Review Article

Use of artificial intelligence in breast surgery: a narrative review

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Background and Objective: We have witnessed tremendous advances in artificial intelligence (AI) technologies. Breast surgery, a subspecialty of general surgery, has notably benefited from AI technologies. This review aims to evaluate how AI has been integrated into breast surgery practices, to assess its effectiveness in improving surgical outcomes and operational efficiency, and to identify potential areas for future research and application.

Methods: Two authors independently conducted a comprehensive search of PubMed, Google Scholar, EMBASE, and Cochrane CENTRAL databases from January 1, 1950, to September 4, 2023, employing keywords pertinent to AI in conjunction with breast surgery or cancer. The search focused on English language publications, where relevance was determined through meticulous screening of titles, abstracts, and full-texts, followed by an additional review of references within these articles. The review covered a range of studies illustrating the applications of AI in breast surgery encompassing lesion diagnosis to postoperative follow-up. Publications focusing specifically on breast reconstruction were excluded.

Key Content and Findings: AI models have preoperative, intraoperative, and postoperative applications in the field of breast surgery. Using breast imaging scans and patient data, AI models have been designed to predict the risk of breast cancer and determine the need for breast cancer surgery. In addition, using breast imaging scans and histopathological slides, models were used for detecting, classifying, segmenting, grading, and staging breast tumors. Preoperative applications included patient education and the display of expected aesthetic outcomes. Models were also designed to provide intraoperative assistance for precise tumor resection and margin status assessment. As well, AI was used to predict postoperative complications, survival, and cancer recurrence.

Conclusions: Extra research is required to move AI models from the experimental stage to actual implementation in healthcare. With the rapid evolution of AI, further applications are expected in the coming years including direct performance of breast surgery. Breast surgeons should be updated with the advances in AI applications in breast surgery to provide the best care for their patients.

Keywords: Artificial intelligence (AI); breast surgery; breast imaging

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Introduction

Background

The first concept of computer systems as an imitator of human intelligence was conceived by Turing in 1950 (1). Artificial intelligence (AI) is a particular computer system or machine that can solve problems that usually require human intelligence. Early generations performed a simple algorithm of 'if, then' rules, but subsequent developments in technology and coding have resulted in complex systems that can operate similarly to human intelligence, including the ability to learn from past errors and cross-check results (1-3). Such capacity, coupled with fast processing times and no requirement for rest has created a formidable tool at the heart of the fourth industrial revolution.

Machine learning (ML) is a subset of AI in which the algorithm improves its performance (mode of analysis and patterns) by learning from new datasets without being explicitly re-programmed. The data used for learning may exist in the form of imported features (e.g., breast lesion density) or the form of raw data (e.g., radiological images). Deep learning (DL) is a subset of ML that involves the stacking of multiple algorithmic components into layers, each feeding into the next, operating on raw data and self-learn high-level features. DL models include convolutional, recurrent, and artificial neural networks (CNN, RNN, and ANN), generative adversarial networks (GAN), deep belief nets, and autoencoders (4-9). CNN are designed specifically to analyze and find features from images as seen in *Figure 1* (10). Large language models (LLMs) are another type of AI that utilizes natural language processing methods to synthesize user inputs and generate human-like speech (11-13). They have been used to aid diagnosis, medical research, and improve hospital workflow (14-20).

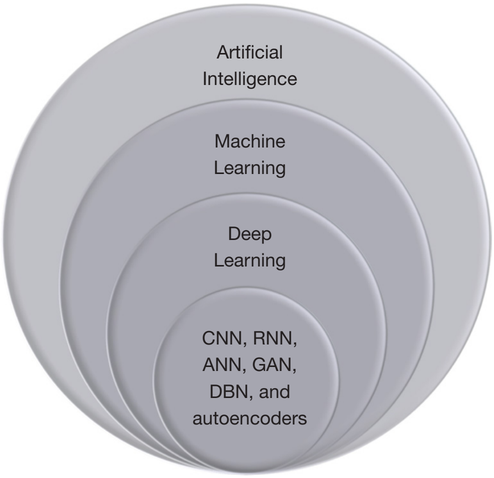

Figure 1 Subsets of artificial intelligence. CNN, convolutional neural networks; RNN, recurrent neural networks; ANN, artificial neural networks; GAN, generative adversarial networks; DBN, deep belief network.

