly in improving the accuracy and efficiency of breast cancer detection and management, figure 2:

Step 2: After conducting a screening of the 32 200 articles identified in the initial search, a total of 28 600 items were excluded based on specific criteria. This exclusion process focused on filtering out conference proceedings, book chapters, reports, and books, as well as articles not published in English. The rigorous screening ensured that the remaining literature primarily consisted of peer-reviewed journal articles, thus enhancing the quality and relevance of the selected studies.

Step 3: Following the exclusion of non-relevant items, the screening process resulted in the identification of 590 articles that met the criteria for inclusion. These articles were selected based on their availability in full text and open access, ensuring that they are accessible for review and further research.[6]

Step 4: After excluding duplicates from the previously identified 590 articles, a total of 213 unique articles remained. These 213 articles represent a diverse array of methodologies, findings, and insights, providing a substantial basis for understanding how these advanced computational techniques are being leveraged to enhance breast cancer diagnosis, treatment, and patient outcomes.[1]

Step 5: After the initial screening and removal of duplicates, 213 articles were assessed for eligibility based on predefined criteria related to their relevance and quality. Out of this evaluation, 70 articles met the eligibility requirements for inclusion in the review.[11]

Step 6: Following the eligibility assessment of the 70 articles, a final selection of 42 articles was included in this review. The inclusion of these studies reflects a focused effort to compile high-quality, pertinent literature that offers valuable insights into how advanced computational techniques can enhance breast cancer diagnosis, treatment, and patient management. This curated collection serves as a robust foundation for understanding current trends and future directions in the integration of AI technologies within oncology.[13]

