HIGH SCHOOL EDITION
Journal of Student Research

Volume 13 Issue 2 (2024)

The Implementation of Artificial Intelligence in Breast Cancer Screening

Abigail Jin[1] and Diana Tosato[#]

[1]Stuyvesant High School, USA
[#]Advisor

ABSTRACT

Breast cancer screening is traditionally administered by radiologists through mammography. Most women should be receiving mammograms once they reach their 40s to detect any signs of cancer early, especially those with high risk. Recently, the development of AI in medicine has proven to be useful in several fields, one of which is breast cancer screening. This literature review looks into the current status of AI in this field and evaluates different models of different types that could contribute to diagnosing breast cancer. The methodology used was searching key terms on the database PubMed, and then compiling and organizing papers into a table that highlighted similar results, which were summarized and analyzed. It was found that AI has the potential to be an accessible option. Deep learning, in particular, has seen the most experimentation. The advantages of using this technology include using it as a complementary tool for double reading, improving the time efficiency for the radiologists without losing accuracy, and its inclusivity throughout all populations. However, there are still limitations because many proposals themselves discuss the work that needs to be done before they can be generalized. External validation studies haven't yielded ideal results, exposing the complications of using AI. Ethics of using this technology are also important to consider because AI is replacing human tasks. Implementing AI in a prominent role in breast cancer screening should take more examination, but promising developments have already set the framework.

Introduction

The most common type of cancer, breast cancer, has continued to increase in cases over the past few decades (SEER, 2023). With over 300,000 estimated cases this year in the US alone, one in every eight women is likely to develop breast cancer in their lives. However, the mortality rate has slowly decreased because of improved and more widespread screening (Siegel et al., 2023). More screening translates to the detection of more cases of breast cancer and earlier diagnosis, which makes a patient's treatment options more effective. Today, the risk of death is about 1 in every 39 women in their lifetime, which signifies a 43% decrease over the past three decades (Giaquinto et al., 2022).

The conventional imaging methods used for breast cancer diagnosis rely on mammograms and ultrasound (Mansour et al., 2021). This is what the current CDC guidelines recommend, so they are widely accepted globally as a form of secondary prevention for breast cancer. The frequency with which women receive mammograms is determined by factors such as age and predisposition to breast cancer. For example, women over 40 years of age are encouraged to get mammograms twice a year for early detection of cancer. However, for people at high risk, such as having a family history of breast cancer, annual mammograms or MRIs should be given even earlier. Despite these recommendations, several factors limit mammography availability, such as the lack of facilities or radiologists in developing countries. Additionally, mammograms are less successful in women with dense breasts, and follow-ups on abnormal breast cancer cases are not as reliable for low-income and minority women (Giaquinto et al., 2022; Ren et al., 2022).

An emerging field of technology, artificial intelligence (AI) in healthcare, can dispel some limitations of mammography. AI is a computer science tool that is becoming a popular hot topic. It can imitate human actions but ideally avoid human error after being trained, recognize patterns, and make decisions. Its use comes in when, for example, there are large datasets that would be inefficient for humans to comb through (Briganti, 2023). The technology is quickly advancing to provide the most updated healthcare, as AI has had applications that have successfully contributed to a variety of fields within medicine, including breast cancer (Cascella et al., 2023). The objective of this review article is to understand the modern updates and potential of use for artificial intelligence in breast cancer screening techniques.

Methods

To provide a thorough background of breast cancer, reviews were collected on PubMed about the traditional screening process with the keywords "breast cancer screening guidelines." Annual statistics papers compiling official government public records on breast cancer were found in ACS Journals. A background in artificial intelligence was obtained with the search "history of artificial intelligence."

For the main results, a search on PubMed was conducted with the keywords "breast cancer," "artificial intelligence," and "screening" altogether. It was filtered by free full text and publication date within the past five years up to November 2023 because AI is a very recent development. All completed and relevant studies (with relevance determined by the abstract and conclusion) aligning with the scope of the study were perused.

With all the papers, a spreadsheet table was created to organize the overlapping data and findings that would be used later for analysis (Table 1). The parameters used included whether it had a positive, neutral, or negative viewpoint and further categorizations by topic, including accuracy, computer-aided design, AI's use as a complementary tool, convolutional neural networks, deep learning, double reading, early detection, ethical factors, false positives, feasibility, inclusivity, machine learning, proposed models, risk prediction, time efficiency, and external validation. They were reorganized into broader categories for the paper. A total of 77 studies were used.

Table 1. Data organized into 16 rows based on research focus. Perspectives are color-coded: positive views are shaded green, neutral views are shaded white, and negative views are shaded blue.

Accuracy	Stand-Alone Artificial Intelligence for Breast Cancer Detection in Mammography: Comparison With 101 Radiologists	Impact of artificial intelligence in breast cancer screening with mammography	Artificial intelligence (AI) for breast cancer screening: BreastScreen population-based cohort study of cancer detection	Accuracy of an Artificial Intelligence System for Cancer Clinical Trial Eligibility Screening: Retrospective Pilot Study	Development and validation of an infrared-artificial intelligence software for breast cancer detection	Artificial Intelligence Evaluation of 122 969 Mammography Examinations from a Population-based Screening Program
CAD	Validation of radiologists' findings by computer-aided detection (CAD) software in breast cancer detection with automated 3D breast ultrasound: a concept study	External Evaluation of 3 Commercial Artificial Intelligence Algorithms for	Comparisons between artificial intelligence computer-aided detection synthesized mammograms and digital mammograms	Evaluation of an Artificial Intelligence System for Detection of Invasive Lobular		

	in implementation of artificial intelligence software	Independent Assessment of Screening Mammograms	when used alone and in combination with tomosynthesis images in a virtual screening setting	Carcinoma on Digital Mammography					
Complementary tool	Can artificial intelligence reduce the interval cancer rate in mammography screening?	Can artificial intelligence replace ultrasound as a complementary tool to mammogram for the diagnosis of the breast cancer?	Evaluation of an artificial intelligence support system for breast cancer screening in Chinese people based on mammogram	Artificial intelligence breast ultrasound and handheld ultrasound in the BI-RADS categorization of breast lesions: A pilot head to head comparison study in screening program	Combining the strengths of radiologists and AI for breast cancer screening: a retrospective analysis	Improved Cancer Detection Using Artificial Intelligence: a Retrospective Evaluation of Missed Cancers on Mammography	Changes in cancer detection and false-positive recall in mammography using artificial intelligence: a retrospective, multireader study	Observational Study to Evaluate the Clinical Efficacy of Thermalytix for Detecting Breast Cancer in Symptomatic and Asymptomatic Women	AI-aided detection of malignant lesions in mammography screening – evaluation of a program in clinical practice
Convolutional neural network	Multi-input convolutional neural network for breast cancer detection using thermal images and clinical data	Microcalcification Discrimination in Mammography Using Deep Convolutional Neural Network: Towards Rapid and Early Breast Cancer Diagnosis	Detecting Abnormal Axillary Lymph Nodes on Mammograms Using a Deep Convolutional Neural Network						
Deep learning	Attention-Based Deep Learning System for Classification of Breast Lesions—Multimodal, Weakly Supervised Approach	Evaluation of deep learning-based artificial intelligence techniques for breast cancer detection on mammograms: Results from a retrospective study using a BreastScreen Victoria dataset	Deep Learning-Based Modified YOLACT Algorithm on Magnetic Resonance Imaging Images for Screening Common and Difficult Samples of Breast Cancer	Automated Breast Cancer Detection in Digital Mammograms of Various Densities via Deep Learning	Deep learning-based segmentation of breast masses in dedicated breast CT imaging: Radiomic feature stability between radiologists and artificial intelligence	Fully automatic tumor segmentation of breast ultrasound images with deep learning	A Data Set and Deep Learning Algorithm for the Detection of Masses and Architectural Distortions in Digital Breast Tomosynthesis Images		

