

Now and Future Use of Artificial Intelligence (Ai) in the Management of Breast Cancer

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ABSTRACT

Breast cancer (BC) remains a major etiology of motility for female gender in the world, accounting for more than 2.3 million new fatalities annually. Despite early detection and treatment advancements, significant challenges persist, particularly in personalized management and preventive interventions. Recent technological innovations, such as the integration of artificial intelligence (AI), have shown promise in improving BC diagnosis and management. AI has been successfully applied in mammography, MRI, and advanced imaging techniques to enhance the accuracy and efficiency of BC detection, offering earlier intervention and personalized care. AI's ability to analyze high-resolution images has proven effective in detecting breast masses, classifying benign and malignant tumors, and assessing breast cancer risk. Additionally, deep learning (DL) algorithms and radiomics have emerged as valuable tools, providing refined predictive analytics and reducing false-positive rates. However, the widespread adoption of AI in clinical settings is hindered by factors like data heterogeneity, confidentiality concerns, limited generalizability, and the need for specialized training among healthcare professionals. Despite these limitations, AI's potential in revolutionizing breast cancer care is immense, providing appreciable development in the are of disease screening accuracy and treatment outcomes. Addressing the existing challenges through collaborative research, standardized data, and ethical frameworks is crucial to realizing the full benefits of AI in BC diagnosis and management.

Key words: Artificial Intelligence, MRI, Breast Cancer, Deep learning (DL), radiomics, Diagnosis

INTRODUCTION

Through the course of the last ten years, breast carcinoma has been the most prevalent cause of mortality among women worldwide, prompting extensive efforts to improve prevention and early detection. In 2020 alone, over 2.3 million women were diagnosed, with 33.5% succumbing to the disease [1]. Even with the present development in technology, which has enhance molecular identification of the causes and associated risk factor among breast cancer patients, there are still issues with individualized therapeutic therapy and preventative. As one of the most serious health challenge faced by women in the recent years, breast cancer has led to significant psychological distress [2] and numerous fatalities. While early treatment can lower mortality rates, late diagnosis often proves fatal. BC development is influenced by several factors such as age, female reproductive status [3], testosterone levels, menopause, family history, genetic diseases [4], and environmental variables. Blood veins, connective tissues, milk ducts, lobules, and lymph nodes make up the breast. When aberrant cells develop into tumours inside these structures, breast cancer results [5]. It may be benign or malignant, with malignant tumors classified as either invasive or non-invasive. Invasive breast

cancer aggressively spreads to nearby tissues, while non-invasive breast cancer remains localized. A 2020 global assessment reported approximately 2.3 million new cases of breast cancer, leading to 685,000 deaths. In the United States, around 13% of women are projected to develop breast cancer in their lifetime. Annually, 287,850 invasive cases and 51,400 non-invasive cases are recorded.

While incidence rates have surged, recent advancements have contributed to a decline in mortality [6]. The integration of computational intelligence (AI) in the detection of breast cancer is a promising development, enhancing detection accuracy through high-resolution imaging of tissue samples. AI, which applies computational models to simulate human cognitive abilities, is proving effective in addressing complex medical challenges, including cancer [48, 49]. Given the genetic and epigenetic variations contributing to cancer's complexity, AI algorithms hold great potential in identifying gene mutations and protein abnormalities at an early stage, improving early diagnosis and intervention [46, 47].

Applications of Artificial Intelligence in Medicine

Applications of AI in Mammography

Mammography is one of the most commonly used techniques for breast cancer screening [7]. It is a non-invasive method known for its minimal discomfort, ease of use, high resolution, and reproducibility. The images obtained can be compared over time and are not restricted by a patient's age or body shape. Mammography enables the detection of breast masses something a physical examination might not be able to feel and effectively differentiates between benign and malignant breast lesions. Mammograms are currently capture with full-field digital mammography (DM) system and come in two formats: raw imaging data for processing and postprocessed raw data for display [8]. In recent studies, AI has been widely applied to mammography analysis, focusing on breast mass and microcalcification detection and classification, breast mass segmentation, density evaluation, cancer risk assessment, and quality improvement of images.

Applications of AI in Breast MRI

MRI is the most sensitive imaging technique for detecting breast cancer and is currently recommended as a supplementary tool to mammography for high-risk patients [9]. It provides a comprehensive assessment of breast masses, including their shape, size, extent, and blood perfusion, using various scanning sequences. However, its limitations, such as low specificity, high cost, prolonged examination time, and patient selectivity, make it less widely used than mammography and ultrasound. While most deep learning (DL) research in breast imaging has focused on mammography, fewer studies have explored its application in breast MRI [10]. DL studies on breast MRI primarily focus on detecting, segmenting, characterizing, and classifying breast lesions [11]. Ignacio Alvarez Illan et al. developed a computer-aided detection (CAD) system to identify and segment non-mass-enhanced lesions in dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI), successfully reducing false positives and achieving satisfactory results [12].

