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Review Article

Review of Artificial Intelligence Applicability of Various Diagnostic Modalities, their Advantages, Limitations, and Overcoming the Challenges in Breast Imaging

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Abstract

Integrating all imaging modalities, namely, mammography, ultrasound, magnetic resonance imaging, and tomosynthesis, allows for a comprehensive morphological examination of the breast to distinguish between normal and abnormal breasts. The key target is to correctly detect malignant lesions in the early stages and improve the prognosis of breast cancer patients. Radiologists may increase their efficiency and free up more resources for patients or clinical practice using machine learning software that can include a second opinion, assess malignancy, and assist in patient triage. It would, though, need a lot of training data and its meticulous labeling. Data augmentation and multitask transfer learning are effective for training convolutional neural networks in medical image processing. This review article provides an introductory summary of artificial intelligence (AI) development in imaging, as well as the increasingly increasing AI development through various imaging modalities along with their advantages and limitations.

Key words: Artificial intelligence, Digital breast tomosynthesis, Magnetic resonance imaging, Mammography, Ultrasonography

INTRODUCTION

Mammography, ultrasound, magnetic resonance imaging (MRI), and tomosynthesis are some of the modalities used in modern diagnostic senology, the branch of medicine that deals with breast disorders. Integrating all imaging modalities allows for a comprehensive morphological examination of the breast to distinguish between normal and abnormal breasts. The key target is to correctly detect malignant lesions in the early stages and improve the prognosis of breast cancer patients.

A single modality is inadequate to detect breast cancer, necessitating several procedures to diagnose a lesion accurately. As a result, this review article provides an introductory summary of artificial intelligence (AI) development in imaging, as well as the increasingly increasing AI development through various imaging modalities along with their advantages and limitations.

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THE EVOLUTION OF AI IN IMAGING

In 1967, Winsberg *et al.* created a method to detect changes in optical densities on mammogram films and highlight regions with shaded rectangles to display left and right breast differences.[1] Lodwick *et al.* focused on developing computer systems capable of automatically diagnosing conditions from radiological images.[2] Although very novel computer simulations yielded promising results, these attempts were ultimately unsuccessful due to a lack of computing resources, digital images, and sophisticated imaging processing techniques.[3,4]

Let's have an overview of applicability of AI using various modalities such as mammography, digital breast

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tomosynthesis (DBT), sonography, and MRI apart from discussing their advantages and challenges.

MAMMOGRAPHY

The proper patient positioning, exposure, technique, and automatic exposure device result in the best image quality. The appropriate compression to the breast tissue distributes it evenly, reduces its thickness, and significantly decreases geometric unsharpness, motion blur, radiation dose, artifacts due to skin fold, and scattered radiation apart from enhancing the spatial resolution.[5]

SCREENING MAMMOGRAPHY

The primary reason for screening mammography in an asymptomatic patient is to look for occult breast cancer. It entails the physician taking a thorough history and performing a clinical breast examination.[6] According to the American College of Radiology, screening mammography should be done annually after the age of 40 and in high-risk cases.[7] Patients with a history of irradiation and prior breast cancer, as well as first-degree relatives with breast cancer, should be screened sooner. Any patients with new or expanding lumps should be offered diagnostic mammography.[8]

DIAGNOSTIC MAMMOGRAPHY

In patients with a palpable mass and any radiographic abnormality on a screening mammogram, two standard views – craniocaudal projection (CC view) and mediolateral view (MLO view) – of each breast are taken, with additional views as needed. Diagnostic mammography should be considered in patients with specific signs and symptoms such as clear or bloody nipple discharge, nipple retraction, skin dimpling, or a history of carcinoma breast.[9]

AI AND DIGITAL MAMMOGRAPHY APPLICATIONS

Breast cancer is one of the most lethal ailments, and it is the second leading cause of death in women. When malignant, cancerous lumps form in the breast cells. In today's computer-assisted diagnostic (CAD) analysis, there are two main components: Computer-aided identification (CADe) uses computer output to pinpoint the position of suspected lesions, while computer-aided diagnosis (CADx) produces a report that describes the lesions' characteristics.[10] Conventional machine learning techniques with manual extraction of features are being displaced by deep learning constituting automatic extraction of features.[11] Rodrguez-Ruiz *et al*. concluded that AI improved a radiologist's performance in identifying breast cancer compared to unaided image reading. The input datasets consisted of 240 digital mammography images of 100 normal, 100 malignant, and 40 false-positive cases. To delineate microcalcifications and soft-tissue lesions, deep learning (convolutional neural network [CNNs]) feature classifiers and image recognition algorithms were used. The area under the curve (AUC) (0.89 vs. 0.87, $P = 0.002$), sensitivity (86 vs. 83%, $P = 0.046$), and specificity (79 vs. 77%, $P = 0.06$) values favored the AI system as a radiology assistance.[12] Huynh *et al*. concluded that transfer learning could enhance existing CADx approaches by contrasting support vector machine classifiers based on CNN extracted image features to their previous computer-extracted features (AUC 0.86) to distinguish benign and malignant lesions.[13]

