Pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks

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The submission for the LUNA16 challenge: false positive reduction track uses the solution presented by Setio et al. [1], for which the multi-view convolutional networks (ConvNets) was used. For each candidate, a set of 2-D patches from differently oriented planes is extracted. The architecture comprises multiple streams of 2-D ConvNets, where the first fully connected layers from all streams are concatenated to be passed to the classification layer. In our previous study [1], half of the LUNA16 candidates were used to develop and evaluate the ConvNets. In LUNA16 challenge, we evaluated the performance of the ConvNets when all candidates are used.

1 Data

We performed evaluation in 5-fold cross-validation across the selected 888 LIDC-IDRI cases. We split 888 cases into 5 subsets and kept the number of candidates on each subset similar. For each fold, we used 3 subsets for training, 1 subset for validation, and 1 subset for testing.

Data augmentation is applied on all candidates to increase the variance of presentable candidates. For each candidate, we performed random zooming $[-0.9, +1.1]$, random rotation $[-20^0, +20^0]$, and translation [-1 mm,+1 mm]. To prevent over-fitting during training, we randomly sample positive and negative candidates with equal distribution.
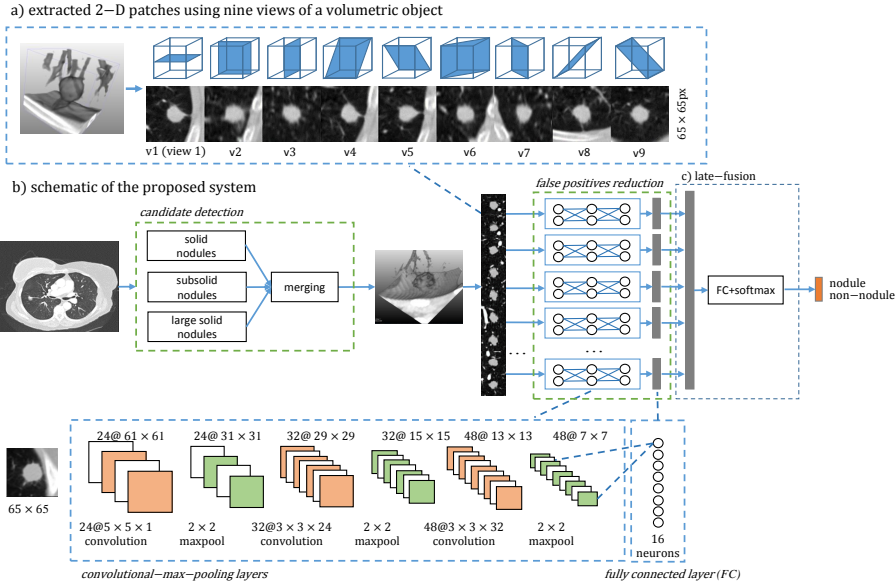
Figure 1: An overview of the proposed CAD system. (a) An example of extracted 2-D patches from nine symmetrical planes of a cube. The candidate is located at the center of the patch with a bounding box of 50×50 mm and 65×65 px. (b) Candidates are detected by merging the outputs of detectors specifically designed for solid, subsolid and large nodules. The false positive reduction stage is implemented as a combination of multiple ConvNets. Each of the ConvNets stream processes 2-D patches extracted from a specific view. (c) Different methods for fusing the output of each ConvNet stream. Grey and orange boxes represent concatenated neurons from the first fully connected layers and the nodule classification output. Neurons are combined using fully connected layers with softmax or a fixed combiner (product-rule).

2   Methods

We use the architecture implemented in [1]. The architecture is constructed by combining various streams of ConvNets, referred as a multi-view architecture. Each stream processes patches from a specific view of the candidate. The information from the first fully connected layers are combined using the late fusion. The architecture is shown in figure 1. We trained the system two times (with different random initial weights) and averaged the predictions from two systems to obtain the final prediction.

References

[1] A. A. A. Setio, F. Ciompi, G. Litjens, P. Gerke, C. Jacobs, S. van Riel, M. W. Wille, M. Naqibullah, C. Sanchez, and B. van Ginneken, "Pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks," *IEEE Transactions on Medical Imaging*, 2016.