Herent et al. [13] designed a DL model for detecting, characterizing, and classifying breast MRI lesions—including mammary glands, benign tumors, invasive ductal carcinoma, and other malignant growths—showing strong performance. Antropova et al. [14] integrated dynamic and volumetric DCE-MRI components into breast lesion classification using convolutional neural networks (CNNs), demonstrating significant improvements in classification accuracy [15]. Lei et al. [16] organized a study with 19 breast imaging radiologists—eight from academia and eleven from private practice—to classify benign and malignant lesions using DCE-MRI. They compared conventional CAD evaluation software, including kinetic maps, with AI-assisted CAD software. The findings revealed that AI-enhanced systems improved radiologists' ability to differentiate between benign and malignant breast lesions. Despite its limitations, breast MRI remains an essential screening tool for high-risk breast cancer patients.

AI in Breast Cancer

AI has been integrated into nearly every industrial sector to enhance productivity, efficiency, and accuracy

[17]. Advances in computational power, data availability, and AI is now more reliable, accessible and driven by objectives than it was previously due to algorithm performance [52]. It is also employed in areas such as intrusion detection systems, image synthesis [50], optical character recognition (OCR), and facial expression recognition. In the healthcare sector, AI is applied in various fields, including patient monitoring [18], medication and hospital administration [19]. Complex image analysis has benefited greatly from AI, which has made quantitative assessments through automation while reducing radiation exposure in breast radiological examinations. By simulating human decision-making with operational precision, AI offers superintelligence. Its advantages include instant feature learning, the ability to process multidimensional data, and access to diagnostic information from various clinical studies. As a result, medical professionals, researchers, and oncologists increasingly recognize AI's potential in breast cancer diagnosis, a growing interest driven by recent advancements in AI technology [20]. AI research often focuses on simulations developed using data sets that have a greater incidence of cancer than those used in periodic testing tools [51], leading to notable improvements in imaging assessment and breast cancer diagnosis across various AI algorithm categories [51]. Deep learning (DL) algorithms, in particular, have shown greater promise than traditional machine learning (ML) approaches, proving especially effective in breast cancer imaging research [21]. Buckner et al. reviewed the applications of ML, computer-assisted detection, and computer-assisted diagnosis, highlighting their ability to reduce false positives (FP) generated by the Chan-Vese segmentation method when initialized with the marker-controlled watershed algorithm (MCWS). The computer-assisted diagnosis system employs blended learning, integrating four Support Vector Machine (SVM)-based classifiers, each analyzing specific tissue components [22]. Despite AI's advancements, mammography may still fail to detect certain malignancies due to factors such as breast density, tumor size, or subtle cancer indicators that are difficult to identify in metastatic cases. However, AI has demonstrated high accuracy in digital mammography, and its sensitivity in detecting various morphological breast cancer characteristics—such as asymmetry and distortion—has proven highly effective [53].

Cutting-Edge AI Approaches in Breast Cancer Diagnosis

Radiomics is a cutting-edge method that extracts diverse quantitative characteristics from medical images [23], playing a crucial role in the diagnosis and management of breast cancer (BC). This approach aids in tumor prediction, staging, and assessing therapeutic responses [24]. Radiotherapy remains highly effective in BC prognosis; however, radiomics has a limitation—it cannot accurately predict survival rates for locally advanced breast cancer (LABC) following neoadjuvant therapy or post-surgical treatment [25]. Meanwhile, AI applications in BC diagnostics emphasize reproducibility, a fundamental aspect of experimental science. However, several factors—such as biological variability, mislabeled samples, cross-contamination, and excessive cell passage—can hinder reproducibility [26]. To address these challenges, researchers employ statistical methods to eliminate irrelevant factors, improving data reliability. The generalizability of AI models remains an important research focus, requiring preprocessing of medical datasets before data mining [27]. Despite its challenges, AI's role in BC diagnostics presents significant social benefits. In developing countries, AI adoption is increasing, with cost-effective solutions like the DeepMind automated system providing affordable diagnostic support. The World Health Organization (WHO) acknowledges its potential to benefit both developed and underdeveloped nations [21].

The Conception and Respective Correlations of AI, ML, and DL

AI encompasses techniques that enable computers to replicate human behavior. In breast cancer screening, its primary functions include tumor segmentation and classification into benign or malignant categories [28]. Machine learning (ML) is a data-driven approach where variables and characteristics represent observable patterns. A subset of ML, deep learning (DL), utilizes deep neural networks that mimic and enhance the structure of human brain neurons [29], making it highly effective for image classification and recognition. DL employs a hierarchical, modular structure to extract information, progressing from simple to complex patterns. While ML and DL share similarities, they also have key differences. Figure 1 below illustrates the link between AI, ML, and DL. ML builds mathematical models based on training data [30], using these models to predict outcomes by testing new data. Training in machine learning entails determining the difference between benign and malignant instances using an assessment metric called the objective function.