ADVANTAGES OF USING AI WITH MAMMOGRAPHY IMAGES

AI is not just a computerized approach but an interface between humans and machines. Radiologists can gain more time for patients or clinical practice using machine learning tools that enable them to automate tasks that enhance their efficiency. Standardized views, availability of images for comparison, systematized reporting style, and classifiable outcome are the necessary properties that make mammography appropriate for training machine learning algorithms. It can give a second opinion, tell us how normal cases will turn out, make predictions about malignancy, and help us prioritize patients. It is especially advantageous in heavily populated and developing countries with limited medical resources. The problem of excessive workload and doctor scarcity can be partly minimized using AI algorithms.[14]

CHALLENGES FACED USING AI IN MAMMOGRAPHY IMAGES AND METHODS TO OVERCOME

AI algorithms require massive volumes of training data; moreover, supervised learning and CNN-based techniques require complicated and time-consuming data labeling.[15] Where medical images are involved, these deep learning algorithms can prove to be problematic. The main challenge that interferes with teaching machine learning algorithms is acquiring accurate annotated image data, not the data's availability. The translation of free text files of radiologists necessitates the use of sophisticated text mining techniques.[16]

The two realistic options that can be used to solve the problem at least partially include data augmentation and transfer learning. Data augmentation with affine transformations, including localization, rotation, and scaling, can be used to create new data from old data. Moreover, multitask transfer learning is effective for training deep CNN (DCNN) in medical image processing,[17] especially when testing samples from a modality are limited.[18]

Furthermore, label noise can be a significant constraint in algorithm design, particularly when domain experts label data. One should think about how to deal with noise and how best to resolve uncertainty while using such data to train a deep learning algorithm. The other choice is to specify the loss function clearly in the first iteration. Usually, a binary classification: Normal versus abnormal is used in medical imaging. However, as they can vary greatly, there is a broad generalization. Alternatively, an exhaustive annotation of the whole subclasses could turn the deep learning system into a multiclass system. Thus, this contributes to the dilemma of expert availability for annotation and is, as a result, frequently impractical.[16]

Another data-related problem is the existence of an unbalanced class structure. When it comes to searching pictures for the various diagnostic medical imaging classes, finding the correct ones may be challenging. Although AI-based CAD systems have shown the capacity for improving breast and lung images, they can also erroneously categorize normal structures as abnormal. This false-positive identification is a major stumbling block affecting recall rates, performance, and costs which can be mitigated by the radiologist who can differentiate true-positive from false-positive cases.[19,20] A 2016 study discovered that four different CAD systems linked to the computed tomography scan revealed the previously undetected lung nodules, including 17% of lesions <3 mm and more than 70% of cancers from 3 to 6 mm sizes which are usually underestimated by professionals.[21]

The fine-tuning of algorithms to tasks with large data sets is not easy. To begin with, it is not easy to train a CNN to detect both masses and calcifications. And hence, sometimes, different CNNs are trained for both types of lesions, and only the results are merged in the performance of the AI support structure.[22] However, the algorithms must also be reliable and repeatable for mammograms collected by separate technologists using multiple vendor machines. Testing the deep learning algorithms from different vendors is essential since most vendors incorporate their own post-processing data to prepare mammograms which means that a CNN trained on one vendor's data might not be applicable on another. Thus, the ML strategies must be implemented to normalize mammograms.[23]

DBT

DBT tends to localize minor breast lesions in thick breast tissue. It is also advantageous when overlapping structures on 2D imaging may obscure an area of interest leading to a false-negative result. Sometimes, the summation artifact of overlapping normal structures might give a false-positive result. Breast cancer, even if not calcified, may be diagnosed with DBT. The breast positioning of MLO and CC views is like conventional mammography and does not require any special operator experience. Although radiation is minimal and within the safety limits, radiation exposure with DBT is still more than conventional mammography.[24]

AI AND DBT

Using a multistage transfer learning approach, DCNN has been developed recently to classify malignant and benign lesions in optical breast tomosynthesis (DBT).[25] It is advantageous even when the training sample size is small. AdaBoost algorithm, with deep learning, has been suggested for the recognition and early detection of breast cancer.[26]

The use of machine learning to produce synthetic mammograms can accentuate suspicious findings. However, they can also altogether remove normal tissue and mask the relevant findings. The use of a multiplanar reconstruction fitted through the most suspicious lesions detected by a conventional CAD system in a DBT examination improved reader performance compared to that with full-field digital mammography.

