Radiomics and deep learning methods in expanding the use of screening breast MRI

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Key Points

- *The use of screening breast MRI is expanding beyond high-risk women to include intermediate- and average-risk women.*
- *The study by Pötsch et al uses a radiomics-based method to decrease the number of benign biopsies while maintaining high sensitivity.*
- *Future studies will likely increasingly focus on deep learning methods and abbreviated MRI data.*

Screening breast MRI is more sensitive for the detection of breast cancer than mammography and ultrasound, as MRI is a functional modality while mammography and ultrasound are morphologic modalities. Dynamic contrast-enhanced MRI can demonstrate the altered perfusion and diffusion around cancers due to neoangiogenesis and abnormal vascular permeability [1]. Given its high sensitivity, MRI is recommended by multiple international guidelines for supplemental screening of high-risk women [1]. Evidence is now accumulating to support the role of screening MRI in intermediate-risk women (who have a 15–20% lifetime risk of developing breast cancer). For example, studies of screening MRI in women with negative mammogram and personal history of breast cancer showed a high cancer detection rate, in the range of 17–19 cancers per 1000 MRIs [1, 2]. Recent studies have also demonstrated benefit of screening MRI for women at average risk for breast cancer. A study [3] of women with an average lifetime risk of breast cancer and any mammographic density detected 22.6 additional cancers per 1000 after negative screening mammogram with or without ultrasound, and the cancer detection rate of MRI remained high at incident rounds with 6.9 cancers per 1000. A study [4] of abbreviated MRI compared to digital breast tomosynthesis for screening of average-risk women with dense breasts showed a cancer yield

of 11.8 per thousand for MRI compared to 4.8 for tomosynthesis. Finally, the DENSE study from the Netherlands [5] evaluated average-risk women with extremely dense breasts and demonstrated sixfold fewer interval cancers in the group screened with mammography and supplemental MRI compared with the group screened with mammography only. These studies demonstrate the advantage of screening MRI is its high sensitivity and negative predictive value, in women of all risk categories. As studies show that abbreviated MRI has comparable accuracy to full diagnostic protocol MRI [6], it is expected that adoption of abbreviated MRI protocols will increase access to screening MRI and more average- and intermediate-risk women will undergo MRI screening.

For any screening test, the negative predictive value and positive predictive value vary with the prevalence of disease in the population. Therefore, as indications for screening MRI expand, the positive predictive value will fall if the screened population has a lower burden of disease. In the studies of screening MRI for intermediate- and average-risk women mentioned above, the positive predictive value of a biopsy recommendation ranged from 19.6 to 35.7% [2–5]. This is in the range of the 25.6% mean positive predictive value of a biopsy recommendation after digital screening mammogram in the USA [7]. Improving the positive predictive value is of course desirable as it will result in fewer benign biopsies and fewer follow-up imaging recommendations. The study by Pötsch et al in this issue of *European Radiology* [8] seeks to increase the positive predictive value of MRI using a neural network classifier of radiomic features.

Radiomics is the field in which large numbers of quantitative features are extracted from medical images and pooled in large-scale analyses [9]. Radiomics studies in general follow a

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methodology of (1) image acquisition, (2) image segmentation, (3) feature extraction, (4) feature selection, and (5) predictive modeling [9]. In the study by Pötsch et al [8], the authors extracted 86 radiomic features including the enhancement characteristics of the entire volume of a breast lesion over several post-contrast time-points. The authors then trained an artificial intelligence (AI) classifier to predict benignity or malignancy based on the radiomic features. Classification thresholds could be set by the user, and when the authors set a threshold of 100% sensitivity, they found that 10 of 69 (14.5%) benign lesions could be correctly identified and biopsy could have been avoided. While this number may be only a modest improvement, it is important to note that it maintains a level of no false negatives. Specificity could be increased with a trade-off in sensitivity, although this may not be desirable given that the strength of MRI is its high sensitivity. A study on the impact of radiologist and referring physician decision-making would be useful to inform the threshold at which to set an acceptable sensitivity.

The radiomics features selected by Pötsch et al [8] included volumetric characteristics, such that the spatial distribution of the parameters was analyzed in addition to the parameters themselves. The features that were found to be most predictive of malignancy were descriptors of the volumetric distribution of vascular permeability and the extracellular compartment, as well as changes in signal intensity over time related to wash-in and wash-out of contrast within the lesion [8]. Note that these time-resolved features of dynamic contrast enhancement were evaluated over 7 min, which may be too long given the trend toward abbreviated MRI. Radiomics studies of ultrafast dynamic contrast-enhanced MRI performed at high temporal resolution have shown promising results in lesion classification [9, 10]. This suggests that the wash-in data obtained from abbreviated MRI with ultrafast imaging could replace the wash-out data from conventional low temporal resolution contrast-enhanced MRI.

Other radiomics studies of lesion classification [9] have used a range of different features, including morphologic features such as compactness and sphericity, texture features, nonenhanced T1-weighted signal, T2-weighted signal, and diffusion-weighted information, as well as features of peripheral non-tumor tissue. A limitation of radiomics studies is that they rely on these handcrafted features, which must first be identified and extracted by the operator. A more robust approach may be deep learning-based feature extraction, in which a deep learning model learns from the images themselves in an unsupervised fashion, without requiring the input of specific extracted features. Studies have already shown that radiomics-style handcrafted feature extraction performs less accurately than deep learning techniques in classifying benign from malignant lesions [9, 11]. It is likely that future studies of MR lesion characterization will increasingly focus on deep learning techniques rather than radiomics-style techniques.

Future research in radiomics and AI should incorporate clinical, genetic, and pathologic information to improve the accuracy of models of tumor identification, tumor biology, and individualized risk assessment. Studies will also need to demonstrate generalizability across scanners, imaging protocols, and patient populations. Ultimately, the goal is to develop AI tools that improve the performance of radiologists and increase quality of care. The study by Pötsch et al [8] demonstrates that radiomics and AI tools could potentially be used to decrease benign biopsy rates. In this rapidly evolving field, future studies evaluating abbreviated MR methods and including a generalized screening patient population will be required.

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Methodology

• Editorial comment

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