SEGMENTATION LABEL PROPAGATION USING DEEP CONVOLUTIONAL NEURAL NETWORKS AND DENSE CONDITIONAL RANDOM FIELD

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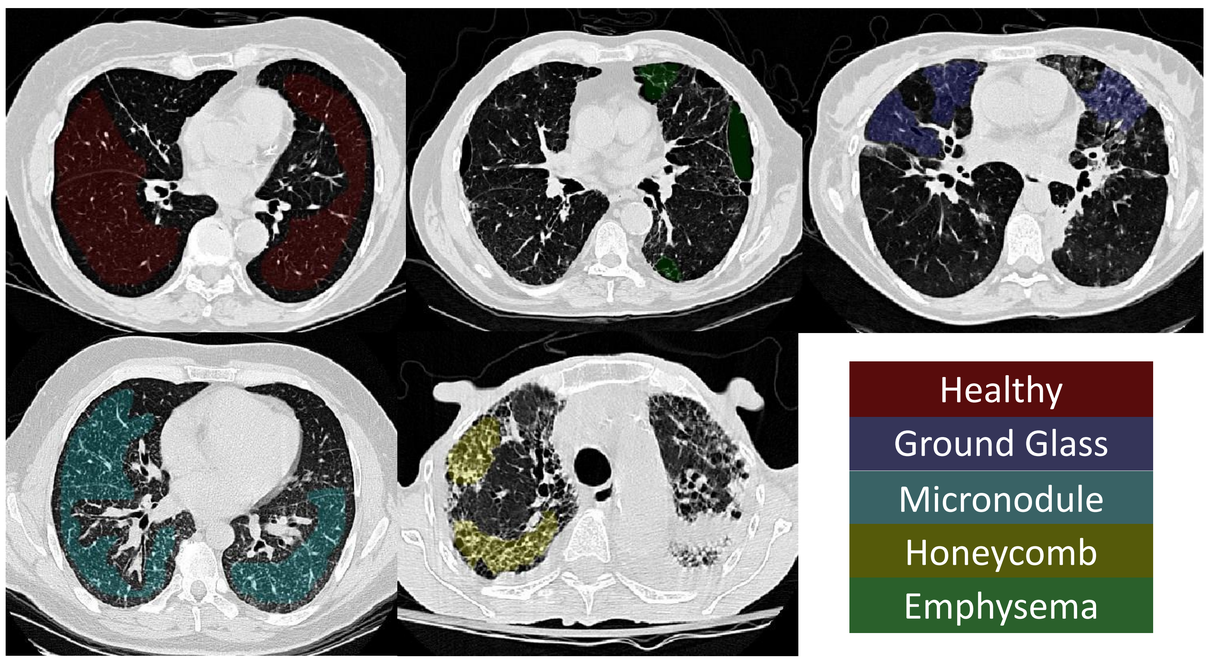
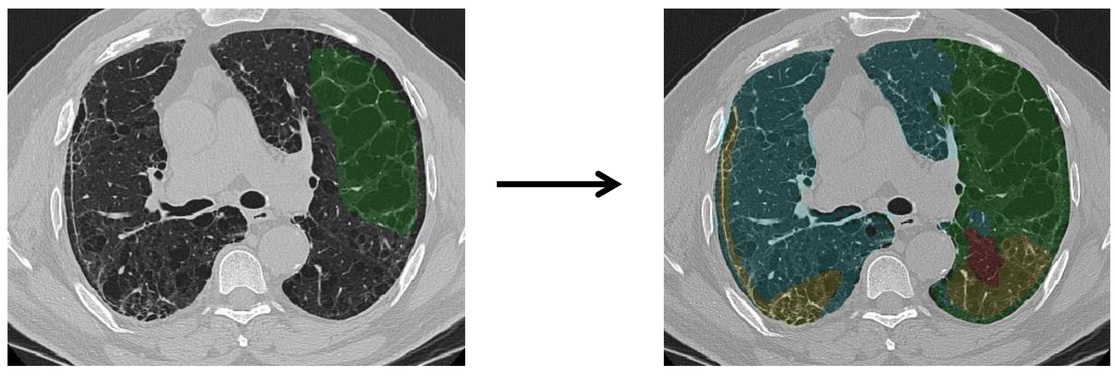
Introduction



