SUPPLEMENTARY MATERIALS

Development of Deep Learning-Based CAD

Deep learning-based computer-aided diagnosis (CAD) for breast ultrasound (US) (S-Detect™ for Breast in RS80A, Samsung Medison Co., Ltd., Seoul, Korea) consists of three steps. The first step is segmentation to extract the boundaries of the lesion, the second is classification to extract the Breast Imaging Reporting and Data System (BI-RADS) lexicon of the lesion, and the last is classification to determine whether the lesion is benign or malignant.

Figure 1 is a conceptual depiction of the deep learning-based CAD system for breast US. The segmentation algorithm for extracting the boundaries of a lesion is modified from the Fully Convolutional Network (FCN) (1). The FCN is an algorithm for fully automated segmentation. However, lesions in US images are often unclear; hence, S-Detect™ for Breast uses a semi-automated segmentation method to reduce errors by specifying the location of the lesion. In the preprocessing module, the input image is transformed so that the coordinates of the user-selected point are in the center of the image, and segmentation is performed on the transformed image. Because the lesion is located in the center of the modified image, the central region is enhanced in the feature layers to improve segmentation performance.

In the second step, BI-RADS lexicon classification, a new rectangular region is generated using the boundary of the lesion extracted in the first step, and it is classified as an input image. In the pre-processing module, three images with different margins are generated for the input image for analysis not only of the lesion area but also of the farther peripheral area. We used AlexNet (2), a type of Convolutional Neural Network to output the classification results for the five lexicon items of shape, orientation, margin, posterior features, and echo pattern for one image input.

In the benign/malignant classification step, the lesion area obtained in the first step is used as an input image to classify whether the lesion is benign or malignant. We modified GoogLeNet (3) for gray image input and two-class output as benign/malignant and removed two auxiliary classifiers. To support three different decision modes with different sensitivities, three networks with different probabilities are used and the results are combined into a logical operation. We converted ImageNet images into gray images, trained the network with them, and used this network as a pre-trained network (4). Images of 790 masses obtained using the RS80A system (Samsung Medison Co., Ltd.) and of 6775 other breast masses obtained using other US systems (iU22, Philips Healthcare, Bothell, WA, USA; A30, Samsung Medison Co., Ltd.) were used for training. Management decisions for either biopsy or follow-up were used as ground truths for training the benign/malignant classifier.

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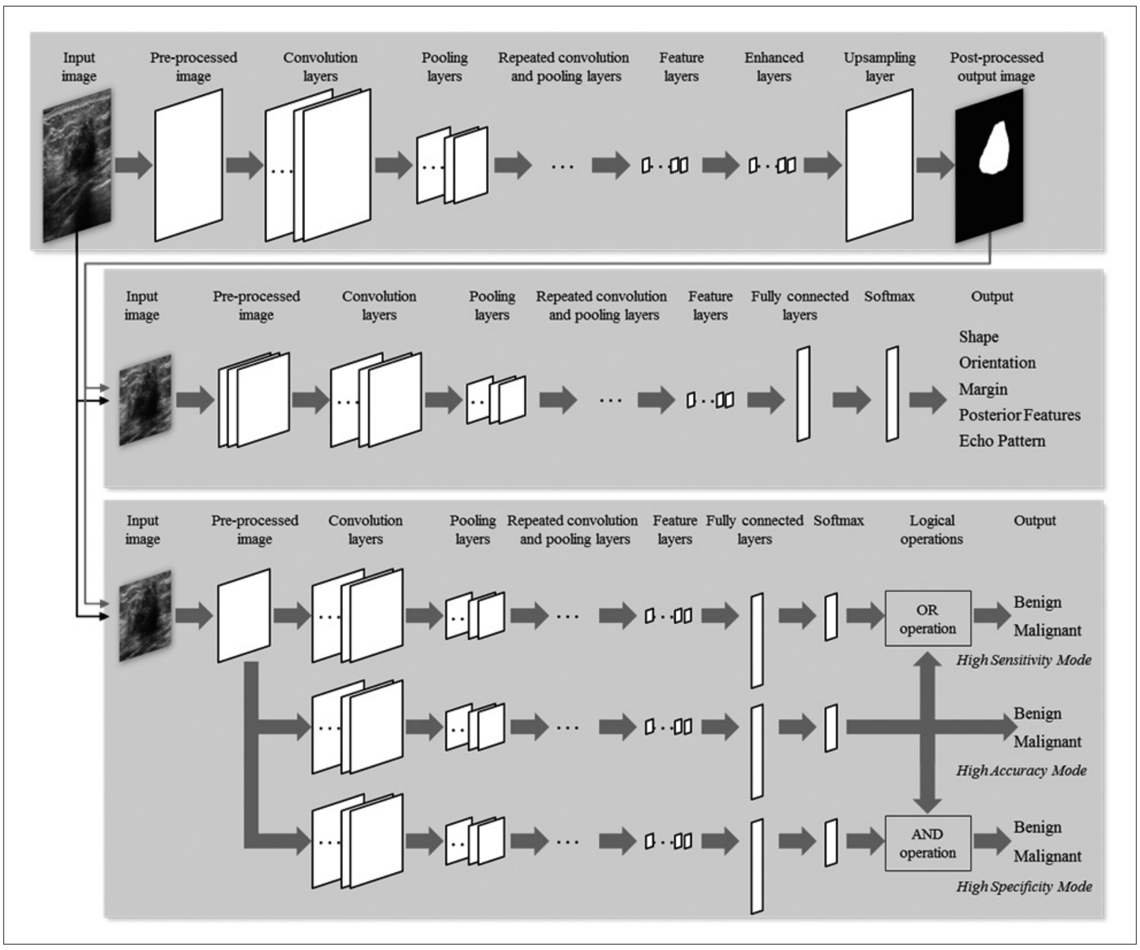

Fig. 1. Conceptual depiction of deep learning-based computer-aided design system for breast ultrasonography.