Radiomics is the translation of images to minable data by decoding their quantitative features such as intensity, shape, size, and texture extracted from the background. Massive and well-curated data sets help data mining, that is, discovering patterns in large datasets. Further studies have shown that the radiomics features of the parenchyma from DBT in women with breast cancer vary from those who do not have cancer and that offer the possibility of predicting disease risk.[27]

ULTRASONOGRAPHY (USG)

The use of high-frequency, 7.5–13 MHz probes delineates the internal structure of the breast with better lateral and tissue contrast resolution and lesion characterization. Ultrasound is used in concurrence with mammography for better lesion characterization. It is non-ionizing and hence the modality of choice in young females and women with mammographically dense breasts. Since it is real time, it helps in accurate localization for biopsy of the lesion.[28]

AI AND SONOGRAPHY

Fujioka *et al*. inferred that deep learning with CNN has high diagnostic efficiency (AUC = 0.913 and 0.728–0.845, P = 0.01–0.14) for ultrasound-based differentiation between benign and malignant breast lesions. They obtained 480 images of 96 benign lesions and 467 images of 144 malignant lesions retrospectively for training purposes. A deep learning model was built using the CNN architecture GoogLeNet and used to evaluate test data consisting of 48 benign and 72 malignant lesions. To conclude, the CNN model and radiologists had a sensitivity of 0.958 and 0.583–0.917, specificity of 0.925 and 0.604–0.771, and accuracy of 0.925 and 0.658–0.792, respectively.[29] Tanaka *et al*. concluded that the CNN-based CAD method is intended to support physicians in the detection and clinical practice of breast cancer utilizing deep learning with ultrasound images. The images of 1536 breast masses (897 malignant and 639 benign) were taken using various angles by an ultrasound imaging probe from a large-scale clinical trial performed by the Japan Association of Breast and Thyroid Sonography. They used two fine-tuned CNN models (VGG19 and Res152) trained through augmentation, applied a mass level classification method to enable the CNN to classify a lesion using all views. Independent test set constituting 154 masses (77 malignant and 77 benign) revealed a sensitivity of 90.9% (95% confidence interval 84.5–97.3), a specificity of 87.0% (79.5–94.5), and an AUC of 0.951 (0.916–0.987) compared to that of the two CNN models.[30] Another study uses shear-wave elastography data to suggest a segmentation-free radiomics system for classifying malignant and benign breast tumors.[31]

ADVANTAGES OF USING AI WITH SONOGRAPHY IMAGES

Ultrasound is the modality used traditionally for distinguishing between benign and malignant breast masses. Its use has increased substantially as it can also detect mammographically occult cancers. Its non-ionizing nature, ease to use, affordability, and capability to provide real-time feedback and tracking are advantageous compared to other modalities such as mammography, DBT, and MRI.[28]

In recent years, AI algorithms have been increasingly applied to breast USG, mostly in feasibility studies for automated detection, differential diagnosis, and segmentation.

The studies reveal that AI can help revolutionize USG algorithms by making them accessible even in settings with a lack of expert radiologists. Apart from reducing the radiologists' workload and improving workflow productivity, AI systems offer a second opinion on results that are missing or misinterpreted and help to avert perception errors.[32]

CHALLENGES FACED USING AI WITH SONOGRAPHY IMAGES

An AI technology is guided by the volume and consistency of training data. The substantial AI model for USG can only be developed using a multivendor, large-scale dataset with a wide-ranging spectrum of benign and malignant pathologies. The same lesion is quantified in various forms because of different ultrasound equipment with various transducers and technical settings. Older ultrasonographic images have lower resolution and higher noise, whereas newer ones have higher resolution and lower noise. The training dataset used in older algorithms may not be valid for modern images.[33]

The number of images used per patient in AI development has not been made consistent. For most training and validation, though more than 1 image per patient is needed, but based on the recently proposed Checklist for AI in Medical Imaging, specific details on the number of patients and images are also required.