Rationale and knowledge gap

AI models are rapidly evolving and present one of the most significant developments in information processing and problem solving in health care the past 50 years (21). As widespread health data collection creates enormous volumes of information, this data must be processed by consequently more complex systems. AI models are currently applied to optimize different aspects of patients' care including disease risk prediction, diagnosis, treatment decision-making, predicting treatment response, and predicting survival (2,4,5,22-24). By being able to operate on large volumes of data with high precision, AI models offer distinct advantages over unassisted human performance. A recent publication has successfully elucidated the applications of AI technologies within breast reconstructive procedures, where the authors highlight the promising role of AI in advancing breast reconstruction techniques (25). However, authors state refinement of AI algorithm with cross-disciplinary partnerships for prioritizing their dataset. The scope of breast surgery is much greater than reconstruction alone and further research is needed to characterize the current and prospective implementation of AI in the field.

Objective

Breast cancer is increasing in prevalence and is the leading cause of cancer death among women (26-29). Breast surgery can be used as a prototypical example for the application of AI in healthcare. It is a field comprising population health, risk prediction, diagnostic tests, medical and surgical treatments and integrated health systems and economics, all of which can directly benefit from various mechanisms of AI (30,31). We performed this review aiming to summarize the current literature findings on the application of AI in diagnosing breast lesions as well as preoperative, intraoperative, and postoperative applications of AI in breast surgery. We present this article in accordance with the Narrative Review reporting checklist (available at https://gs.amegroups.com/article/view/10.21037/gs-23-414/rc).

Table 1 Search strategy for this review

Item	Specification
Date of search	13/9/2023
Databases searched	PubMed, Google Scholar, EMBASE, Cochrane CENTRAL
Search terms used	#1 ("artificial intelligence" [Mesh] OR "machine learning" [Mesh] OR "deep learning" [Mesh]))
	#2 ("breast surgery" [Mesh] OR "breast neoplasm" [Mesh]) #1 AND #2
Timeframe	1/1/1950 to 4/9/2023
Inclusion and exclusion criteria	Studies that discussed any application of artificial intelligence in breast surgery were included in this review
	Studies reported in a language other than English were excluded
Selection process	I.S., B.L., K.J., D.G. and Y.X. conducted the selection, searched and discussed which studies were relevant until consensus was reached

Methods

PubMed, Google Scholar, EMBASE, and Cochrane CENTRAL databases were searched by two authors for relevant studies using the keywords: ("artificial intelligence" [Mesh] OR "machine learning" [Mesh] OR "deep learning" [Mesh]) AND ("breast surgery" [Mesh] OR "breast cancer" [Mesh]) from January 1st, 1950 to 4th of September, 2023. Relevant English publications were included in our review without publication time constraints. Publication relevance was determined by title and abstract screening followed by a full-text screening. In addition, the reference lists of the included publications were screened for inclusion of further relevant studies. We included studies that discussed the applications of AI in different aspects of breast surgery from breast lesion diagnosis to postoperative follow-up (*Table 1*). Publications focusing specifically on breast reconstructions were excluded from this review.

Results

AI applications in breast lesion diagnosis

Recent advances in CNN-based computer vision algorithms and growing training datasets has allowed AI to be used in medical imaging and histopathology for breast pathologies (32-35). Such systems can not only create streamlined workflows for reporting clinicians but may also improve diagnostic accuracy. This is especially true in large population breast screening programs (6,7,33,34). Modern feedforward ANN utilize multilayered perceptron to analyze images by classifying them to different color channels, processing the pixel-level images using nonlinear functions, and outputting probability distributions (36). As such, these algorithms have the promise to detect lesions not easily visible to human observers.