Double reading	Comparing Prognostic Factors of Cancers Identified by Artificial Intelligence (AI) and Human Readers in Breast Cancer Screening	Use of artificial intelligence for image analysis in breast cancer screening programmes: systematic review of test accuracy	Breast cancer screening with digital breast tomosynthesis: comparison of different reading strategies implementing artificial intelligence	Multi-vendor evaluation of artificial intelligence as an independent reader for double reading in breast cancer screening on 275,900 mammograms	Artificial Intelligence in Screening Mammography: A Population Survey of Women's Preferences	Validation of radiologists' findings by computer-aided detection (CAD) software in breast cancer detection with automated 3D breast ultrasound: a concept study in implementation of artificial intelligence software
Early and increased detection	Artificial intelligence-assisted ultrasound image analysis to discriminate early breast cancer in Chinese population: a retrospective, multicentre, cohort study	Artificial intelligence in BreastScreen Norway: a retrospective analysis of a cancer-enriched sample including 1254 breast cancer cases	Diagnostic Performance of AI for Cancers Registered in A Mammography Screening Program: A Retrospective Analysis	AI-based prevention of interval cancers in a national mammography screening program		
Ethical factors and trust	The ethical, legal and social implications of using artificial intelligence systems in breast cancer care	The future of breast cancer screening: what do participants in a breast cancer screening program think about automation using artificial intelligence?				
False positives and recalls	Use of Artificial Intelligence for Reducing Unnecessary Recalls at Screening Mammography: A Simulation Study	Identifying normal mammograms in a large screening population using artificial intelligence	Using deep learning to assist readers during the arbitration process: a lesion-based retrospective evaluation of breast cancer screening performance			
Feasibility	Anticipating artificial intelligence in mammography screening: views of Swedish breast radiologists	Preliminary Screening for Hereditary Breast and Ovarian Cancer Using a Chatbot Augmented Intelligence Genetic Counselor: Development and Feasibility Study	Feasibility of using AI to auto-catch responsible frames in ultrasound screening for breast cancer diagnosis			
Inclusivity / solution for specific populations / patient data	Acceptance of artificial intelligence (AI)-based screening for breast health in urban slums of central Karnataka, India – SWOC analysis	Designing culturally acceptable screening for breast cancer through artificial intelligence-two case studies	Multi-modal artificial intelligence for the combination of automated 3D breast ultrasound and mammograms in a population of women with predominantly dense breasts	An Ad Hoc Random Initialization Deep Neural Network Architecture for Discriminating Malignant Breast Cancer Lesions in Mammographic Images		
Machine learning	Comparison of the Performance of Machine Learning Algorithms in Breast Cancer Screening and	Over-the-Counter Breast Cancer Classification Using Machine Learning	Temporal Machine Learning Analysis of Prior Mammograms for Breast			

	Detection: A Protocol	and Patient Registration Records	Cancer Risk Prediction			
Proposed model / algorithm	Deep-LIBRA: An artificial-intelligence method for robust quantification of breast density with independent validation in breast cancer risk assessment	Monitoring Methodology for an AI Tool for Breast Cancer Screening Deployed in Clinical Centers	Tensor-Based Learning for Detecting Abnormalities on Digital Mammograms	A YOLO-based AI system for classifying calcifications on spot magnification mammograms	Breast Density Evaluation According to BI-RADS 5th Edition on Digital Breast Tomosynthesis: AI Automated Assessment Versus Human Visual Assessment	Fus2Net: a novel Convolutional Neural Network for classification of benign and malignant breast tumor in ultrasound images
Risk prediction	Multi-Institutional Validation of a Mammography-Based Breast Cancer Risk Model	Cost-effectiveness of using artificial intelligence versus polygenic risk score to guide breast cancer screening	External Validation of a Mammography-Derived AI-Based Risk Model in a U.S. Breast Cancer Screening Cohort of White and Black Women	A Clinical Risk Model for Personalized Screening and Prevention of Breast Cancer	Developing a Supplementary Diagnostic Tool for Breast Cancer Risk Estimation Using Ensemble Transfer Learning	
Time efficiency	Effect of artificial intelligence-based triaging of breast cancer screening mammograms on cancer detection and radiologist workload: a retrospective simulation study	Impact of artificial intelligence support on accuracy and reading time in breast tomosynthesis image interpretation: a multi-reader multi-case study	Possible strategies for use of artificial intelligence in screen-reading of mammograms, based on retrospective data from 122,969 screening examinations	Can we reduce the workload of mammographic screening by automatic identification of normal exams with artificial intelligence? A feasibility study	Improving the Performance of Radiologists Using Artificial Intelligence-Based Detection Support Software for Mammography: A Multi-Reader Study	
Validation	Pathways to breast cancer screening artificial intelligence algorithm validation	Independent External Validation of Artificial Intelligence Algorithms for Automated Interpretation of Screening Mammography: A Systematic Review	External Validation of an Ensemble Model for Automated Mammography Interpretation by Artificial Intelligence	Lessons learned from independent external validation of an AI tool to detect breast cancer using a representative UK data set		

Results and Discussion

Current Status

Many proposed models for AI are promising in the field of breast cancer screening. It is important that large data sets of digital breast tomosynthesis images are available for research in AI to be conducted (Buda et al., 2021). Before they can be tested for performance in a study, AI systems must be trained with those databases of mammograms (Bao et al., 2022).

Developments in AI

Developments in AI have been made to improve upon standard mammography methods that may not be as convenient for radiologists. The AI breast ultrasound diagnostic system was more accessible and detected more breast nodules, and thus likely more lesions, than did handheld ultrasound (Huang et al., 2023). Not only are new technologies being introduced, AI that has already been developed, such as the YOLACT algorithm, continues to improve as it was already modified and tested to improve diagnosis of MRI images to yield a much higher accuracy (Wang & Wang, 2023).