[54]. This training can be supervised, where labeled data and predefined targets guide the model's learning process. Consequently, various research institutions and companies are actively developing AI technologies for different healthcare applications. Supervised Machine Learning (SML) [31] enhances differential diagnosis by providing healthcare professionals with predictive insights and early warnings about potential health risks. In mammography, labeled cancer images enable the algorithm to recognize malignancy features. In contrast, unsupervised learning [32] operates without predefined labels or diagnostic markers, while semi-supervised learning incorporates limited labeled data during training. Additionally, integrating supplementary methodologies can enhance efficiency and minimize errors in breast cancer diagnosis. AI-driven automated image analysis significantly improves upon manual screening processes by efficiently extracting relevant information from vast amounts of imaging data, reducing time-consuming and labor-intensive efforts compared to traditional manual inspections [33].

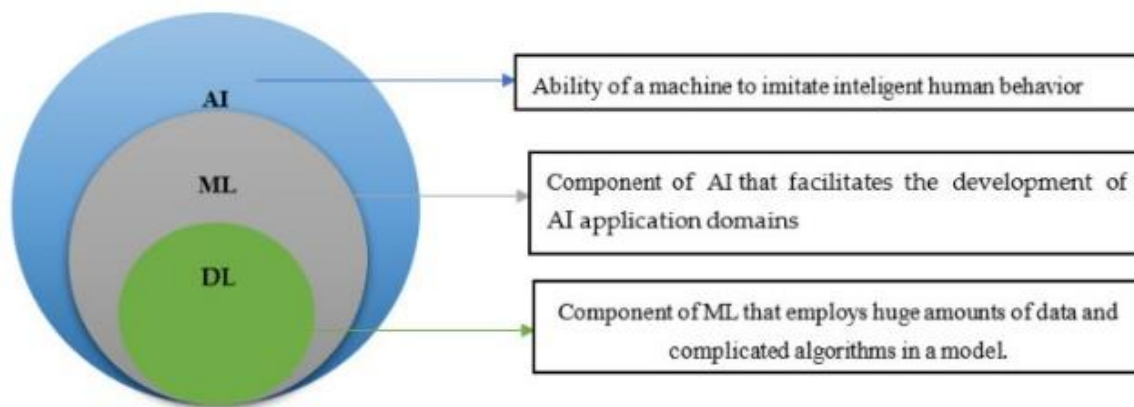


Figure 1: BC Diagnosis Advantages

AI-powered mammography has the capability to identify cancer up to twenty-four month years earlier than human oncologists, potentially enabling earlier treatment and saving more lives. By assisting doctors in making more confident diagnoses, AI enhances efficiency [34]. It also alleviates the workload of radiologists, as AI does not experience fatigue and can analyze mammogram images tirelessly. This leads to improved accuracy and earlier cancer detection. Additionally, AI contributes to better medical care by supporting more precise diagnostic evaluations [35]. AI-based diagnostic tools have significantly improved radiologists' efficiency, often yielding results superior to those obtained by radiologists alone. By utilizing advanced machine learning algorithms, AI differentiates between structures and image components; however, its clinical application remains limited due to low specificity [36]. Notably, AI has enhanced the accuracy of computer-aided detection (CAD). Convolutional neural networks (CNNs), a deep learning technology optimized for image assessment and classification, exhibit diagnostic accuracy comparable to or even surpassing that of radiologists [37]. AI also aids in detecting breast cancers that may go unnoticed during screening, particularly in dense breast tissues, which have lower sensitivity. Research indicates that dense breasts are associated with a higher rate of false-negative results [38], meaning that some women may receive reassuring mammography results despite having cancer. However, AI-based diagnosis of breast cancer faces several challenges, which contribute to its limitations, as discussed in the following section.

Limitation of AI in BC Diagnosis

This marks the distinction between AI and human intelligence. For AI to function autonomously, it must be able to generate, replicate, and process data without human intervention. Achieving this level of independence would make AI systems a true form of artificial intelligence. However, this requires a universally accessible code, which can only be realized through the fair and equitable distribution of data [39]. To facilitate AI integration into healthcare, hospitals worldwide must adopt user-friendly databases and intuitive software within their information technology systems. Moreover, fostering trust and confidence among clinicians is essential to encourage the widespread implementation of AI in medical decision-making. As a result, healthcare professionals should receive comprehensive training on AI applications.

Technological advancements have introduced apps for monitoring health conditions such as heart rate and diabetes, yet similar innovations for breast cancer detection remain underdeveloped. Developing AI-driven tools in this area could enhance patient care and satisfaction. However, ethical concerns such as data confidentiality, privacy breaches, patient autonomy, and informed consent must be carefully addressed when using AI in breast cancer diagnosis. To mitigate these risks, strict regulations and precautionary measures have been put in place to protect personal information. Additionally, radiomics is not yet widely integrated into clinical practice [39]. It is hoped that policymakers will address these limitations to ensure AI remains a valuable and effective diagnostic tool.