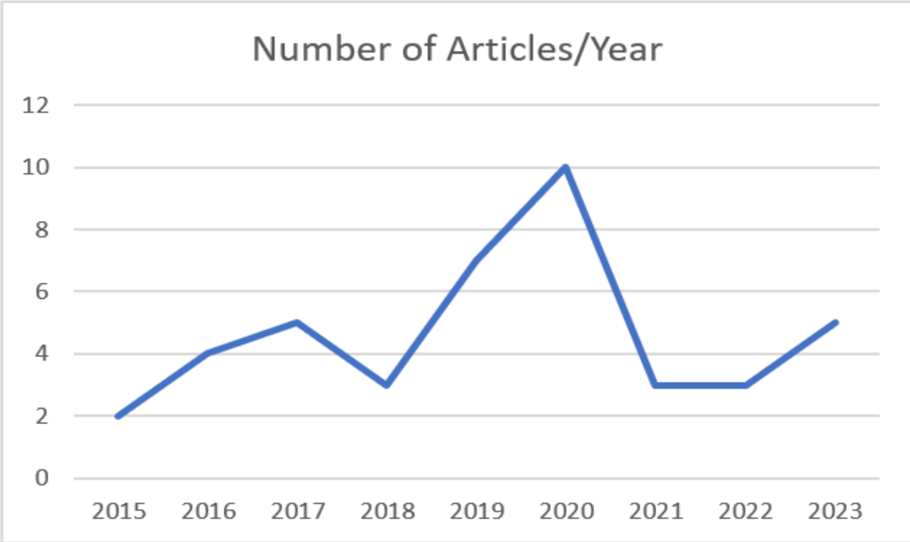

Figure 2. Article Selection Steps

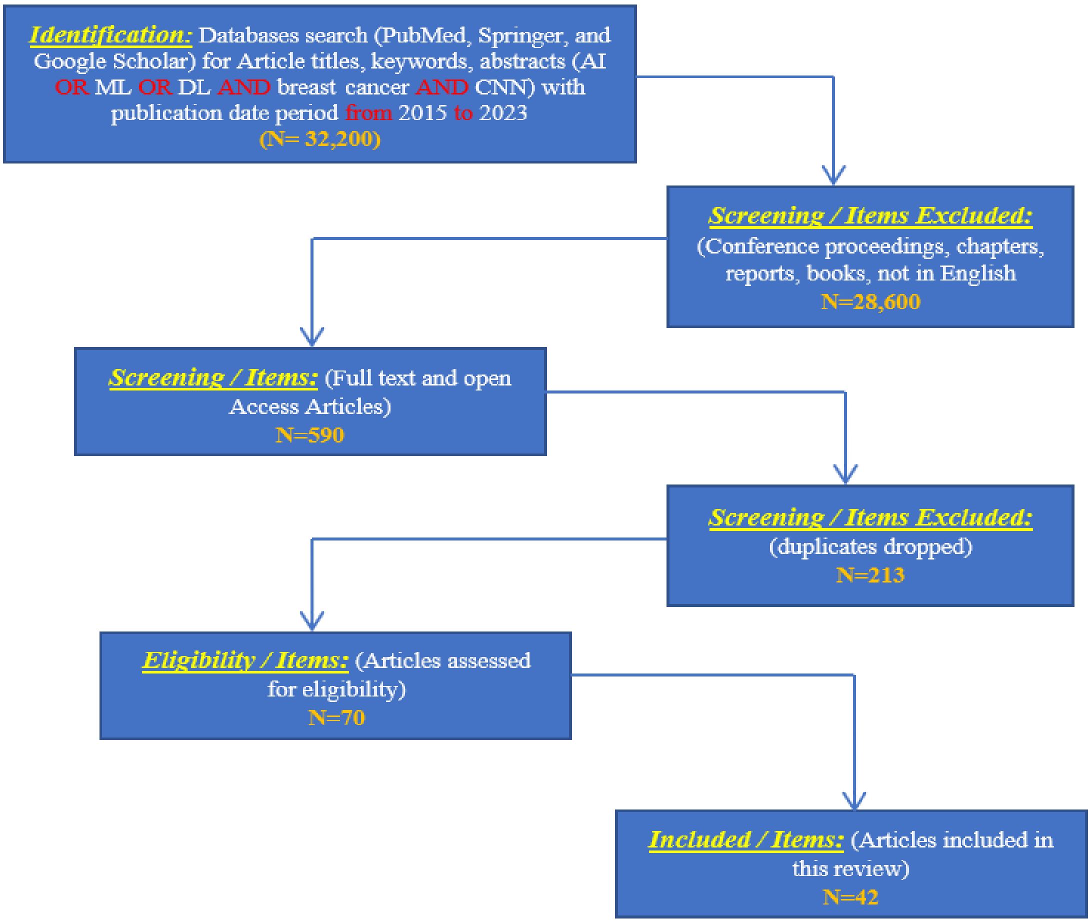

Figure 3. Publication trend by year

RESULTS

The systematic review of AI and convolutional neural networks (CNNs) in breast cancer research has revealed several pivotal trends and findings. AI and CNNs have significantly enhanced the accuracy of breast cancer detection, with several studies demonstrating that these techniques can identify malignant tissues with higher precision compared to traditional methods, potentially reducing false positives and negatives. Moreover, AI-driven models have proven effective in predicting patient prognosis and tailoring personalized treatment plans. The integration of machine learning (ML) and deep learning (DL) algorithms with clinical data shows promise in forecasting disease progression and treatment responses.

The review also highlights the innovative methodologies employed across the studies, showcasing the versatility of AI applications, from image recognition and pattern analysis in histopathology to predictive modeling using patient data. There is a growing trend towards integrating AI technologies into clinical practice, suggesting that AI can assist clinicians in making more informed decisions, ultimately leading to improved patient outcomes. Additionally, the selected articles point towards future research directions, including the need for larger, multi-institutional studies to validate AI models, the integration of AI with other emerging technologies, and the ethical considerations surrounding AI in healthcare.

