Supplementary

Appendix 1

Methods

Fibroglandular tissue segmentation

The automatic segmentation model was implemented using the two-dimensional (2D) convolutional neural network, High-Resolution Net (HR-Net), which has shown to have excellent performance in various segmentation tasks. Before dynamic contrast enhancement (DCE), each slice of the sequence was separated and then concatenated with the slice of the initial uptake, with an 8–10-min delay of DCE sequences at the same position to be used as the input of our model. The signal intensities of the input images were normalized using the minmax normalization method. Hyperparameters, including the number of epochs and the learning rate, were experimentally determined by monitoring the loss of the validation set. In this study, 10% of the data were randomly extracted from the whole development set to be used for validation. The determined learning rate, the batch size, and the number of epochs were 0.001, 4, and 100, respectively. Tversky loss function [Tversky loss function for image segmentation using three-dimensional (3D) fully convolutional deep networks] was implemented to improve the model performance. To increase the robustness of input data variations, random flipping and rotation of 2D images, random cropping, and addition of random Gaussian noises were performed at each iteration during the training process. The model was trained and tested using Keras 2.3 on a system equipped with a single NVIDIA GeForce GTX 1080 Ti graphics processing unit.

Appendix 2

Results

Fibroglandular tissue segmentation and the lesion-labeling model

The Dice similarity coefficient between the automatic and manual labeling of fibroglandular tissue segmentation and lesion labeling were 0.972 and 0.860, respectively.

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