Contrast-enhanced mammography: better with AI?

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COMMENTARY

Contrast-enhanced mammography: better with AI?

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Breast cancer is the most common cancer and also the most frequent cause of cancer-related mortality in women [1]. Population-based breast cancer screening provides the possibility for early detection of breast cancer. Early detection and subsequent precision treatment are important to improve outcomes. Currently, full-field digital mammography (FFDM) and digital breast tomosynthesis (DBT) fulfill a crucial role in breast cancer screening and evaluation. They rely on changes in breast morphology caused by breast cancer. Unfortunately, especially for women with dense breasts, this has limited accuracy [2, 3]. Contrast-enhanced breast magnetic resonance imaging (MRI) is considered the best imaging technique for breast cancer detection, but MRI may not be suitable for every patient, and is associated with relatively high costs of the test, limited availability of scanners, and long waiting times [3, 4].

Since its emergence in 2011, contrast-enhanced mammography (CEM) has received increasing attention. A CEM examination is performed with iodinated contrast agent and uses dual-energy mammography. Enhancement of tumors is based on the same physiological principle as in breast MRI. Compared with FFDM and DBT, CEM has great feasibility and potential in primary breast cancer screening, improving the detection ability of tumors shielded by dense breast tissue through contrast enhancement, and at the same time, CEM also has potential advantages such as lower cost and only slightly reduced sensitivity compared with MRI [3]. In the clinical setting [5, 6], CEM has been shown to improve the accuracy in women with abnormal screening findings or symptoms of breast cancer, and it has also been shown to approach the accuracy of breast MRI for preoperative staging and monitoring response to neoadjuvant chemotherapy in breast cancer patients albeit only providing 2D information [3].

The increasing recognition of the potential value of artificial intelligence-based analysis in breast imaging has logically also resulted in artificial intelligence models developed for CEM to perform breast imaging-related tasks, such as segmentation and classification [1, 7–10]. Early radiomics-based machine learning-based algorithms were trained to classify breast lesions, as well as to distinguish invasive and non-invasive breast cancers and predict molecular subtypes of breast cancers using CEM images [3]. In a preoperative study in 2022, Mao et al [1] investigated the performance of CEM-based intratumoral and peritumoral radiomics for prediction of the effect of neoadjuvant chemotherapy in breast cancer, reporting an area under the receiver operating characteristic curve (AUC) based on the selected radiomics features of 0.85 (95% confidence interval (CI): 0.72, 0.98). In another small study in 2023, Zheng et al [8] developed an artificial intelligence model that segmented single-mass breast lesions and classified them on CEM to assist the diagnostic workflow. The segmentation task based on fully automated pipeline system achieved a Dice coefficient of 0.837 ± 0.132 in the prospective test set, and the classification task (benign vs malignant) achieved an AUC of 0.891 (95% CI: 0.816, 0.945). Beuque et al likewise [10] developed a comprehensive machine learning tool able to fully automatically identify, segment, and classify breast lesions on the basis of CEM images in patients recalled from screening. Their results showed that a deep learning model accurately identified (sensitivity = 90%) and delineated suspicious lesions (Dice coefficient = 0.71) on CEM images, and that the combined output of deep learning and a handcrafted

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radiomics model achieved good diagnostic performance, with an AUC of 0.95 (95% CI: 0.94–0.96).

In this issue of *European Radiology*, Qian et al [11] present a deep neural network for lesion classification on CEM images to facilitate breast cancer diagnosis in the clinic (benign vs malignant). In this retrospective study, the authors collected a total of 2496 female patients with suspicious lesions detected at screening of whom 35.5% had a malignant breast lesion to train an end-to-end deep multi-feature fusion neural network, combining the information of bilateral, dual-view, and dual-energy mammography images. The proposed network achieved a classification accuracy of 0.90 (95% CI: 0.88, 0.92) and an AUC of 0.96 (95% CI: 0.95, 0.97) on an internal test set, and an accuracy of 0.85 (95% CI: 0.82, 0.89) with an AUC of 0.92 (95% CI: 0.89, 0.95) was reported on an external test set.

One unique aspect of this study is that the authors compared non-fusion models with feature fusion models [11]. Usually, the deep learning models extract the features through the base layer, and then analyze the features through the fully connected layer, and finally make relevant predictions. However, when multiple images are used as input, simple feature extraction and concatenation may not be able to obtain feature correlations between different input images. In this study, each paired low-energy image and dual-energy subtraction image was concatenated as a two-channel input, so the authors employed four feature extractors with shared weights to extract features from the craniocaudal (CC) and mediolateral oblique (MLO) view images of both breasts using both the low-energy and the high-energy input. In particular, the authors designed a multi-feature fusion strategy, including a left–right fusion module and a CC-MLO fusion module. Compared to the no-fusion model, the left–right fusion model performed better (AUC of 0.92 vs 0.95), and the multi-fusion model combining left–right fusion with CC-MLO fusion performed best, with an AUC of 0.96. The improvement by the CC-MLO fusion implies that the network learns from multiple views of the same lesion. The improved performance achieved by the left–right fusion model demonstrates that also networks learn features of a breast by comparing them to those of the contralateral breast. A further strength of the study is that the generalizability of the developed multi-feature fusion model was evaluated on two external datasets, showing that the model is relatively robust. This study also has some limitations [11]. First, the proposed model was only trained using data from a single center. Collecting multi-center training data may potentially improve the generalization ability of the model. Second, the accuracy of the model for Breast Imaging Reporting and Data System category 4 lesions needs to be improved, and further work is needed to strengthen the prediction ability of the model for lesions presenting with microcalcification.

In summary, artificial intelligence methods for CEM are rapidly being developed and already achieve an impressive accuracy for lesion classification and segmentation. The described models show potential generalizability and clinical applicability [8, 11], and may therefore obtain an important role in the clinical use of CEM, potentially improving its clinical value. Although current related research is still limited, the continuous development and advancement of imaging technology and artificial intelligence, also for CEM, will eventually benefit the healthcare of patients with breast disease.

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Declarations

Guarantor The scientifc guarantor of this publication is R.M. Mann.

Conflict of interest R.M. Mann is advisory Editorial Board member of *European Radiology*, associate Editor for breast imaging of *Radiology* and member of the executive board of the European Society of Breast Imaging (EUSOBI), chairperson of its scientific committee. R.M. Mann declares cooperation with and research grants for studies unrelated to this work from: Siemens Healthineers, Bayer healthcare, Beckton & Dickinson, Screenpoint medical, Koning, PA Imaging.

Statistics and biometry No complex statistical methods were necessary for this paper.

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Study subjects or cohorts overlap Not applicable.

Methodology
• Commentary

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