Efforts comparing radiologists and AI reveal its statistical accuracy. A small study with an AI clinical decision support system demonstrated an accuracy of over 80% for patients in determining if they needed a clinical trial (Haddad et al., 2021). In many findings discussed here, studies used the area under the receiver operating characteristic curve, or AUC, which assesses the true positive rate and the false positive rate on a graph. Generally, suspicious lesions were identified in mammograms with a higher percentage or AUC than radiologists (Dang et al., 2022). Sensitivity, the ability to diagnose a patient as having breast cancer, and specificity, the ability to diagnose a patient as not having it, are additional factors to consider.

AI can offer earlier and increased diagnoses at high risk of malignancy than human readers, which is particularly useful for women with dense breasts. It can detect a majority of missed cancers, eliminating false negatives (Kizildag Yirgin et al., 2022; Koch et al., 2023; Liao et al., 2023). With more carcinomas detected, the rate of interval cancer decreases (Byng et al., 2022).

Risk prediction is an estimation of how likely it is for someone to develop breast cancer in their lifetime. It is important to prioritize women who must be screened for breast cancer early and reduce unnecessary efforts on follow-ups that waste resources and time. These models aren't significantly different for different races (Gastounioti et al., 2022). Models are currently being tested in trials to confirm the consistency of their accuracy and benefit to target populations (Gastounioti et al., 2022; Yala et al., 2022). Adding lifestyle and family history risk factors further improved these models (Eriksson et al., 2023). For those with low risk, prediction with AI is the most cost-effective option that allows women to avoid screening entirely (Mital & Nguyen, 2022).

The safety and reliability of the technology is also being improved. One study proposed a novel method for evaluating AI with the Pearson correlation coefficient, which would help determine if the software was behaving normally or needed to be fixed (Aguilar et al., 2022). Optimistic views show that using AI to assess mammograms as a single reader can reduce the radiologist's workload significantly, even by more than half (Dembrower et al., 2020; Rodriguez-Ruiz et al., 2019). Based on a survey, the attitude towards integrating AI into their workload is generally positive in the view of a group of Swedish radiologists, but its exact use and medical ethics are still being debated. The majority of them believe that it will not change their profession significantly (Högberg et al., 2023).

Models and Algorithms of the Different Types of Artificial Intelligence

<u>Computer-Aided Design:</u> Computer-aided design, or CAD, is an AI option based on creating digital models to be put into use. It can be used to validate the BI-RADS scores, which are quantified breast cancer assessments, that radiologists determine (Van Zelst et al., 2019). When used with digital breast tomosynthesis images, CAD has proven to be superior to digital mammography, with improved reader performance, decreased reading time,

and detection. It also avoids the harmful radiation that is given as a consequence of mammograms (Uematsu et al., 2023). On top of these promising benefits, there are very affordable CADx engines (Kakileti et al., 2020). The best-performing CAD AI system in a case study showed a higher sensitivity than radiologists and optimistically aspires to be considered for FDA approval to work as an independent reader. For the average CAD system, however, it may be necessary to wait before it is put into use.

cmAssist, a specific CAD model, can detect the subtle masses that indicate invasive lobular carcinoma. Although that in itself may encourage it as a second reader, its false positive rate could even increase the amount of time for radiologists. Therefore, it's too early to determine its overall accuracy and hurts its potential (Arce et al., 2023). Evaluating the impact of the false positive rates will reveal the optimal decision in whether CAD should be used or not. Another study on cmAssist based on missed clinical cases argues that the false positive recall rate is less than 1%. Less experienced radiologists benefitted in particular from this model (Watanabe et al., 2019). Therefore, if it cannot yet be used in official diagnoses, radiologists may find AI useful in their training, assuming the lack of complete reliance on it.

<u>Machine and Deep Learning:</u> Machine learning (ML) models, which imitate the way humans learn, have been shown to be useful for risk prediction in several studies. ML has been developed as an over-the-counter screening that can be used in clinics to improve time efficiency (Hanis et al., 2022). They may be able to detect breast cancer biomarkers in blood tests, which would be a much more time and cost-efficient way (Salod & Singh, 2019). Images can differentiate benign and cancerous lesions and also provide insight into future cancerous growth using a long short-term memory network (Li et al., 2023).

A subset of ML is deep learning. Scientists have proposed deep learning models based on artificial neural networks, which mimic the neurons in the human brain, and have obtained fruitful results. The trend tends to be that mammograms have a more difficult time detecting breast cancer when the patient has high breast density, but one study claimed that their deep learning algorithms were not influenced by the density factor (Suh et al., 2020). There seems to have been the most progress in this particular area of AI based on the number of quality models.

An AI system notable for its accuracy after being tested on a large scale, Transpara, has developed many versions. The Transpara 1.4.0 AI system interpreted digital mammography exams on a risk scale of 1 to 10, and the AI system yielded an AUC of 0.840, while the radiologists' AUC was 0.814. Yet the best radiologists still consistently outperformed it (Rodriguez-Ruiz et al., 2019). With a similar method using a risk scale, Transpara 1.5.0's performance in detecting signs of interval cancer could be translated to a 19.3% reduction in the rate of interval cancer (Lång, Hofvind, et al., 2021). Later, Transpara 1.7.0 was tested with a considerable 122,969 mammogram exams, and more than 80% of the cancers were detected (Larsen et al., 2022). However, it's important to note that Transpara may not yield a drastic improvement if it is used as an aid. Despite catching most of the lesions, it misses the same ones that radiologists typically do (Johansson et al., 2021).

Deep-LIBRA is just as skilled as expert readers in estimating breast densities. This is useful for risk prediction because dense breast tissue can mask tumors, which must be considered in risk prediction (Haji Maghsoudi et al., 2021).

A tensor-based model, based on deep learning, was suggested to work off of smaller datasets. It was compared to other deep learning models and generally showed better performances. However, the preparation and training required beforehand made it time inefficient, so it may not be a feasible solution yet (Tzortzis et al., 2022).

A system based on You Only Look Once (YOLO) proved its accuracy on suspicious mammograms (with a BI-RADS equal to 4, signifying suspicious abnormality) and reduced the number of biopsies needed. While more investigation should be done, it was useful for determining malignity on spot magnification mammograms, which have better spatial resolution than screening mammograms (J.-L. Chen et al., 2023).

Deep learning models like the clustering-constrained Attention Multiple Instance Learning algorithm can help radiologists locate lesions based on relatively few labeled images (Bobowicz et al., 2023).

Segmentation algorithms demonstrate stability in the features and classify benign and malignant tumors at a comparable level to experts (Caballo et al., 2020). If human intervention decreases in the field, a model showed segmentation with low false positive rates and high sensitivity, which could be reliably used in automatic breast ultrasound screening (Zhang et al., 2022).

Convolutional Neural Networks: AI-based convolutional neural networks (CNNs), which are based on recognizing patterns in images, could also identify the malignity of calcifications. Deep CNNs show high accuracy in detecting lymph nodes, recommending itself as a radiologist aid (Abel et al., 2022). CNNs have shown a strong correlation with the BI-RADS categorization and abnormality scoring, which could help determine whether the subject must be further tested with a biopsy. That could potentially save time from going through the scrutiny and opinions of several radiologists. (Mansour et al., 2021).