Digital mammography (DM)

DM is a breast imaging technique that produces 2-dimensional radiographic images. This imaging modality is used for breast cancer screening because of its feasibility and efficacy in detecting asymmetries, distorted architecture, and abnormal calcifications in breast lesions. Nevertheless, DM image interpretation is difficult and needs extensive experience (37). Smaller lesions can be missed due to obscuration by the overlying breast tissue. This is encountered mostly in younger females who have high breast tissue densities due to higher concentrations of fibroglandular tissue. Therefore, DM images are taken in a mediolateral oblique view and a craniocaudal view (38).

The application of AI in DM image interpretation was introduced in the 1990s and has since evolved with the advances of DL (39-42). DL-based models such as CNNs autonomously learn to identify specific imaging features to differentiate benign breast lesions from malignant ones (43-45). Several studies have been conducted to evaluate the efficacy of AI-based systems on detecting and classifying breast lesions on DM images and have found that AI-based DM image evaluation is noninferior and may be superior to radiologists (39,40,42,46-49). A study conducted by Romero-Martín *et al.* evaluated the performance of DL-based systems in DM image assessment. Their findings suggest that DL-based systems have an equivalent sensitivity in detecting and classifying breast lesions when compared to the best standard (radiologists). In addition, DL methods have been shown to decrease over-investigation by decreasing breast imaging recall rates (subsequent images for evaluating a suspicious lesion) (48). Another study by Burhenne *et al.* detected the missed findings in 77% of false-negative mammographic images by subsequent applications of AI (50). Thus, AI applications in mammography can improve breast cancer screening programs' efficiency with reduced need for human efforts (51,52). Moreover, AI-based models have been proven efficacious in predicting the risk of developing breast cancer in the future by utilizing data collected from DM images (53,54).

Digital breast tomosynthesis (DBT)

DBT is an X-ray-based imaging modality that takes images from different angles to create a partial tomographic 3-dimensional (3D) image, minimizing the problem of tissue superposition (55). However, the complexities associated with DBT result in difficult image interpretation, and longer reading times when compared to DM (56). This has represented another area for AI models to improve efficiency and accuracy.

When evaluated versus the best available standard (radiologists), AI-based DBT image assessment models show non-inferior efficacy in detecting and classifying breast lesions with reduced false-negative rates (39,46-48,57). AI-based DBT interpretation systems are cost-effective, as they improve radiologists' performance and reduce DBT reading time (58,59). However, in contrast to in DM evaluation, AI-based DBT image evaluation models can result in higher recall rates for further evaluation (48). This may be because DL models can pick up trivial microcalcifications in breast tissue (60).

There exist differences in the utility of different AI models when it comes to DBT analysis. DL models that use multiple images as an input to compare DBT images show better performance in detecting and classifying breast masses when compared to those their single-view counterparts (42,61-64). This benefit extends to techniques that uses multiple views of the ipsilateral breast as the aforementioned input (64). In 2023, Ren *et al.* proposed a framework for a multi-view detection framework to adaptively refine single view detection scores by matching lesions between two ipsilateral screening views of each breast (65). Their framework, developed from 8,034 DBT cases, improved screening performance without significantly increasing analysis run-time. Another subset of DL, GAN, can generate new images from an input set of images. This was successfully applied in breast imaging to generate DM images from already existing DBT images. Hence, more patient data is acquired without additional radiation exposure (66).

Images imported to AI-based diagnostic models are suspected to include lesions. These images are usually extracted by hand from entire DM or DBT scans (43). AI models can be used to support radiologists in their work by preselecting suspicious lesions for subsequent assessment by radiologists (51,52). These models can even calculate the regional probability of cancers from the DM or DBT scan (38). Accordingly, complete DM and DBT scans can be used as input to DL image assessment models (67-69). In 2017, Kooi *et al.* trained a CNN on a dataset of 45,000 mammographic images and found it non-inferior to radiologists at triaging images, and superior to a computer aided detection model that relied on human input (43).