Additional documentation might be required to include specifications for a generalizable AI system that targets various datasets (training/validation/test). The requirement of a large number of annotated images (usually more than thousands), being both time and labor intensive, impedes the development of well-performing and stable AI systems, not to mention the subjective bias that may come into play. Hence the role of semi-supervised methods is elevated, as it reduces the number of images to be manually labelled, allowing for a larger dataset than would otherwise have been possible. The images are usually cropped with a fixed margin around the region of interest after the image annotation. Then, these images are resized to a fixed size before adding them as an input to AI models. Most of the recent algorithms were trained using data from a small range of institutions and ultrasound systems, so they do not work well in varied environments.

Data augmentation constitutes a series of data manipulation methods, such as flipping, rotation, translation, and the addition of noise to create new images. It avoids overfitting and increases the volume of data. Even though processes such as resizing and data augmentation are necessary for AI model training, they change the characteristics of breast lesions and might reduce the classification performance. Byra *et al*. proposed that images should not be rotated with shifts in the longitudinal direction. For example, the posterior acoustic shadowing suggesting a malignant lesion gets anterior by longitudinal flipping.[34,35]

MRI BREAST

Multiparametric assessment of breast lesions helps in differentiating benign and malignant lesions.

AI AND MRI

One hundred and eleven breast DCE MRI examinations (54 malignant and 57 benign lesions) were evaluated with the improvement of the average AUC of all readers from 0.71 to 0.76 (*P* = 0.04) when using the AI system.[36] The CADx device was trained using a training sample of 121 breast lesions (77 malignant and 44 benign). Six breast imaging radiologists evaluated the risk of malignancy and the need for biopsy using a different test set of 60 lesions (30 malignant and 30 benign). As CADx was used, radiologists' overall output was substantially increased, as shown by improvements in the mean area under the receiver operating characteristic curve (from 0.80 to 0.84, *P* = 0.007), mean sensitivity (from 83 to 88%, *P* = 0.001), and the average number of biopsy referrals for malignant cases (1.7 additional biopsies for malignant lesions for CADx use, *P* = 0.001). While the mean specificity increased (from 50% to 53%), the rise was not statistically relevant (*P* = 0.2).[37]

ADVANTAGES OF USING AI WITH MRI

Availability of potentially extractable large data sets from MRI breast eases its use for AI applications. MR images encompass hidden information that is not always perceivable from human interpretation but can be extracted using machine learning methods and analyzed for a better disease understanding. It aids in faster, accurate, and tailored diagnosis and prognosis.[38]

CHALLENGES FACED USING AI WITH MRI

Training data sets for deep learning networks require annotated images, and extracting information from multimodal image processing is a significant challenge for AI in medical imaging.[39] DCE MRI and DWI are complicated advanced breast imaging methods. The hardware and software configurations used by various vendors may result in visible variations in image quality and appearance. Besides that, acquisition guidelines differ significantly within different suppliers and can require various spatiotemporal resolutions, contrast agents, and imaging parameters (TR, TE, fat suppression, etc.). Post-processing, such as tumor delineation and segmentation, can further complicate this image. Quantitative functions, either manually engineered or taught by CNNs, are used in machine learning models and can be significantly influenced by such improvements. Due to the impossibility of gathering data for all potential acquisition protocols, these factors must be carefully addressed during the creation, preparation, and evaluation of machine learning models. The challenge of developing stable machine learning models that generalize through several contexts remains, in several respects, an accessible research issue. Another crucial concern to answer is whether CNN-based features are more immune to certain differences than hand-engineered features. There are two approaches to building efficient machine learning models independent of acquisition parameters: Image standardization/harmonization and more robust feature extraction/selection.[40] However, further research is needed to examine a wider variety of imaging parameters and functions.

CONCLUSION

We are just at the inception stage of AI-based breast imaging. Rapid advancements in imaging technologies and algorithms have paved the way for modern clinical applications of AI, including detection, management, prognosis, and risk assessment. Images, in addition to hereditary, pathologic, and clinical factors, are particularly relevant in the study of breast cancer. Despite the escalating published research on this topic, the current analysis offers an overview of a paradigm that is likely to develop in the immediate future. Radiologists today have expanded imaging capability and access to imaging datasets due to the advancement of newer imaging techniques. The integration of an AI enabled breast imaging workflow helps to act as a catalyst for personalized, multidisciplinary applications, and clinical strategic coordination from various data sources.

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