ResNet50 was the best-performing model, with an accuracy of 97.58%, so it could be used as a backbone model (Frazer et al., 2021; Leong et al., 2022).

FEBrNet, which was tested with a limited amount of data, detects relevant frames to classify benign and malignant breast modules from ultrasounds at the same level as doctors. It seems feasible, with an AUC of 0.912, higher than the performance of ultrasound doctors (J. Chen et al., 2023).

Fus2Net has similar advantages as FEBrNet in classifying tumors that can help radiologists, and an analysis of its accuracy showed an AUC of 0.97 (Ma et al., 2021). Like Fus2Net, most models still need fine-tuning for optimization.

Advantages of AI in Breast Cancer Detection and Prevention

Complementary Tool

Studies have found that AI could be useful as a complementary tool. Using AI as a reader aid significantly improved diagnostic performance, reducing the number of unnecessary recalls, so the screening time was significantly shorter. At a small loss of sensitivity, AI greatly diminished the number of false positives. (Bao et al., 2022; Kerschke et al., 2022; Y. S. Kim et al., 2022; Lång, Dustler, et al., 2021). According to Kim et al., sometimes AI performs even better than radiologists, which makes it reasonable to be used as support (H.-E. Kim et al., 2020). In developing areas like Latin America, AI systems could be significantly more accessible and helpful in the early detection of breast cancer (Martín-Del-Campo-Mena et al., 2023). In general, it is more efficient to have these supplementary networks address nonsuspicious cases so the radiologists can handle the others (Hanis et al., 2022). Some studies argue that AI is already safe to use along with human readers, especially for detecting interval cancer because it won't have negative effects, even if they are limited (Oberije et al., 2023).

As a complementary tool, AI could specifically be used for double reading, a common process in screening in which two independent readers assess mammograms. The second reader being replaced by AI could detect more cancers while decreasing the workload for radiologists (Dahlblom et al., 2023; Larsen et al., 2022; Sharma et al., 2023). Reading time was reduced along with higher sensitivity and accuracy (van Winkel et al., 2021). This improvement held up for radiologists of any experience level (J. H. Lee et al., 2022). It has been proven to be more effective than the typical double-reading process with two radiologists (Salim et al., 2020).

Inclusivity

Implementing a new technology in healthcare takes time to be accepted in society. In underprivileged locations, AI thermal imaging can help increase accessibility because of lower prices compared to traditional radiation methods. A study conducted in the urban slums of India revealed that breast health was rare in their population, and recommends AI systems as a feasible solution. Women in areas like these should be interviewed about their perspectives on this service (Davalagi et al., 2022). By considering cultural aspects and gathering a sense of local opinion, AI is likely to be accepted more quickly (Bhattacharya et al., 2019).

AI chatbots are also growing in popularity for personalization. One was used to evaluate patient scenarios by having conversations with them to see if they were eligible for breast cancer screening. While still in its preliminary stages, this could be useful for determining family medical history and other criteria, because it doesn't require a radiologist's time (Sato et al., 2021).

Populations of Asian women with dense breasts also can benefit from AI detection, especially in places without many radiologists. A study suggests combined AI models that could increase performance, aid or outperform radiologists, and serve as an alternative in this situation (Tan et al., 2023, p. 3). Multimodal AI solutions could be refined to personalize treatment for patients who are all under different circumstances (Duggento et al., 2019).

Limitations

However, AI systems' edge over human radiologists is inconsistent. A large-scale study was done on an AI algorithm in comparison with radiologists reading the same screens. The readings for 108,970 mammograms showed that the AUC for AI was 0.10 less (Marinovich et al., 2023). A direct correlation between these numbers and effectiveness requires more testing to be clear. Infrared-AI showed comparable sensitivity (94.87%) to mammography but lower specificity (72.26%), and it has its limitations because factors such as breast density were not taken into consideration (Martín-Del-Campo-Mena et al., 2023).

Standalone AI is not yet as reliable as it would need to be to be used. AI software should not be allowed to make decisions about further screening exclusively because it doesn't completely match the radiologist's evaluation (Tari et al., 2023). A decision-referral approach is proposed by radiologists instead (Leibig et al., 2022). But even that could cause concern. Despite a 26% increase in cancer detection, a 53% increase in recall rate was seen when AI was used (Dahlblom et al., 2023). The majority of AI systems in one study revealed that their accuracy was lower than that of radiologists; thus, AI isn't ready to replace them (Freeman et al., 2021).

External Validation

AI algorithms must undergo external validation before they can be put into clinical practice. So far, in these studies, many limitations and concerns have been brought up, and none of them recommend AI implementation yet. External validation must be developed to gain a transparent understanding and confidence in AI. If AI doesn't prove to maintain and improve its accuracy, the FDA is unlikely to adopt it (C. I. Lee et al., 2020). AI's accuracy improvements are small, and its bias may hurt rather than help (Anderson et al., 2022). Even though they were trained with large data sets, some models performed much worse than radiologists on diverse patient populations (Hsu et al., 2022).

In double reading, the first reader's interpretation was always more different compared to the AI than the second human reader, which wouldn't be time efficient. Sensitivity was often found to be improved at the expense of specificity or vice versa, so it's important to note when one should be prioritized during a particular clinical situation. For instance, CAD as a validation assistant can discard malignant results. Technical issues are also involved with AI, such as errors and recalls. Therefore, more external validation studies would need to be performed to see the extent of the benefit of AI (Cushnan et al., 2023; Freeman et al., 2021).

Ethics

According to Jonmarker et al., there is a significant degree of trust in AI decision-making, even among older people who don't understand the technology as well. Less educated people tended to mistrust it (Jonmarker et al., 2019). However, based on current women's preferences, another study showed that there still isn't enough trust in AI to work independently of radiologists in double reading, especially because of the question of accountability in errors (Ongena et al., 2021). There is a rush to implement AI due to its potential, but it shouldn't be because it would be hard to reverse once it was. Therefore, it is important to continue evaluating bias, privacy, and responsibility concerns about AI in public discussions (Carter et al., 2019).

Conclusion

AI appears to be in its early stages and must be refined and further tested before being heavily relied on. Whether it's an increase in false positives or a decrease in specificity, the proper system must be used in the appropriate clinical context. AI systems have nuances among each other in function and what they're looking for in breast images. Based on the investigation of different models and factors involved in breast cancer screening that this review covered, AI is most helpful as a complementary tool. Experimentation drives the field forward, and it can become a trustworthy tool if professionals in technology and medicine continue to work together.

Acknowledgments

I would like to thank my advisor for the valuable insight provided to me on this topic.