Color patches labeled by doctors

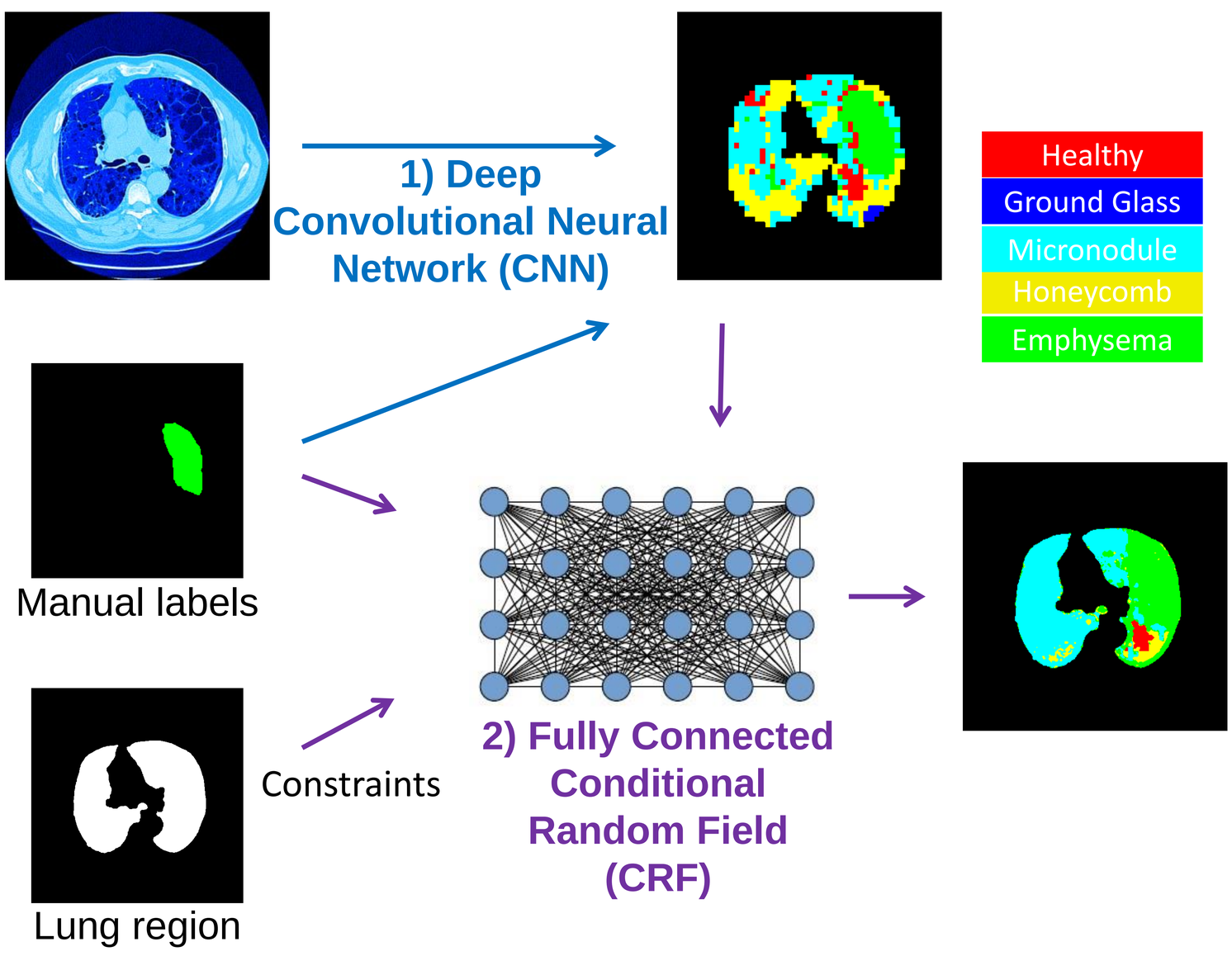
- Missed Labeling of regions of interest is a common issue in existing medical image datasets. Only less than 15% of the lung regions are labeled in [1].
- We propose a segmentation propagation algorithm to assist doctors during the labeling process.