Data Heterogeneity and Complexity of Medical Images

The majority of the early advances in computer vision were based on photographs of commonplace items like homes, vehicles, and fruits. The ImageNet Large Scale Visual Recognition Challenge is one of the most well-known contests in this area which was launched in over twenty five years ago. It featured a training dataset with over 1.2 million color images in Joint Photographic Expert Group (JPEG) format, categorized into 1,000 classes. The average resolution of these images was relatively low, measuring 482×415 pixels [18]. In contrast, medical images, typically stored in the Digital Imaging and Communications in Medicine (DICOM) format, differ significantly from the ImageNet dataset. The DICOM standard was developed to facilitate various medical imaging processes and has played a crucial role in advancing the field, particularly in the digitization of radiology. This standard supports multiple resolutions and bit-depth allocations. For instance, mammographic images can reach resolutions as high as 3000×4000 pixels [40]. While most medical imaging techniques generate grayscale images, some, such as PET/CT, Doppler ultrasound (US), and secondary capture objects (e.g., advanced visualization images), are stored and displayed in color.

In many clinical applications, the importance of medical imaging ranges from detecting diseases to monitoring their progression [41]. Mostafiz et al. [45] stated Lesion segmentation, classification, and disease detection (localization and classification) are among the particular tasks that can be successfully completed by machine learning in each application. For instance, when analyzing a chest CT scan, radiologists identify pulmonary nodules, assess their characteristics, and classify them as either benign or malignant [41]. Some tasks require quantitative analysis, such as volumetric assessments of anatomical structures—for example, measuring hippocampal volume—which necessitate segmentation tools. Additionally, certain objectives focus on generating numerical values rather than classifying objects, as seen in bone age assessment using hand radiographs [42]. Image-based outcome predictions are also possible, such as estimating the likelihood of hematoma expansion based on an initial head CT scan. Given the vast number of clinical scenarios and the complexity of tasks involved, it is impractical for a single individual or organization to address all these challenges using current methodologies.

Challenges Associated with Medical Imaging Data Curation

ImageNet transformed computer vision research by highlighting the importance of data curation alongside feature extraction and algorithm development [43]. Its success stemmed from the collaborative contributions of many individuals, leading to a vast and diverse image database [41]. When it comes to standard photographic images with easily identifiable objects, the general public was capable of classifying and annotating them, making it relatively easy to establish ground truth. In contrast, labeling medical images requires specialized knowledge from trained radiologists, and large-scale annotation depends on multiple experienced professionals, making the process both expensive and labor-intensive. Moreover, detecting subtle abnormalities in medical images can vary significantly even among experts, affecting the accuracy of interpretations. Discrepancies in inter- and intra-observer agreement can be particularly high for certain medical conditions, further complicating the labeling process. The specialized expertise required for medical image annotation significantly reduces the pool of qualified contributors, making crowdsourcing an impractical solution for this task.

Concerns Regarding Patient Privacy

Creating large public databases of medical images has historically been challenging, primarily due to concerns about inadvertently disclosing protected health information (PHI). This concern is heightened by the fact that DICOM images often contain PHI embedded in unpredictable locations within their metadata [40]. Additionally, medical images may have PHI burned into the pixel data, such as annotations or digitized films with handwritten information. Moreover, advancements in facial recognition technology have made it possible to re-identify patients from three-dimensional reconstructions of their facial structures, raising significant confidentiality risks when such datasets are publicly shared [44]. Even accessories like necklaces and wristbands may display patient names or be distinct enough to facilitate identification in volumetric images. To mitigate these risks, many organizations manually review and curate each image before releasing datasets to the public. However, this process is both costly and labor-intensive.

CONCLUSION

In conclusion, the integration of AI into breast cancer management presents a transformative approach to improving early detection, diagnosis, and treatment outcomes. Artificial Intelligence's application in mammography, MRI, and advanced imaging techniques enhances both accuracy and efficiency of cancer detection, allowing for earlier intervention and personalized care [55]. Emerging techniques such as radiomics and deep learning further expand AI's potential, offering refined predictive analytics and reduced false-positive rates. Despite these advancements, challenges remain, including data heterogeneity, limited clinical implementation, ethical concerns, and the need for extensive training for healthcare professionals. Addressing these limitations through collaborative efforts in research, data standardization, and ethical frameworks will pave the way for AI to revolutionize breast cancer care, ultimately reducing mortality rates and improving quality of life for patients.