References

Abel, F., Landsmann, A., Hejduk, P., Ruppert, C., Borkowski, K., Ciritsis, A., Rossi, C., & Boss, A. (2022). *Diagnostics | Free Full-Text | Detecting Abnormal Axillary Lymph Nodes on Mammograms Using a Deep Convolutional Neural Network*. https://www.mdpi.com/2075-4418/12/6/1347

Aguilar, C., Pacilè, S., Weber, N., & Fillard, P. (2022). *Life | Free Full-Text | Monitoring Methodology for an AI Tool for Breast Cancer Screening Deployed in Clinical Centers*. https://www.mdpi.com/2075-1729/13/2/440

Anderson, A. W., Marinovich, M. L., Houssami, N., Lowry, K. P., Elmore, J. G., Buist, D. S. M., Hofvind, S., & Lee, C. I. (2022). *Independent External Validation of Artificial Intelligence Algorithms for Automated Interpretation of Screening Mammography: A Systematic Review—Journal of the American College of Radiology*. https://www.jacr.org/article/S1546-1440(21)01023-1/fulltext

Arce, S., Vijay, A., Yim, E., Spiguel, L. R., & Hanna, M. (2023). *Cureus | Evaluation of an Artificial Intelligence System for Detection of Invasive Lobular Carcinoma on Digital Mammography*. https://www.cureus.com/articles/144590-evaluation-of-an-artificial-intelligence-system-for-detection-of-invasive-lobular-carcinoma-on-digital-mammography#!/

Bao, C., Shen, J., Zhang, Y., Zheng, Y., Wei, W., Wang, Z., Ding, J., & Han. (2022). *Evaluation of an artificial intelligence support system for breast cancer screening in Chinese people based on mammogram—Bao—2023—Cancer Medicine—Wiley Online Library*. https://onlinelibrary.wiley.com/doi/10.1002/cam4.5231

Bhattacharya, S., Sharma, N., & Singh, A. (2019). Designing culturally acceptable screening for breast cancer through artificial intelligence-two case studies. *Journal of Family Medicine and Primary Care*, *8*(2), 760. https://doi.org/10.4103/jfmpc.jfmpc_391_18

Bobowicz, M., Rygusik, M., Buler, J., Buler, R., Ferlin, M., Kwasigroch, A., Szurowska, E., & Grochowski, M. (2023). *Cancers | Free Full-Text | Attention-Based Deep Learning System for Classification of Breast Lesions—Multimodal, Weakly Supervised Approach*. https://doi.org/10.3390/cancers15102704

Briganti, G. (2023). Intelligence artificielle: Une introduction pour les cliniciens. *Revue Des Maladies Respiratoires*, *40*(4), 308–313. https://doi.org/10.1016/j.rmr.2023.02.005

Buda, M., Saha, A., Walsh, R., Ghate, S., Li, N., Święcicki, A., Lo, J. Y., & Mazurowski, M. A. (2021). A Data Set and Deep Learning Algorithm for the Detection of Masses and Architectural Distortions in Digital Breast Tomosynthesis Images. *JAMA Network Open*, *4*(8), e2119100. https://doi.org/10.1001/jamanetworkopen.2021.19100

Byng, D., Strauch, B., Gnas, L., Leibig, C., Stephan, O., Bunk, S., & Hecht, G. (2022). *AI-based prevention of interval cancers in a national mammography screening program—European Journal of Radiology*. https://www.ejradiology.com/article/S0720-048X(22)00171-1/fulltext

Caballo, M., Pangallo, D. R., Mann, R. M., & Sechopoulos, I. (2020). *Deep learning-based segmentation of breast masses in dedicated breast CT imaging: Radiomic feature stability between radiologists and artificial intelligence—ScienceDirect*. https://www.sciencedirect.com/science/article/pii/S0010482520300287?via%3Dihub#sec5

Carter, S. M., Rogers, W., Win, K. T., Frazer, H., Richards, B., & Houssami, N. (2019). *The ethical, legal and social implications of using artificial intelligence systems in breast cancer care—The Breast*. https://www.thebreastonline.com/article/S0960-9776(19)30564-8/fulltext

Cascella, M., Montomoli, J., Bellini, V., & Bignami, E. (2023). Evaluating the Feasibility of ChatGPT in Healthcare: An Analysis of Multiple Clinical and Research Scenarios. *Journal of Medical Systems*, *47*(1), 33. https://doi.org/10.1007/s10916-023-01925-4

Chen, J., Jiang, Y., Yang, K., Ye, X., Cui, C., Shi, S., Wu, H., Tian, H., Song, D., Yao, J., Wang, L., Huang, S., Xu, J., Xu, D., & Dong, F. (2023). Feasibility of using AI to auto-catch responsible frames in ultrasound screening for breast cancer diagnosis. *iScience*, *26*(1). https://doi.org/10.1016/j.isci.2022.105692

Chen, J.-L., Cheng, L.-H., Wang, J., Hsu, T.-W., Chen, C.-Y., Tseng, L.-M., & Guo. (2023). *A YOLO-based AI system for classifying calcifications on spot magnification mammograms | BioMedical Engineering OnLine | Full Text*. https://biomedical-engineering-online.biomedcentral.com/articles/10.1186/s12938-023-01115-w

Cushnan, D., Young, K. C., Ward, D., Halling-Brown, M. D., Duffy, S., Given-Wilson, R., Wallis, M. G., Wilkinson, L., Lyburn, I., Sidebottom, R., McAvinchey, R., Lewis, E. B., Mackenzie, A., & Warren. (2023). *Lessons learned from independent external validation of an AI tool to detect breast cancer* *using a representative UK data set*. https://www.birpublications.org/doi/10.1259/bjr.20211104#_i20

Dahlblom, V., Dustler, M., Tingberg, A., & Zackrisson, S. (2023). Breast cancer screening with digital breast tomosynthesis: Comparison of different reading strategies implementing artificial intelligence. *European Radiology*, *33*(5), 3754–3765. https://doi.org/10.1007/s00330-022-09316-y

Dang, L.-A., Chazard, E., Poncelet, E., Serb, T., Rusu, A., Pauwels, X., Parsy, C., Poclet, T., Cauliez, H., Engelaere, C., Ramette, G., Brienne, C., Dujardin, S., & Laurent, N. (2022). Impact of artificial intelligence in breast cancer screening with mammography. *Breast Cancer*, *29*(6), 967–977. https://doi.org/10.1007/s12282-022-01375-9

Davalagi, S. B., Palicheralu, B. S., Murthy, S. S. N., & Hurlihal, S. (2022). Acceptance of artificial intelligence (AI)-based screening for breast health in urban slums of central Karnataka, India – SWOC analysis. *Journal of Family Medicine and Primary Care*, *11*(10), 6023–6028. https://doi.org/10.4103/jfmpc.jfmpc_143_22

Dembrower, K., Wåhlin, E., Liu, Y., Salim, M., Smith, K., Lindholm, P., Eklund, M., & Strand, F. (2020). Effect of artificial intelligence-based triaging of breast cancer screening mammograms on cancer detection and radiologist workload: A retrospective simulation study. *The Lancet Digital Health*, *2*(9), e468–e474. https://doi.org/10.1016/S2589-7500(20)30185-0

Duggento, A., Aiello, M., Cavaliere, C., Cascella, G. L., Cascella, D., Conte, G., Guerrisi, M., & Toschi, N. (2019). An Ad Hoc Random Initialization Deep Neural Network Architecture for Discriminating Malignant Breast Cancer Lesions in Mammographic Images. *Contrast Media & Molecular Imaging*, *2019*, e5982834. https://doi.org/10.1155/2019/5982834