Ultrasound (US)

US of the breast is an imaging modality that depends on sending sound waves through the breast tissue and simultaneously detecting the backscattered waves to construct the image. Thus, US carries no risk of ionizing radiation. It is, however, an operator-dependent imaging modality that can be difficult to read. The images are displayed as they are generated, and breast US should therefore be performed by an expert for direct interpretation (69). Yet, resource constraints often prevent a radiologist's expertise from being available at the time of imaging. This represents another opportunity for AI to reduce burden on healthcare systems.

DL was initially used in conjunction with US for classifying breast lesions into benign or malignant (68-72). Studies on breast lesion detection and classification using DL from US images have concluded a high accuracy in detecting and classifying lesions when the input is full US images, and a much higher accuracy when the input consists of US images of suspicious lesions (71,73-76). To classify US images of breast lesions, radiologists use the Breast Imaging Reporting and Data System (BI-RADS) that incorporates the probability of lesion malignancy and the recommended management (77). However, inter-observer variability can be high, and misclassification can result. DL models have been applied to effectively assist radiologists in choosing the appropriate BI-RADS class (78,79). DL systems have also been implemented for image segmentation of breast lesions (detecting the lesion size and extent) (80-82). Moreover, DL applications with US have broadened to include predicting the molecular subtype of malignant breast lesions. This was investigated for predicting triple negative, HER2 (+), and HR (+) subtypes and showed high efficacy (1,78).

AI models increase radiologists' classification specificity in cases where the radiologist has already detected a lesion (83-85). Some lesions in the breast could, however, be missed by the radiologist (86). Another proposed method is the application of an AI system integrated into the US device where, when the US is performed, the system directly analyzes the constructed image and provides timely detection of breast lesions (87).

Another application of DL in breast US imaging is in the assessment axillary lymph nodes for malignant lesion metastases. DL models have superior accuracy when compared to radiologists in detecting suspicious axillary lymph nodes for biopsy (88). DL models have also been used to predict axillary lymph node metastasis using the features of the breast lesion without the need for axillary US images (89). It does so by aiding in extracting relevant information by retaining only the intermediate lesion position in the images (89). It also utilizes random horizontal flipping, elastic transformation, and random cropping to simulate various scenarios (89). When compared to radiologists, DL models display comparable sensitivity and specificity (90). Such models could be further improved and implemented in US imaging to reduce the time needed for axillary lymph node imaging.

Another model was designed to predict response to neoadjuvant chemotherapy (NAC) using only the initial lesion US image (91). GAN have been applied in US imaging for reconstructing high-resolution images using low-resolution ones, for reducing the required time for 3D image acquisition, and for generating US images of the breast with and without lesions for educational purposes (for radiologists and DL models) (92,93).

Magnetic resonance imaging (MRI)

MRI of the breast depends on exciting water molecules using a heavy magnetic field and short-pulsed radio waves. When water molecules fall back to their ground form, radio waves are transmitted. These radio waves are detected to create the MR image (3D image). When an intravenous contrast is administered, a 4D image is created, with time captured as a fourth dimension. It is worth mentioning that MRI is the most sensitive breast cancer imaging modality (94).

Several AI models have been applied to breast MRI for breast lesion detection, classification, and segmentation. Here, AI models also show a superior specificity and a comparable sensitivity when compared to the best standard (radiologists) (95-98). Models have also been designed and successfully applied to predict the molecular subtype of breast cancer based on MRI image data (99-103). In 2021, Liu *et al.* evaluated the ability of a novel CNN architecture to predict 5-year cancer recurrence after MRI imaging of breast lesions. The AI was able to identify image features relevant to prognostic outcomes and increased the accuracy of tumour classification (103).