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REFERENCES

1. Nicolis, O., De Los Angeles, D., & Taramasco, C. (2024). A contemporary review of breast cancer risk factors and the role of artificial intelligence. *Frontiers in Oncology*, 14, 1356014. <https://doi.org/10.3389/fonc.2024.1356014>
2. Uzun O. D., Ikechukwu E. D., Uzun, B., & Ozsahin, I. (2022). The Systematic Review of Artificial Intelligence Applications in Breast Cancer Diagnosis. *Diagnostics*, 13(1), 45. <https://doi.org/10.3390/diagnostics13010045>
3. Fortin, J., Leblanc, M., Elgbeili, G., Cordova, M. J., Marin, M.-F., & Brunet, A. (2021). The mental health impacts of receiving a breast cancer diagnosis: A meta-analysis. *British Journal of Cancer*, 125(11), 1582–1592. <https://doi.org/10.1038/s41416-021-01542-3>
4. Siegel, R., Naishadham, D., & Jemal, A. (2013). Cancer statistics, 2013. *CA: A Cancer Journal for Clinicians*, 63(1), 11–30. <https://doi.org/10.3322/caac.21166>
5. Collaborative Group on Hormonal Factors in Breast Cancer. (2002). Breast cancer and breastfeeding: Collaborative reanalysis of individual data from 47 epidemiological studies in 30 countries, including 50302 women with breast cancer and 96973 women without the disease. *Lancet* (London, England), 360(9328), 187–195. [https://doi.org/10.1016/S0140-6736\(02\)09454-0](https://doi.org/10.1016/S0140-6736(02)09454-0)
6. Chiao, J.-Y., Chen, K.-Y., Liao, K. Y.-K., Hsieh, P.-H., Zhang, G., & Huang, T.-C. (2019). Detection and classification the breast tumors using mask R-CNN on sonograms. *Medicine*, 98(19), e15200. <https://doi.org/10.1097/MD.00000000000015200>
7. Zhou, L.-Q., Wang, J.-Y., Yu, S.-Y., Wu, G.-G., Wei, Q., Deng, Y.-B., Wu, X.-L., Cui, X.-W., & Dietrich, C. F. (2019). Artificial intelligence in medical imaging of the liver. *World Journal of Gastroenterology*, 25(6), 672–682. <https://doi.org/10.3748/wjg.v25.i6.672>

8. Korn, R. L., Rahmanuddin, S., & Borazanci, E. (2019). Use of Precision Imaging in the Evaluation of Pancreas Cancer. *Cancer Treatment and Research*, 178, 209–236. https://doi.org/10.1007/978-3-030-16391-4_8
9. Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. *Nature Reviews. Cancer*, 18(8), 500–510. <https://doi.org/10.1038/s41568-018-0016-5>
10. Xu, X., Fu, L., Chen, Y., Larsson, R., Zhang, D., Suo, S., Hua, J., & Zhao, J. (2018). Breast Region Segmentation using Convolutional Neural Network in Dynamic Contrast Enhanced MRI. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, 2018, 750–753. <https://doi.org/10.1109/EMBC.2018.8512422>
11. Villanueva-Meyer, J. E., Chang, P., Lupo, J. M., Hess, C. P., Flanders, A. E., & Kohli, M. (2019). Machine Learning in Neurooncology Imaging: From Study Request to Diagnosis and Treatment. *AJR. American Journal of Roentgenology*, 212(1), 52–56. <https://doi.org/10.2214/AJR.18.20328>
12. Truhn, D., Schrading, S., Haaburger, C., Schneider, H., Merhof, D., & Kuhl, C. (2019). Radiomic versus Convolutional Neural Networks Analysis for Classification of Contrast-enhancing Lesions at Multiparametric Breast MRI. *Radiology*, 290(2), 290–297. <https://doi.org/10.1148/radiol.2018181352>