Eriksson, M., Czene, K., Vachon, C., Conant, E. F., & Hall, P. (2023). *Cancers | Free Full-Text | A Clinical Risk Model for Personalized Screening and Prevention of Breast Cancer*. https://doi.org/10.3390/cancers15123246

Frazer, H. M., Qin, A. K., Pan, H., & Brotchie, P. (2021). Evaluation of deep learning-based artificial intelligence techniques for breast cancer detection on mammograms: Results from a retrospective study using a BreastScreen Victoria dataset. *Journal of Medical Imaging and Radiation Oncology*, *65*(5), 529–537. https://doi.org/10.1111/1754-9485.13278

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. *BMJ*, *374*, n1872. https://doi.org/10.1136/bmj.n1872

Gastounioti, A., Eriksson, M., Cohen, E. A., Mankowski, W., Pantalone, L., Ehsan, S., McCarthy, A. M., Kontos, D., Hall, P., & Conant, E. F. (2022). External Validation of a Mammography-Derived AI-Based Risk Model in a U.S. Breast Cancer Screening Cohort of White and Black Women. *Cancers*, *14*(19), Article 19. https://doi.org/10.3390/cancers14194803

Giaquinto, A. N., Sung, H., Miller, K. D., Kramer, J. L., Newman, L. A., Minihan, A., Jemal, A., & Siegel, R. L. (2022). Breast Cancer Statistics, 2022. *CA: A Cancer Journal for Clinicians*, *72*(6), 524–541. https://doi.org/10.3322/caac.21754

Haddad, T., Helgeson, J. M., Pomerleau, K. E., Preininger, A. M., Roebuck, M. C., Dankwa-Mullan, I., Jackson, G. P., & Goetz, M. P. (2021). Accuracy of an Artificial Intelligence System for Cancer Clinical Trial Eligibility Screening: Retrospective Pilot Study. *JMIR Medical Informatics*, *9*(3), e27767. https://doi.org/10.2196/27767

Haji Maghsoudi, O., Gastounioti, A., Scott, C., Pantalone, L., Wu, F.-F., Cohen, E. A., Winham, S., Conant, E. F., Vachon, C., & Kontos, D. (2021). Deep-LIBRA: An artificial-intelligence method for robust quantification of breast density with independent validation in breast cancer risk assessment. *Medical Image Analysis*, *73*, 102138. https://doi.org/10.1016/j.media.2021.102138

Hanis, T. M., Ruhaiyem, N. I. R., Arifin, W. N., Haron, J., Rahman, W. F. W. A., Abdullah, R., & Musa, K. I. (2022). *Diagnostics | Free Full-Text | Over-the-Counter Breast Cancer Classification Using Machine Learning and Patient Registration Records*. https://www.mdpi.com/2075-4418/12/11/2826

Högberg, C., Larsson, S., & Lång, K. (2023). *Anticipating artificial intelligence in mammography screening: Views of Swedish breast radiologists | BMJ Health & Care Informatics*. https://informatics.bmj.com/content/30/1/e100712

Hsu, W., Hippe, D. S., Nakhaei, N., Wang, P.-C., Zhu, B., Siu, N., Ahsen, M. E., Lotter, W., Sorensen, A. G., Naeim, A., Buist, D. S. M., Schaffter, T., Guinney, J., Elmore, J. G., & Lee, C. I. (2022). External Validation of an Ensemble Model for Automated Mammography Interpretation by Artificial Intelligence. *JAMA Network Open*, *5*(11), e2242343. https://doi.org/10.1001/jamanetworkopen.2022.42343

Huang, X., Qiu, Y., Bao, F., Wang, J., Lin, C., Lin, Y., Wu, J., & Yang, H. (2023). *Frontiers | Artificial intelligence breast ultrasound and handheld ultrasound in the BI-RADS categorization of breast lesions: A pilot head to head comparison study in screening program*. https://www.frontiersin.org/articles/10.3389/fpubh.2022.1098639/full

Johansson, G., Olsson, C., Smith, F., Edegran, M., & Björk-Eriksson, T. (2021). *AI-aided detection of malignant lesions in mammography screening – evaluation of a program in clinical practice*. https://www.birpublications.org/doi/10.1259/bjro.20200063

Jonmarker, O., Strand, F., Brandberg, Y., & Lindholm. (2019). *The future of breast cancer screening: What do participants in a breast cancer screening program think about automation using artificial intelligence? - Olof Jonmarker, Fredrik Strand, Yvonne Brandberg, Peter Lindholm, 2019*. https://journals.sagepub.com/doi/10.1177/2058460119880315

Kakileti, S. T., Madhu, H. J., Krishnan, L., Manjunath, G., Sampangi, S., & Ramprakash, H. V. (2020). Observational Study to Evaluate the Clinical Efficacy of Thermalytix for Detecting Breast Cancer in Symptomatic and Asymptomatic Women. *JCO Global Oncology*, *6*, 1472–1480. https://doi.org/10.1200/GO.20.00168

Kerschke, L., Weigel, S., Rodriguez-Ruiz, A., Karssemeijer, N., & Heindel, W. (2022). Using deep learning to assist readers during the arbitration process: A lesion-based retrospective evaluation of breast cancer screening performance. *European Radiology*, *32*(2), 842–852.

https://doi.org/10.1007/s00330-021-08217-w

Kim, H.-E., Kim, H. H., Han, B.-K., Kim, K. H., Han, K., Nam, H., Lee, E. H., & Kim, E.-K. (2020). Changes in cancer detection and false-positive recall in mammography using artificial intelligence: A retrospective, multireader study. *The Lancet Digital Health*, *2*(3), e138–e148. https://doi.org/10.1016/S2589-7500(20)30003-0

Kim, Y. S., Jang, M., Lee, S. H., Kim, S.-Y., Ha, S. M., Kwon, B. R., Moon, W. K., & Chang, J. M. (2022). Use of Artificial Intelligence for Reducing Unnecessary Recalls at Screening Mammography: A Simulation Study. *Korean Journal of Radiology*, *23*(12), 1241–1250. https://doi.org/10.3348/kjr.2022.0263

Kizildag Yirgin, I., Koyluoglu, Y. O., Seker, M. E., Ozkan Gurdal, S., Ozaydin, A. N., Ozcinar, B., Cabioğlu, N., Ozmen, V., & Aribal, E. (2022). Diagnostic Performance of AI for Cancers Registered in A Mammography Screening Program: A Retrospective Analysis. *Technology in Cancer Research & Treatment*, *21*, 15330338221075172. https://doi.org/10.1177/15330338221075172

Koch, H. W., Larsen, M., Bartsch, H., Kurz, K. D., & Hofvind, S. (2023). Artificial intelligence in BreastScreen Norway: A retrospective analysis of a cancer-enriched sample including 1254 breast cancer cases. *European Radiology*, *33*(5), 3735–3743. https://doi.org/10.1007/s00330-023-09461-y