Like their integrations with US technology, DL models have been designed for detecting axillary lymph node metastasis using MRI scans. These models have shown superior accuracy in detecting pathological axillary lymph nodes when compared to radiologists (104-106). AI models have also been used to predict the NAC treatment response of breast cancer. Some models use the pre- and post MRI scans whereas others use only the initial MRI scans (107-110). GAN have been applied in breast MRI to normalize the variations in MRI intensity and noise distribution between different brands of MRI machines (111). They have also been applied to minimize issues that arise from heterogeneous fat suppression (112).

Positron emission tomography (PET)

PET and scintigraphy scans are nuclear medicine imaging modalities that use radionuclide-attached metabolites circulating in the body. When radionuclides decay, photons are emitted, the detection of which can be used to construct 3D PET and 2D scintigraphy images. Thus, nuclear medicine scans represent the metabolic activity of tissues rather than anatomical structure alone (112).

In breast cancer, PET scans are used for cancer staging. DL has been used to assist radiologists in detecting axillary lymph node metastasis on PET scans (113). In 2021, Li *et al.* found that AI assistance considerably improved the diagnostic accuracies of clinicians in a retrospective trial involving 414 pre-procedure PET scans of the axilla from patients with biopsy-proven breast cancer (113). The sensitivity of the radiologists was improved but their specificity remained unaffected. CNN have been similarly applied to detect distant breast cancer metastases from scintigraphy scans, displaying high accuracy (114). Another use of DL in conjunction with PET scans is the evaluation of the tumor burden on the whole body as measured by the metabolic tumor volume. However, DL models have not achieved satisfying sensitivity in this application (115). In 2020, Choi *et al.* have investigated the applicability of DL in predicting tumor response to NAC using PET scans as input. Their results showed improved performance in comparison with the conventional predictors (116).

Thermal imaging

AI was also applied in other proposed imaging modalities including thermal imaging. On digital infrared imaging, thermal activity is increased in the breast tissues surrounding the malignant tumor. DL models have demonstrated high accuracy in detecting breast tumours from digital infrared images (117). The benefit of DL integration with thermal imaging extends to forecast modelling, where DL has been successfully applied to predict personal breast cancer risk (118).

Pathology

The gold standard for diagnosing breast cancer is biopsy evaluation by pathology (119). This allows for classifying and grading breast cancer as well as detecting lymph node metastasis, planning for treatment, evaluating resection margins status, and predicting patients' prognosis (120-122). However, pathological evaluation of microscopic biopsies carries the risk of inter-observer variability.

Applying AI models in analyzing microscopic images can assist pathologists in achieving faster, more precise, and reproducible breast cancer diagnosis (123,124). By reducing the workload on pathologists, AI integration can help compensate for resource strain within healthcare systems (12,125,126). In 2022, Cheng *et al.* applied CNN and RNN models in pathological classifications of breast fibroepithelial lesions into benign fibroadenomas and phylloid tumors. These models could accurately differentiate between and classify lesion types using images of the whole slide (127). AI-based models have also exhibited promising performance in applications to assess the risk of breast ductal carcinoma in situ (DCIS) invasion (128-130).

Preoperative applications of AI in breast surgery

Decision-making in cancer treatments is complex as it involves a diversity of data that need to be considered (131). Moreover, with the advances in medicine, new therapeutic options are proposed. Given the large amount of data for consideration and the rapid updates in the field, AI assistance in treatment decision-making would reduce the burden on clinicians and help them revise their treatment decisions (132,133). Bouaud *et al.* designed a decision support system that is based on guidelines to provide a complete patient care plan. In their study, they investigated the performance of this system in making treatment decisions for breast cancer patients. Clinicians changed their treatment decisions after reviewing the decision support system recommendations in 17% of the cases. The changed decisions were beneficial in 75% of these cases (134). In 2019, Xu *et al.* have also compared the decisions of their designed decision support system to the decisions of oncologists. The compared decisions were not concordant in 45% of the assessed cases. This nonconcordance was caused by variations in the clinical judgment in 21% of the cases, greater oncologists' adherence to the guidelines in 15%, and inaccessibility to the suggested treatment by the system in 5% (135). Another decision-making support system evaluation was conducted by Xu *et al.* in 2020 for breast cancer patients. Their support system resulted in treatment decision change by the physician in 5% of the patients and thus higher concordance with breast cancer treatment guidelines. In 63% of these cases, physicians changed their decisions because of considering the treatment option recommended by the system. Other reasons for treatment decision changes included highlighting certain patient factors by the system in 23% of the cases, and the system logic for decision making in 13% of the cases (136). Applying ML in decision making would allow surgeons with low operational volume to take decisions similar to the most experienced surgeons, as ML models learn and gain experience with each input (137).