13. Herent, P., Schmauch, B., Jehanno, P., Dehaene, O., Saillard, C., Balleyguier, C., Arfi-Rouche, J., Jégou, S. (2019). Detection and characterization of MRI breast lesions using deep learning, *Diagnostic and Interventional Imaging*. Volume 100, Issue 4, Pages 219-225, <https://doi.org/10.1016/j.diii.2019.02.008>.
14. Antropova, N., Abe, H., & Giger, M. L. (2018). Use of clinical MRI maximum intensity projections for improved breast lesion classification with deep convolutional neural networks. *Journal of medical imaging (Bellingham, Wash.)*, 5(1), 014503. <https://doi.org/10.1117/1.JMI.5.1.014503>
15. Gallego-Ortiz, C., & Martel, A. L. (2019). A graph-based lesion characterization and deep embedding approach for improved computer-aided diagnosis of nonmass breast MRI lesions. *Medical Image Analysis*, 51, 116–124. <https://doi.org/10.1016/j.media.2018.10.011>
16. Lei, Y. M., Yin, M., Yu, M. H., Yu, J., Zeng, S. E., Lv, W. Z., Li, J., Ye, H. R., Cui, X. W., & Dietrich, C. F. (2021). Artificial Intelligence in Medical Imaging of the Breast. *Frontiers in oncology*, 11, 600557. <https://doi.org/10.3389/fonc.2021.600557>
17. Siegel, R. L., Miller, K. D., Fuchs, H. E., & Jemal, A. (2022). Cancer statistics, 2022. *CA: A Cancer Journal for Clinicians*, 72(1), 7–33. <https://doi.org/10.3322/caac.21708>
18. Prevedello, L. M., Halabi, S. S., Shih, G., Wu, C. C., Kohli, M. D., Chokshi, F. H., Erickson, B. J., Kalpathy-Cramer, J., Andriole, K. P., & Flanders, A. E. (2019). Challenges Related to Artificial Intelligence Research in Medical Imaging and the Importance of Image Analysis Competitions. *Radiology. Artificial Intelligence*, 1(1), e180031. <https://doi.org/10.1148/ryai.2019180031>
19. Marinovich, M. L., Wylie, E., Lotter, W., Pearce, A., Carter, S. M., Lund, H., Waddell, A., Kim, J. G., Pereira, G. F., Lee, C. I., Zackrisson, S., Brennan, M., & Houssami, N. (2022). Artificial intelligence (AI) to enhance breast cancer screening: Protocol for population-based cohort study of cancer detection. *BMJ Open*, 12(1), e054005. <https://doi.org/10.1136/bmjopen-2021-054005>
20. Sun, P., Feng, Y., Chen, C., Dekker, A., Qian, L., Wang, Z., & Guo, J. (2022). An AI model of sonographer's evaluation+ S-Detect + elastography + clinical information improves the preoperative identification of benign and malignant breast masses. *Frontiers in Oncology*, 12, 1022441. <https://doi.org/10.3389/fonc.2022.1022441>
21. Sharma, S., & Mehra, R. (2020). Conventional Machine Learning and Deep Learning Approach for Multi-Classification of Breast Cancer Histopathology Images—A Comparative Insight. *Journal of Digital Imaging*, 33(3), 632–654. <https://doi.org/10.1007/s10278-019-00307-y>
22. Burt, J. R., Torosdagli, N., Khosravan, N., RaviPrakash, H., Mortazi, A., Tissavirasingham, F., Hussein, S., & Bagci, U. (2018). Deep learning beyond cats and dogs: Recent advances in diagnosing breast cancer with deep neural networks. *The British Journal of Radiology*, 91(1089), 20170545. <https://doi.org/10.1259/bjr.20170545>