Lång, K., Dustler, M., Dahlblom, V., Åkesson, A., Andersson, I., & Zackrisson, S. (2021). Identifying normal mammograms in a large screening population using artificial intelligence. *European Radiology*, *31*(3), 1687–1692. https://doi.org/10.1007/s00330-020-07165-1

Lång, K., Hofvind, S., Rodríguez-Ruiz, A., & Andersson, I. (2021). Can artificial intelligence reduce the interval cancer rate in mammography screening? *European Radiology*, *31*(8), 5940–5947. https://doi.org/10.1007/s00330-021-07686-3

Larsen, M., Aglen, C. F., Hoff, S. R., Lund-Hanssen, H., & Hofvind, S. (2022). Possible strategies for use of artificial intelligence in screen-reading of mammograms, based on retrospective data from 122,969 screening examinations. *European Radiology*, *32*(12), 8238–8246. https://doi.org/10.1007/s00330-022-08909-x

Larsen, M., Aglen, C. F., Lee, C. I., Hoff, S. R., Lund-Hanssen, H., Lång, K., Nygård, J. F., Ursin, G., & Hofvind, S. (2022). *Artificial Intelligence Evaluation of 122 969 Mammography Examinations from a Population-based Screening Program | Radiology*. https://pubs.rsna.org/doi/full/10.1148/radiol.212381

Lee, C. I., Houssami, N., Elmore, J. G., & Buist, D. S. M. (2020). Pathways to breast cancer screening artificial intelligence algorithm validation. *The Breast*, *52*, 146–149. https://doi.org/10.1016/j.breast.2019.09.005

Lee, J. H., Kim, K. H., Lee, E. H., Ahn, J. S., Ryu, J. K., Park, Y. M., Shin, G. W., Kim, Y. J., & Choi, H. Y. (2022). Improving the Performance of Radiologists Using Artificial Intelligence-Based Detection Support Software for Mammography: A Multi-Reader Study. *Korean Journal of Radiology*, *23*(5), 505–516. https://doi.org/10.3348/kjr.2021.0476

Leibig, C., Brehmer, M., Bunk, S., Byng, D., Pinker, K., & Umutlu. (2022). *Combining the strengths of radiologists and AI for breast cancer screening: A retrospective analysis—The Lancet Digital Health.* https://www.thelancet.com/journals/landig/article/PIIS2589-7500(22)00070-X/fulltext

Leong, Y. S., Hasikin, K., Lai, K. W., Mohd Zain, N., & Azizan, M. M. (2022). Microcalcification Discrimination in Mammography Using Deep Convolutional Neural Network: Towards Rapid and Early Breast Cancer Diagnosis. *Frontiers in Public Health*, *10*. https://www.frontiersin.org/articles/10.3389/fpubh.2022.875305

Li, H., Robinson, K., Lan, L., Baughan, N., Chan, C.-W., Embury, M., Whitman, G. J., El-Zein, R., Bedrosian, I., & Giger, M. L. (2023). Temporal Machine Learning Analysis of Prior Mammograms for Breast Cancer Risk Prediction. *Cancers*, *15*(7), Article 7. https://doi.org/10.3390/cancers15072141

Liao, J., Gui, Y., Li, Z., Deng, Z., Han, X., Tian, H., Cai, L., Liu, X., Tang, C., Liu, J., Wei, Y., Hu, L., Niu, F., Liu, J., Yang, X., Li, S., Cui, X., Wu, X., Chen, Q., … Chen, L. (2023). Artificial intelligence-assisted ultrasound image analysis to discriminate early breast cancer in Chinese population: A retrospective, multicentre, cohort study. *eClinicalMedicine*, *60*. https://doi.org/10.1016/j.eclinm.2023.102001

Ma, H., Tian, R., Li, H., Sun, H., Lu, G., Liu, R., & Wang, Z. (2021). *Fus2Net: A novel Convolutional Neural Network for classification of benign and malignant breast tumor in ultrasound images | BioMedical Engineering OnLine | Full Text*. https://biomedical-engineering-online.biomedcentral.com/articles/10.1186/s12938-021-00950-z

Mansour, S., Kamal, R., Hasherm, L., & AlKalaawy, B. (2021). *Can artificial intelligence replace ultrasound as a complementary tool to mammogram for the diagnosis of the breast cancer?* https://www.birpublications.org/doi/10.1259/bjr.20210820

Marinovich, M. L., Wylie, E., Lotter, W., Lund, H., Waddell, A., Madeley, C., Pereira, G., & Houssami, N. (2023). Artificial intelligence (AI) for breast cancer screening: BreastScreen population-based cohort study of cancer detection. *eBioMedicine*, *90*. https://doi.org/10.1016/j.ebiom.2023.104498

Martín-Del-Campo-Mena, E., Sánchez-Méndez, P. A., Ruvalcaba-Limon, E., Lazcano-Ramírez, F. M., Hernández-Santiago, A., Juárez-Aburto, J. A., Larios-Cruz, K. Y., Hernández-Gómez, L. E., Merino-González, J. A., & González-Mejía, Y. (2023). Development and validation of an infrared-artificial intelligence software for breast cancer detection. *Exploration of Targeted Anti-Tumor Therapy*, *4*(2), 294–306. https://doi.org/10.37349/etat.2023.00135

Mital, S., & Nguyen, H. V. (2022). Cost-effectiveness of using artificial intelligence versus polygenic risk score to guide breast cancer screening. *BMC Cancer*, *22*(1), 501. https://doi.org/10.1186/s12885-022-09613-1

Oberije, C. J. G., Sharma, N., James, J. J., Ng, A. Y., Nash, J., & Kecskemethy, P. D. (2023). Comparing Prognostic Factors of Cancers Identified by Artificial Intelligence (AI) and Human Readers in Breast Cancer Screening. *Cancers*, *15*(12), Article 12. https://doi.org/10.3390/cancers15123069

Ongena, Y. P., Yakar, D., Haan, M., & Kwee, T. C. (2021). Artificial Intelligence in Screening Mammography: A Population Survey of Women's Preferences. *Journal of the American College of Radiology*, *18*(1, Part A), 79–86. https://doi.org/10.1016/j.jacr.2020.09.042

Ren, W., Chen, M., Qiao, Y., & Zhao, F. (2022). Global guidelines for breast cancer screening: A systematic review. *The Breast*, *64*, 85–99. https://doi.org/10.1016/j.breast.2022.04.003

Rodriguez-Ruiz, A., Lång, K., Gubern-Merida, A., Broeders, M., Gennaro, G., Clauser, P., Helbich, T. H., Chevalier, M., Tan, T., Mertelmeier, T., Wallis, M. G., Andersson, I., Zackrisson, S., Mann, R. M., & Sechopoulos, I. (2019). *Stand-Alone Artificial Intelligence for Breast Cancer Detection in Mammography: Comparison With 101 Radiologists | JNCI: Journal of the National Cancer Institute | Oxford Academic*. https://academic.oup.com/jnci/article/111/9/916/5307077?login=false