The preferred management option for early-stage breast cancer is conservative breast surgery with sentinel lymph node biopsy and subsequent radiotherapy (138-140). However, some patients experience complete cure from neoadjuvant systemic treatment (NAST). For such patients, it may be reasonable to adopt a "watch-and-wait" approach before starting therapeutic surgery (138). For that reason, precise detection of the patient's response to NAST is necessary to avoid subjecting the patient to unnecessary surgery. At the same time, precise detection is crucial to eliminate the risk of missing residual malignant foci. AI-models have been successfully applied in this area to detect responses to NAST using MRI images and pathological specimens. Thereafter, AI models were designed to evaluate patients' responses to NAST by combining patients' imaging and biopsy findings with patient data. These models showed high accuracy in excluding residual malignant foci in the breast and axilla following NAST and determining eligibility for breast surgery (141-145).

An extra application of AI models is for educating breast cancer patients before breast surgery. A randomized control trial aimed at evaluating the ability of an AI model to educate women about the expected aesthetic outcomes following locoregional breast cancer surgery is currently being carried out. The model is expected to improve women's satisfaction with breast surgery, raise their psychological status, and reduce the need for subsequent plastic surgeries (146). A ML model was also applied in predicting the financial burden of breast cancer surgery. The investigated model showed high prediction accuracy (147).

Intraoperative applications of AI in breast surgery

In breast-conserving surgery, ensuring clear margins is crucial to prevent the recurrence of breast cancer. Malignant foci in the resection margins necessitate subsequent re-excision surgery (148). Hence, intraoperative evaluation of resection margins is of significant value (149,150). Laser Raman spectroscopy (LRS) is an optical imaging technique that generates a biochemical tissue signature by detecting the vibration in the molecular bonds. Thus, microcalcifications as well as immortalized and transformed cancer tissues can be detected (151-156). In 2021, Kothari *et al.* developed a ML model that was integrated with LRS to evaluate resection margins intraoperatively in vivo. This model could rapidly generate multiple models of tissue classification and directly calculate the probability of malignancy in the margins (157). Applying this type of system in breast conservative therapy could improve resection margin precision and reduce the need for re-excision surgeries.

Postoperative applications of AI in breast surgery

Lymphedema is a devastating condition that can occur immediately following axillary procedures, such as mastectomy with axillary clearance, or up to 20 years thereafter. This condition can present with a variety of symptoms (158). In 2018, Fu *et al.* designed ML models that assesses the occurrence of lymphedema following breast surgery based on symptoms reported by the patients. The designed model was tested and proved high accuracy (159). LLMs, like ChatGPT, are currently the most discussed AI tool to utilize in medicine, including breast surgery. Lukac *et al.* concluded that while it has potential, its current version is incapable of providing suitable recommendations for patients with primary breast cancer (160). Another possible devastating complication from axillary clearances is injury to the long thoracic, thoracodorsal, or intercostobrachial nerve, which sometimes must be sacrificed (161-163). AI could potentially be used to determine certain characteristics of breast tumors and axillary lymphadenopathy, making it safer to encroach more delicate structures like neurovascular bundles. They could also theoretically be employed to further study patient anatomy from pre-operative scans, which can be used to help predict the risk of nerve injury intra-operatively. During the writing of this manuscript however, the authors were unable to find dedicated studies to this topic.