23. Liu, K.-L., Wu, T., Chen, P.-T., Tsai, Y. M., Roth, H., Wu, M.-S., Liao, W.-C., & Wang, W. (2020). Deep learning to distinguish pancreatic cancer tissue from non-cancerous pancreatic tissue: A retrospective study with cross-racial external validation. *The Lancet. Digital Health*, 2(6), e303–e313. [https://doi.org/10.1016/S2589-7500\(20\)30078-9](https://doi.org/10.1016/S2589-7500(20)30078-9)
24. Balakrishnan, G., Zhao, A., Sabuncu, M. R., Guttag, J., & Dalca, A. V. (2019). VoxelMorph: A Learning Framework for Deformable Medical Image Registration. *IEEE Transactions on Medical Imaging*. <https://doi.org/10.1109/TMI.2019.2897538>
25. Witowski, J., Heacock, L., Reig, B., Kang, S. K., Lewin, A., Pyrasenko, K., Patel, S., Samreen, N., Rudnicki, W., Łuczyńska, E., Popiela, T., Moy, L., & Geras, K. J. (2022). Improving breast cancer diagnostics with artificial intelligence for MRI. *Science Translational Medicine*, 14(664), eabo4802. <https://doi.org/10.1126/scitranslmed.abo4802>
26. Lee, J., Kang, B. J., Kim, S. H., & Park, G. E. (2022). Evaluation of Computer-Aided Detection (CAD) in Screening Automated Breast Ultrasound Based on Characteristics of CAD Marks and False-Positive Marks. *Diagnostics (Basel, Switzerland)*, 12(3), 583. <https://doi.org/10.3390/diagnostics12030583>
27. Shah, S. M., Khan, R. A., Arif, S., & Sajid, U. (2022). Artificial intelligence for breast cancer analysis: Trends & directions. *Computers in Biology and Medicine*, 142, 105221. <https://doi.org/10.1016/j.combiomed.2022.105221>
28. Zhang, Y.-N., Xia, K.-R., Li, C.-Y., Wei, B.-L., & Zhang, B. (2021). Review of Breast Cancer Pathological Image Processing. *BioMed Research International*, 2021, 1994764. <https://doi.org/10.1155/2021/1994764>
29. Xue, P., Wang, J., Qin, D., Yan, H., Qu, Y., Seery, S., Jiang, Y., & Qiao, Y. (2022). Deep learning in image-based breast and cervical cancer detection: A systematic review and meta-analysis. *NPJ Digital Medicine*, 5, 19. <https://doi.org/10.1038/s41746-022-00559-z>
30. Freeman, K., Geppert, J., Stinton, C., Todkill, D., Johnson, S., Clarke, A., & Taylor-Phillips, S. (2021). Use of artificial intelligence for image analysis in breast cancer screening programmes: Systematic review of test accuracy. *The BMJ*, 374, n1872. <https://doi.org/10.1136/bmj.n1872>
31. Mendes, J., Domingues, J., Aidos, H., Garcia, N., & Matela, N. (2022). AI in Breast Cancer Imaging: A Survey of Different Applications. *Journal of Imaging*, 8(9), 228. <https://doi.org/10.3390/jimaging8090228>
32. Shao, D., Dai, Y., Li, N., Cao, X., Zhao, W., Cheng, L., Rong, Z., Huang, L., Wang, Y., & Zhao, J. (2021). Artificial intelligence in clinical research of cancers. *Briefings in Bioinformatics*, 23(1), bbab523. <https://doi.org/10.1093/bib/bbab523>
33. Hickman, S. E., Woitek, R., Le, E. P. V., Im, Y. R., Mouritsen Luxhøj, C., Aviles-Rivero, A. I., Baxter, G. C., MacKay, J. W., & Gilbert, F. J. (2021). Machine Learning for Workflow Applications in Screening Mammography: Systematic Review and Meta-Analysis. *Radiology*, 302(1), 88–104. <https://doi.org/10.1148/radiol.2021210391>
34. Wei, M., Du, Y., Wu, X., Su, Q., Zhu, J., Zheng, L., Lv, G., & Zhuang, J. (2020). A Benign and Malignant Breast Tumor Classification Method via Efficiently Combining Texture and Morphological Features on Ultrasound Images. *Computational and Mathematical Methods in Medicine*, 2020, 5894010. <https://doi.org/10.1155/2020/5894010>
35. Dutta, K., Roy, S., Whitehead, T. D., Luo, J., Jha, A. K., Li, S., Quirk, J. D., & Shoghi, K. I. (2021). Deep Learning Segmentation of Triple-Negative Breast Cancer (TNBC) Patient Derived Tumor Xenograft (PDX) and Sensitivity of Radiomic Pipeline to Tumor Probability Boundary. *Cancers*, 13(15), 3795. <https://doi.org/10.3390/cancers13153795>
36. Yuan, J., Hu, Z., Mahal, B. A., Zhao, S. D., Kensler, K. H., Pi, J., Hu, X., Zhang, Y., Wang, Y., Jiang, J., Li, C., Zhong, X., Montone, K. T., Guan, G., Tanyi, J. L., Yi, F., Xu, X., Morgan, M. A., Long, M., ... Zhang, L. (2018). Integrated Analysis of Genetic Ancestry and Genomic Alterations across Cancers. *Cancer Cell*, 34(4), 549-560.e9. <https://doi.org/10.1016/j.ccell.2018.08.019>
37. Tagliafico, A. S., Piana, M., Schenone, D., Lai, R., Massone, A. M., & Houssami, N. (2019). Overview of radiomics in breast cancer diagnosis and prognostication. *The Breast : Official Journal of the European Society of Mastology*, 49, 74–80. <https://doi.org/10.1016/j.breast.2019.10.018>