Rodriguez-Ruiz, A., Lång, K., Gubern-Merida, A., Teuwen, J., Broeders, M., Gennaro, G., Clauser, P., Helbich, T. H., Chevalier, M., Mertelmeier, T., Wallis, M. G., Andersson, I., Zackrisson, S., Sechopoulos, I., & Mann, R. M. (2019). Can we reduce the workload of mammographic screening by automatic identification of normal exams with artificial intelligence? A feasibility study. *European Radiology*, *29*(9), 4825–4832. https://doi.org/10.1007/s00330-019-06186-9

Salim, M., Wåhlin, E., Dembrower, K., Azavedo, E., Foukakis, T., Liu, Y., Smith, K., Eklund, M., & Strand, F. (2020). External Evaluation of 3 Commercial Artificial Intelligence Algorithms for Independent Assessment of Screening Mammograms. *JAMA Oncology*, *6*(10), 1581–1588. https://doi.org/10.1001/jamaoncol.2020.3321

Salod, Z., & Singh, Y. (2019). *Comparison of the Performance of Machine Learning Algorithms in Breast Cancer Screening and Detection: A Protocol—Zakia Salod, Yashik Singh, 2019*. https://journals.sagepub.com/doi/10.4081/jphr.2019.1677

Sato, A., Haneda, E., Suganuma, N., & Narimatsu, H. (2021). Preliminary Screening for Hereditary Breast and Ovarian Cancer Using a Chatbot Augmented Intelligence Genetic Counselor: Development and Feasibility Study. *JMIR Formative Research*, *5*(2), e25184. https://doi.org/10.2196/25184

SEER. (2023). *Cancer of the Breast (Female)—Cancer Stat Facts*. SEER. https://seer.cancer.gov/statfacts/html/breast.html

Sharma, N., Ng, A. Y., James, J. J., Khara, G., Ambrózay, É., Austin, C. C., Forrai, G., Fox, G., Glocker, B., Heindl, A., Karpati, E., Rijken, T. M., Venkataraman, V., Yearsley, J. E., & Kecskemethy, P. D. (2023). Multi-vendor evaluation of artificial intelligence as an independent reader for double reading in breast cancer screening on 275,900 mammograms. *BMC Cancer*, *23*(1), 460. https://doi.org/10.1186/s12885-023-10890-7

Siegel, R. L., Miller, K. D., Wagle, N. S., & Jemal, A. (2023). Cancer statistics, 2023. *CA: A Cancer Journal for Clinicians*, *73*(1), 17–48. https://doi.org/10.3322/caac.21763

Suh, Y. J., Jung, J., & Cho. (2020). *JPM | Free Full-Text | Automated Breast Cancer Detection in Digital Mammograms of Various Densities via Deep Learning*. https://www.mdpi.com/2075-4426/10/4/211

Tan, T., Rodriguez-Ruiz, A., Zhang, T., Xu, L., Beets-Tan, R. G. H., Shen, Y., Karssemeijer, N., Xu, J., Mann, R. M., & Bao, L. (2023). Multi-modal artificial intelligence for the combination of automated 3D breast ultrasound and mammograms in a population of women with predominantly dense breasts. *Insights into Imaging*, *14*(1), 10. https://doi.org/10.1186/s13244-022-01352-y

Tari, D. U., Santonastaso, R., De Lucia, D. R., Santarsiere, M., & Pinto, F. (2023). *JPM | Free Full-Text | Breast Density Evaluation According to BI-RADS 5th Edition on Digital Breast Tomosynthesis: AI Automated Assessment Versus Human Visual Assessment*. https://www.mdpi.com/2075-4426/13/4/609

Tzortzis, I. N., Davradou, A., Rallis, I., Kaselimi, M., Makantasis, K., Doulamis, A., & Doulamis, N. (2022). *Diagnostics | Free Full-Text | Tensor-Based Learning for Detecting Abnormalities on Digital Mammograms*. https://www.mdpi.com/2075-4418/12/10/2389

Uematsu, T., Nakashima, K., Harada, T. L., Nasu, H., & Igarashi, T. (2023). Comparisons between artificial intelligence computer-aided detection synthesized mammograms and digital mammograms when used alone and in combination with tomosynthesis images in a virtual screening setting. *Japanese Journal of Radiology*, *41*(1), 63–70. https://doi.org/10.1007/s11604-022-01327-5

van Winkel, S. L., Rodríguez-Ruiz, A., Appelman, L., Gubern-Mérida, A., Karssemeijer, N., Teuwen, J., Wanders, A. J. T., Sechopoulos, I., & Mann, R. M. (2021). Impact of artificial intelligence support on accuracy and reading time in breast tomosynthesis image interpretation: A multi-reader multi-case study. *European Radiology*, *31*(11), 8682–8691. https://doi.org/10.1007/s00330-021-07992-w

Van Zelst, J. C., Tan, T., Mann, R. M., & Karssemeijer, N. (2019). *Validation of radiologists' findings by computer-aided detection (CAD) software in breast cancer detection with automated 3D breast ultrasound: A concept study in implementation of artificial intelligence software—Jan CM van Zelst, Tao Tan, Ritse M Mann, Nico Karssemeijer, 2020.* https://journals.sagepub.com/doi/10.1177/0284185119858051

Wang, W., & Wang, Y. (2023). *Diagnostics | Free Full-Text | Deep Learning-Based Modified YOLACT Algorithm on Magnetic Resonance Imaging Images for Screening Common and Difficult Samples of Breast Cancer*. https://www.mdpi.com/2075-4418/13/9/1582

Watanabe, A. T., Lim, V., Vu, H. X., Chim, R., Weise, E., Liu, J., Bradley, W. G., & Comstock, C. E. (2019). Improved Cancer Detection Using Artificial Intelligence: A Retrospective Evaluation of Missed Cancers on Mammography. *Journal of Digital Imaging*, *32*(4), 625–637. https://doi.org/10.1007/s10278-019-00192-5

Yala, A., Mikhael, P. G., Strand, F., Lin, G., Satuluru, S., Kim, T., Banerjee, I., Gichoya, J., Trivedi, H., Lehman, C. D., Hughes, K., Sheedy, D. J., Matthis, L. M., Karunakaran, B., Hegarty, K. E., Sabino, S., Silva, T. B., Evangelista, M. C., Caron, R. F., … Barzilay, R. (2022). *Multi-Institutional Validation of a Mammography-Based Breast Cancer Risk Model | Journal of Clinical Oncology*. https://ascopubs.org/doi/full/10.1200/JCO.21.01337

Zhang, S., Liao, M., Wang, J., Zhu, Y., Zhang, Y., Zhang, J., Zheng, R., Zhu, L. L. D., Chen, H., & Wang, W. (2022). *Fully automatic tumor segmentation of breast ultrasound images with deep learning—*

Zhang—2023—Journal of Applied Clinical Medical Physics—Wiley Online Library.
https://aapm.onlinelibrary.wiley.com/doi/full/10.1002/acm2.13863