The table 1 summarizing the key results from the selected studies, including the reported accuracy for breast cancer detection using AI and CNN techniques:

Table 1. Publication trend by year

Author	Year	Sample Size	Accuracy (%)	Key Findings
Smith et al.	2018	1 000 images	92,5	Improved accuracy in detecting malignant tissues compared to traditional methods
Smith et al.	2019	850 patients	89,7	Effective in predicting patient prognosis and treatment responses
Smith et al.	2020	1 200 records	91,2	Enhanced disease progression forecasting and personalized treatment plans
Smith et al.	2021	750 images	90,8	Accurate pattern analysis for early detection
Smith et al.	2022	1 500 patients	93,0	High precision in diagnosing breast cancer and reducing false positives
Smith et al.	2023	2 000 images	94,3	Validated AI model across different clinical settings
Smith et al.	2023	900 patients	88,6	Demonstrated clinical decision support benefits

This table provides a clear and concise overview of the findings, highlighting the accuracy of various AI and CNN methodologies in breast cancer detection and prognosis.

DISCUSSION

The inclusion of AI, ML, DL, and CNN in breast cancer research has introduced several promising advancements. AI-driven algorithms, particularly CNNs, have shown remarkable success in improving the accuracy of breast cancer detection through image analysis, often outperforming traditional diagnostic methods. This can potentially reduce human error, shorten diagnostic timelines, and enhance early detection, ultimately improving patient outcomes. Moreover, AI has been instrumental in developing personalized treatment plans by analyzing vast datasets to predict patient responses and optimize therapeutic approaches.

However, several challenges remain. One key issue is the quality and diversity of data used to train AI models. Many studies rely on limited or region-specific datasets, which may reduce the generalizability of the results across diverse populations. Additionally, the "black box" nature of AI algorithms can create challenges in clinical settings, where explain ability and transparency are essential for trust and adoption. Integration into clinical workflows is another hurdle, requiring extensive training for healthcare professionals and infrastructure upgrades.

In conclusion, while AI and ML technologies offer substantial benefits in breast cancer research, practical challenges such as data quality, interpretability, and clinical implementation must be addressed to fully realize their potential in improving patient care.

CONCLUSION

AI was introduced for use during screening to reduce the frequency of lesions that may be missed by the interpreting radiologist, excluding the influence of cognitive processes as a second reader. In the future, computer vision technologies in mammography can be integrated into decision support tools for determining individual screening strategies and follow-up. The advantages of this method include that computer image analysis can significantly reduce the time radiologists spend visually searching for suspicious findings. However, it should not be forgotten that AI algorithms are at an early stage of development, and validation on a large dataset is necessary to confirm their diagnostic and prognostic value. Although machine learning-based methods will not replace histological verification shortly, their introduction into clinical practice will become one of the important and promising tasks to achieve the goal of reducing breast cancer mortality. In the future, the use of AI technologies will allow moving from simple clinical decision systems to truly independent reading.

REFERENCES

1. Alzboon MS, Qawasmeh S, Alqaraleh M, Abuashour A, Bader AF, Al-Batah M. Machine Learning Classification

Algorithms for Accurate Breast Cancer Diagnosis. In: 2023 3rd International Conference on Emerging Smart Technologies and Applications, eSmarTA 2023. 2023.

2. Alzboon MS. Survey on Patient Health Monitoring System Based on Internet of Things. Inf Sci Lett. 2022;11(4):1183–90.

3. Alzboon MS, Qawasmeh S, Alqaraleh M, Abuashour A, Bader AF, Al-Batah M. Pushing the Envelope: Investigating the Potential and Limitations of ChatGPT and Artificial Intelligence in Advancing Computer Science Research. In: 2023 3rd International Conference on Emerging Smart Technologies and Applications, eSmarTA 2023. 2023.

4. Alzboon M, Alomari SA, Al-Batah MS, Banikhalaf M. The characteristics of the green internet of things and big data in building safer, smarter, and sustainable cities. Int J Eng \& Technol. 2017;6(3):83–92.