38. Talo, M. (2019). Automated classification of histopathology images using transfer learning. *Artificial Intelligence in Medicine*, 101, 101743. <https://doi.org/10.1016/j.artmed.2019.101743>
39. George, K., Faziludeen, S., Sankaran, P., & Joseph K, P. (2020). Breast cancer detection from biopsy images using nucleus guided transfer learning and belief based fusion. *Computers in Biology and Medicine*, 124, 103954. <https://doi.org/10.1016/j.compbimed.2020.103954>
40. Monteiro, E., Costa, C., & Oliveira, J. L. (2017). A De-Identification Pipeline for Ultrasound Medical Images in DICOM Format. *Journal of Medical Systems*, 41(5), 89. <https://doi.org/10.1007/s10916-017-0736-1>
41. Lim, H. K., Hong, S. C., Jung, W. S., Ahn, K. J., Won, W. Y., Hahn, C., Kim, I. S., & Lee, C. U. (2013). Automated Segmentation of Hippocampal Subfields in Drug-Naïve Patients with Alzheimer Disease. *AJNR: American Journal of Neuroradiology*, 34(4), 747–751. <https://doi.org/10.3174/ajnr.A3293>
42. Rajpurkar, P., Irvin, J., Ball, R. L., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C. P., Patel, B. N., Yeom, K. W., Shpanskaya, K., Blankenberg, F. G., Seekins, J., Amrhein, T. J., Mong, D. A., Halabi, S. S., Zucker, E. J., ... Lungren, M. P. (2018). Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. *PLoS Medicine*, 15(11), e1002686. <https://doi.org/10.1371/journal.pmed.1002686>
43. Halabi, S. S., Prevedello, L. M., Kalpathy-Cramer, J., Mamonov, A. B., Bilbily, A., Cicero, M., Pan, I., Pereira, L. A., Sousa, R. T., Abdala, N., Kitamura, F. C., Thodberg, H. H., Chen, L., Shih, G., Andriole, K., Kohli, M. D., Erickson, B. J., & Flanders, A. E. (2019). The RSNA Pediatric Bone Age Machine Learning Challenge. *Radiology*, 290(2), 498–503. <https://doi.org/10.1148/radiol.2018180736>
44. Winklhofer, S., Held, U., Burgstaller, J. M., Finkenstaedt, T., Bolog, N., Ulrich, N., Steurer, J., Andreisek, G., & Del Grande, F. (2017). Degenerative lumbar spinal canal stenosis: Intra- and inter-reader agreement for magnetic resonance imaging parameters. *European Spine Journal: Official Publication of the European Spine Society, the European Spinal Deformity Society, and the European Section of the Cervical Spine Research Society*, 26(2), 353–361. <https://doi.org/10.1007/s00586-016-4667-1>
45. Mostafiz, A.M.d., Al, M., Mohammad, S.U. (2022). A machine learning approach for skin disease detection and classification using image segmentation, *Healthcare Analytics*, Volume 2, <https://doi.org/10.1016/j.health.2022.100122>.
46. Mohammad, R. D., Mahsa, D., Sara, D., Igor, B., Mohammad, H., Hamid, R.K. K., (2024). Artificial intelligence breakthroughs in pioneering early diagnosis and precision treatment of breast cancer: A multimethod study, *European Journal of Cancer*, Volume 209, <https://doi.org/10.1016/j.ejca.2024.114227>.
47. Yu, X., Zhao, H., Wang, R. (2024). Cancer epigenetics: from laboratory studies and clinical trials to precision medicine. *Cell Death Discovery*. 10, 28. <https://doi.org/10.1038/s41420-024-01803-z>
48. Sebastian, A. M., & Peter, D. (2022). Artificial Intelligence in Cancer Research: Trends, Challenges and Future Directions. *Life (Basel, Switzerland)*, 12(12), 1991. <https://doi.org/10.3390/life12121991>.
49. Iqbal, M.J., Javed, Z., Sadia, H. (2021). Clinical applications of artificial intelligence and machine learning in cancer diagnosis: looking into the future. *Cancer Cell International*. 21, 270. <https://doi.org/10.1186/s12935-021-01981-1>
50. Tavallaee, M., Bagheri, E., Lu, W., & Ghorbani, A. A. (2009). A detailed analysis of the KDD CUP 99 data set. In *2009 IEEE Symposium on Computational Intelligence for Security and Defense Applications* (pp. 1-6). IEEE. <https://doi.org/10.1109/CISDA.2009.5356528>
51. Uzun Ozsahin, D., Ikechukwu Emegano, D., Uzun, B., & Ozsahin, I. (2022). The Systematic Review of Artificial Intelligence Applications in Breast Cancer Diagnosis. *Diagnostics (Basel, Switzerland)*, 13(1), 45. <https://doi.org/10.3390/diagnostics13010045>
52. Xu, Y., Liu, X., Cao, X., Huang, C., Liu, E., Qian, S., Liu, X., Wu, Y., Dong, F., Qiu, C.-W., Qiu, J., Hua, K., Su, W., Wu, J., Xu, H., Han, Y., Fu, C., Yin, Z., Liu, M., Roepman, R., Dietmann, S., Virta, M., Kengara, F., Zhang, Z., Zhang, L., Zhao, T., Dai, J., Yang, J., Lan, L., Luo, M., Liu, Z., An, T., Zhang, B., He, X., Cong, S., Liu, X., Zhang, W., Lewis, J. P., Tiedje, J. M., Wang, Q., An, Z., Wang, F., Zhang, L., Huang, T., Lu, C., Cai, Z., Wang, F., & Zhang, J. (2021). Artificial intelligence: A

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- powerful paradigm for scientific research. The Innovation, 2(4), 100179. <https://doi.org/10.1016/j.xinn.2021>.
53. Uzun O. D., Ikechukwu E.D., Uzun, B., & Ozsahin, I. (2022). The Systematic Review of Artificial Intelligence Applications in Breast Cancer Diagnosis. *Diagnostics (Basel, Switzerland)*, 13(1), 45. <https://doi.org/10.3390/diagnostics13010045>
54. Khalid, A., Mehmood, A., Alabrah, A., Alkhamees, B. F., Amin, F., AlSalman, H., & Choi, G. S. (2023). Breast Cancer Detection and Prevention Using Machine Learning. *Diagnostics (Basel, Switzerland)*, 13(19), 3113. <https://doi.org/10.3390/diagnostics13193113>
55. Zheng, D., He, X., & Jing, J. (2023). Overview of Artificial Intelligence in Breast Cancer Medical Imaging. *Journal of clinical medicine*, 12(2), 419. <https://doi.org/10.3390/jcm12020419>