Applications of AI in predicting breast surgery outcomes

van Egdom *et al.* designed an ML model that uses patient data and breast cancer characteristics to predict patient-reported outcomes postoperatively. However, when investigated, the model could not find a relationship between the input variables for predicting postoperative patient-reported outcomes (164). ML has, however, been used to effectively predict complications in the abdominal flap donor site following autologous breast surgery. Using these predictions, surgeons can tailor their operative techniques to achieve better outcomes and minimize the burden postoperatively (165).

About 15% of women with breast cancer experience severe pain postoperatively, which can last for years (166,167). Early identification of women's susceptibility to developing postoperative pain would allow for early initiation of medical and psychological treatment for those in need and avoidance of unnecessary interventions for those less susceptible (168,169). Using ML technology, Lötsch *et al.* designed and evaluated a system for predicting persistent pain following breast surgery. The model showed high accuracy in predicting postoperative persistent pain and a much higher negative predictive value (170). Another ML predictive model designed by Sipilä *et al.* showed high negative predictive value but low accuracy (171). In 2020, Juwara *et al.* designed an ML-derived model for predicting neuropathic pain following breast surgery. The model was superior to the traditional prediction model in predicting postoperative neuropathic pain (172).

Identifying women with high risk for recurrence would aid in providing the necessary follow-up and preventing potentially deadly disease progression. Lou *et al.* designed an ML-derived model that could accurately predict the risk of breast cancer recurrence within ten years following breast surgery (173). Other prediction models can provide high accuracy in predicting breast cancer recurrence after three and five years of breast surgery (174,175).

AI has been applied in predicting survival and mortality following breast cancer surgery as well. Huang *et al.* designed and evaluated an ANN model to predict the five-year mortality following surgery for breast cancer. The designed model showed greater accuracy when compared to conventional prediction methods such as the Nottingham prognostic index and breast cancer-specific survival (176-178). An additional ML model was developed by Moncada-Torres in 2021 to predict women's survival after undergoing breast cancer surgery. The model was similarly accurate as conventional prediction methods, if not superior (179).

Discussion

AI technologies are rapidly evolving and gaining interest, and their applications in healthcare are broadening to improve patients' outcomes (180). Models based on AI have the feature of learning from data, and hence, their performance gets improved. Breast surgery for benign or malignant breast lesions has markedly benefited from the advances in AI (4,5,12,13). These systems can rapidly process vast amounts of data and update the saved data, as well as their ability to logically operate with complex rules and decision trees. Thus, AI outperforms human cognitive functions and could assist healthcare providers in a diversity of tasks related to breast surgery from breast lesions detection and diagnosis to postoperative detection of breast surgery complications. As well, AI models assisted in predicting patient's response to therapy and postoperative breast appearance, cancer recurrence, and patient's survival (11,132,133,181,182). Most AI models currently approved by the Food and Drug Administration are designed to assist in breast lesion diagnosis through imaging and histopathological evaluation. Various models have been designed to assist in detecting and classifying breast lesions, describing breast tumor microenvironment and molecular subtype, predicting the risk of breast cancer, as well as predicting and evaluating treatment response. An AI-based model has been applied in US breast imaging to predict malignant lesion response to NAC using features of the lesion US before versus after one or two courses of NAC. In addition, some AI models have the capacity for reconstructing or even generating breast images (4,5,13,14). Our search revealed AI applications aimed at supporting oncologists in treatment decision-making and predicting postoperative outcomes (162,172,173,176,183).