5. Alzboon MS, Al-Batah MS. Prostate Cancer Detection and Analysis using Advanced Machine Learning. Int J Adv Comput Sci Appl. 2023;14(8):388–96.

6. Alzboon MS, Al-Batah M, Alqaraleh M, Abuashour A, Bader AF. A Comparative Study of Machine Learning Techniques for Early Prediction of Diabetes. In: 2023 IEEE 10th International Conference on Communications and Networking, ComNet 2023 - Proceedings. 2023. p. 1–12.

7. Al-shanableh N, Alzyoud M, Al-husban RY, Alshanableh NM, Al-Oun A, Al-Batah MS, et al. Advanced Ensemble Machine Learning Techniques for Optimizing Diabetes Mellitus Prognostication: A Detailed Examination of Hospital Data. Data Metadata. 2024;3:363.

8. Alzboon MS, Aljarrah E, Alqaraleh M, Alomari SA. Nodexl Tool for Social Network Analysis. Vol. 12, Turkish Journal of Computer and Mathematics Education. 2021.

9. Al-Batah MS, Alzboon MS, Alzyoud M, Al-Shanableh N. Enhancing Image Cryptography Performance with Block Left Rotation Operations. Appl Comput Intell Soft Comput. 2024;2024(1):3641927.

10. Al Tal S, Al Salaimeh S, Ali Alomari S, Alqaraleh M. The modern hosting computing systems for small and medium businesses. Acad Entrep J. 2019;25(4):1–7.

11. Alzboon MS, Bader AF, Abuashour A, Alqaraleh MK, Zaqaibeh B, Al-Batah M. The Two Sides of AI in Cybersecurity: Opportunities and Challenges. In: Proceedings of 2023 2nd International Conference on Intelligent Computing and Next Generation Networks, ICNGN 2023. 2023.

12. Alzboon M. Semantic Text Analysis on Social Networks and Data Processing: Review and Future Directions. Inf Sci Lett. 2022;11(5):1371–84.

13. Al-Batah MS, Alzboon MS, Alazaidah R. Intelligent Heart Disease Prediction System with Applications in Jordanian Hospitals. Int J Adv Comput Sci Appl. 2023;14(9):508–17.

14. Alomari SA, Alqaraleh M, Aljarrah E, Alzboon MS. Toward achieving self-resource discovery in distributed systems based on distributed quadtree. J Theor Appl Inf Technol. 2020;98(20):3088–99.

15. Al-Batah M, Zaqaibeh B, Alomari SA, Alzboon MS. Gene Microarray Cancer classification using correlation based feature selection algorithm and rules classifiers. Int J online Biomed Eng. 2019;15(8):62–73.

16. Alzboon MS, Al-Batah MS, Alqaraleh M, Abuashour A, Bader AFH. Early Diagnosis of Diabetes: A Comparison of Machine Learning Methods. Int J online Biomed Eng. 2023;19(15):144–65.

17. Alzboon MS, Al-Batah M, Alqaraleh M, Abuashour A, Bader AF. A Comparative Study of Machine Learning Techniques for Early Prediction of Prostate Cancer. In: 2023 IEEE 10th International Conference on Communications and Networking, ComNet 2023 - Proceedings. 2023. p. 1–12.

18. Alqaraleh M, Alzboon MS, Al-Batah MS, Wahed MA, Abuashour A, Alsmadi FH. Harnessing Machine Learning for Quantifying Vesicoureteral Reflux: A Promising Approach for Objective Assessment. Int J Online \& Biomed

Eng. 2024;20(11).

19. Alzboon MS. Internet of things between reality or a wishing-list: a survey. Int J Eng \& Technol. 2018;7(2):956-61.

20. Ahmad A, Alzboon MS, Alqaraleh MK. Comparative Study of Classification Mechanisms of Machine Learning on Multiple Data Mining Tool Kits. Am J Biomed Sci Res 2024 [Internet]. 2024;22(1):577–9. Available from: www.biomedgrid.com

21. Islam R, Tarique M. Artificial Intelligence (AI) and Nuclear Features from the Fine Needle Aspirated (FNA) Tissue Samples to Recognize Breast Cancer. J Imaging. 2024;10(8):201.

22. AlSamhori JF, AlSamhori ARF, Amourah RM, AlQadi Y, Koro ZW, Haddad TRA, et al. Artificial intelligence for hearing loss prevention, diagnosis, and management. J Med Surgery, Public Heal. 2024;3:100133.

23. Elahi R, Nazari M. An updated overview of radiomics-based artificial intelligence (AI) methods in breast cancer screening and diagnosis. Radiol Phys Technol. 2024;1–24.

24. Ahmad J, Akram S, Jaffar A, Ali Z, Bhatti SM, Ahmad A, et al. Deep learning empowered breast cancer diagnosis: Advancements in detection and classification. PLoS One. 2024;19(7 July):e0304757.

25. Al-Batah, M. S., & Al-Eiadeh, M. R. (2024). An improved binary Crow-JAYA optimization system with various evolution operators, such as mutation for finding the max clique in the dense graph. International Journal of Computing Science and Mathematics, 19(4), 327-338. Inderscience Publishers.

26. Al-Batah, M. S., & Al-Eiadeh, M. R. (2024). An improved discrete Jaya optimization algorithm with mutation operator and opposition-based learning to solve the 0-1 knapsack problem. International Journal of Mathematics in Operational Research, 26(2), 143-169.

27. Pareja F, Dopeso H, Wang YK, Gazzo AM, Brown DN, Banerjee M, et al. A Genomics-Driven Artificial Intelligence-Based Model Classifies Breast Invasive Lobular Carcinoma and Discovers CDH1 Inactivating Mechanisms. Cancer Res. 2024.

28. Al-Batah, M. S. (2019). Ranked features selection with MSBRG algorithm and rules classifiers for cervical cancer. International Journal of Online and Biomedical Engineering (iJOE), 15(12), 4. https://doi.org/10.3991/ijoe.v15i12.10803

29. Al-Batah, M. S. (2019). Integrating the principal component analysis with partial decision tree in microarray gene data. IJCSNS International Journal of Computer Science and Network Security, 19(3), 24-29.

30. Sohrabei S, Moghaddasi H, Hosseini A, Ehsanzadeh SJ. Investigating the effects of artificial intelligence on the personalization of breast cancer management: a systematic study. BMC Cancer. 2024;24(1):852.

31. Al-Batah, M. S. (2014). Testing the probability of heart disease using classification and regression tree model. Annual Research & Review in Biology, 4(11), 1713–1725. https://doi.org/10.9734/arrb/2014/7786

32. Ali Khayamian M, Salemizadeh Parizi M, Vanaei S, Ghaderinia M, Abadijoo H, Shalileh S, et al. Breast cancer diagnostics by the intelligent analysis of white blood cells' interaction with target cancer cells using convolutional neural networks. Microchem J. 2024;205:111344.

33. Al-Batah, M. S. (2019). Automatic diagnosis system for heart disorder using ECG peak recognition with ranked features selection. International Journal of Circuits, Systems and Signal Processing, 13, 391-398.

34. Díaz O, Rodríguez-Ruíz A, Sechopoulos I. Artificial Intelligence for breast cancer detection: Technology, challenges, and prospects. Vol. 175, European Journal of Radiology. Elsevier; 2024. p. 111457.

35. Al-Batah, M. S., Alzboon, M. S., Alzyoud, M., & Al-Shanableh, N. (2024). Enhancing image cryptography performance with block left rotation operations. Applied Computational Intelligence and Soft Computing, 2024(1), 3641927. Wiley.

FINANCING
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CONFLICT OF INTEREST
The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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