Despite the notable breakthrough of AI technologies, some limitations are encountered. Highlighting these drawbacks is essential for making improvements in the models. As AI models' performance improves when more data are imported, the size of datasets used for learning matters. For some models, large datasets are not available (as for breast US imaging). Thus, these models are not trained enough and subsequently do not achieve a satisfactory performance. To overcome this shortcoming, data could be shared across medical centers. This solution cannot always be pursued because of patients' privacy policies, privatized health systems like the USA, and ethical laws regarding the transfer of sensitive patient information (184). Alternative solutions including federated learning and transfer learning are proposed. Federated learning implies sharing the algorithm after learning from data, but patients' data remains within the medical center. Transfer learning refers to learning from different datasets (e.g., US models can learn from DM images) (35,185). Special care must always be taken when data are imported to train AI models. Poor datasets could lead to inaccuracies (e.g., including wrong diagnosis of tumor and inter-observer variability) and various biases could lead to patient population underrepresentation. For these reasons, large multi-central multi-reader datasets are preferred for training AI models (186). Prediction models that provide clinicians with justification for their prediction provide more comprehensive assistance (187,188). However, it was evident from the results of our search that not all AI models are effective in establishing relationships between variables and predicting outcomes. As computing powers and data availability increase, prediction AI models are recommended to incorporate multi-dimensional predictors for stronger prediction evidence. When patients' physical examination and lab data are incorporated with their disease characteristics, the model can get a holistic picture and thus improve its performance. When an AI decision support model was compared to oncologists in terms of adherence to breast cancer treatment guidelines, oncologists showed better adherence. However, this was owing to the multiple input and factors driving the algorithm. The investigated algorithm was designed to take decisions not only based on breast cancer treatment guidelines, but also on some selected literature and information from textbooks (134). Finally, medicolegal dilemmas surround the application of AI in medical practice. Whether final decisions could be made by AI models and who would take the responsibility for wrong decisions are questions yet to be answered. This endorses the need for a regulatory body for AI applications in medicine. As well, if AI is proposed to replace humans, ethical issues of job losses would be encountered. It should be noted that articles with the specific focus of breast reconstruction, an important part of the recuperation process post-mastectomy, were not included in this review. The applications of AI in this domain have been elucidated in prior research. This theme was therefore excluded to maintain our objective of addressing current knowledge gaps.

Further improvements in AI are anticipated and AI models are desired to move from the experimental phase to actual implementation in healthcare. In breast lesion biopsy, future applications of AI might allow for identifying a few deformed cells within normal breast tissue. Regarding breast surgery, AI's possible preoperative applications involve surgical planning. The models could be used in anatomical data analysis for recommending individualized optimal approaches for breast surgeries. Moreover, future intraoperative applications of AI might include assistance in timely image analysis for precise tumor resection and intraoperative decision-making. AI-integrated robotic models, akin to the DaVinci system, that directly perform breast surgery or assist surgeons could also be introduced in the future (3,189,190). Postoperatively, AI could be applied in patient monitoring and follow-up for early detection of breast surgery complications or breast cancer recurrence. As uptake of these technologies increases within healthcare systems, the implications for training new clinicians involved in the surgical management of breast lesions must be considered. Healthcare education in the era of increasing AI integration will be a major topic for research in the coming years. Breast surgeons should be updated with the recent advances and applications of AI in their field to provide the best care for their patients (191,192).

Conclusions

AI algorithms are increasingly applied in all aspects of breast surgery. Different AI models were designed and evaluated to assist in breast tumor detection, classification, segmentation, staging, and grading. Preoperatively, AI models were applied in determining the need for breast cancer surgery and educating women. Intraoperatively, they enhanced surgical precision in tumor resection. Postoperatively, AI was able to predict breast surgery complications, survival, and cancer recurrence. However, more research is required to move AI from the experimental phase to widespread implementation in healthcare. Improved, novel applications of AI are already in development, and breast surgeons should stay updated to provide the best care for their patients.

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Footnote

Reporting Checklist: The authors have completed the Narrative Review reporting checklist. Available at https://gs.amegroups.com/article/view/10.21037/gs-23-414/rc

Peer Review File: Available at https://gs.amegroups.com/article/view/10.21037/gs-23-414/prf

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Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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