Manual labels provided by doctors → Detailed labeling on every pixel

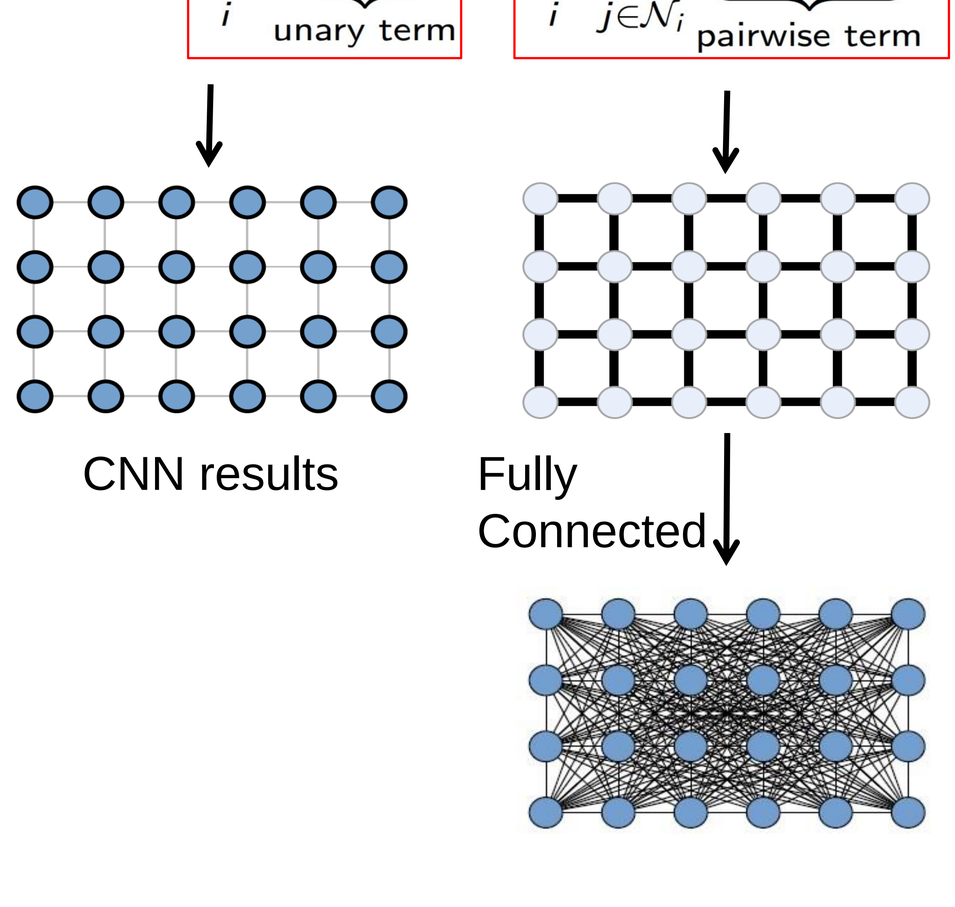
Method

- We formulate the segmentation problem as a maximum a posteriori (MAP) inference in a CRF defined over pixels.
  1) The unary term is computed independently by the convolutional neural network (CNN) classifier for each pixel/patch [4].
  2) The pairwise term evaluates the degree of similarity between every two pixels in the image, and is efficiently solved by message passing [3].

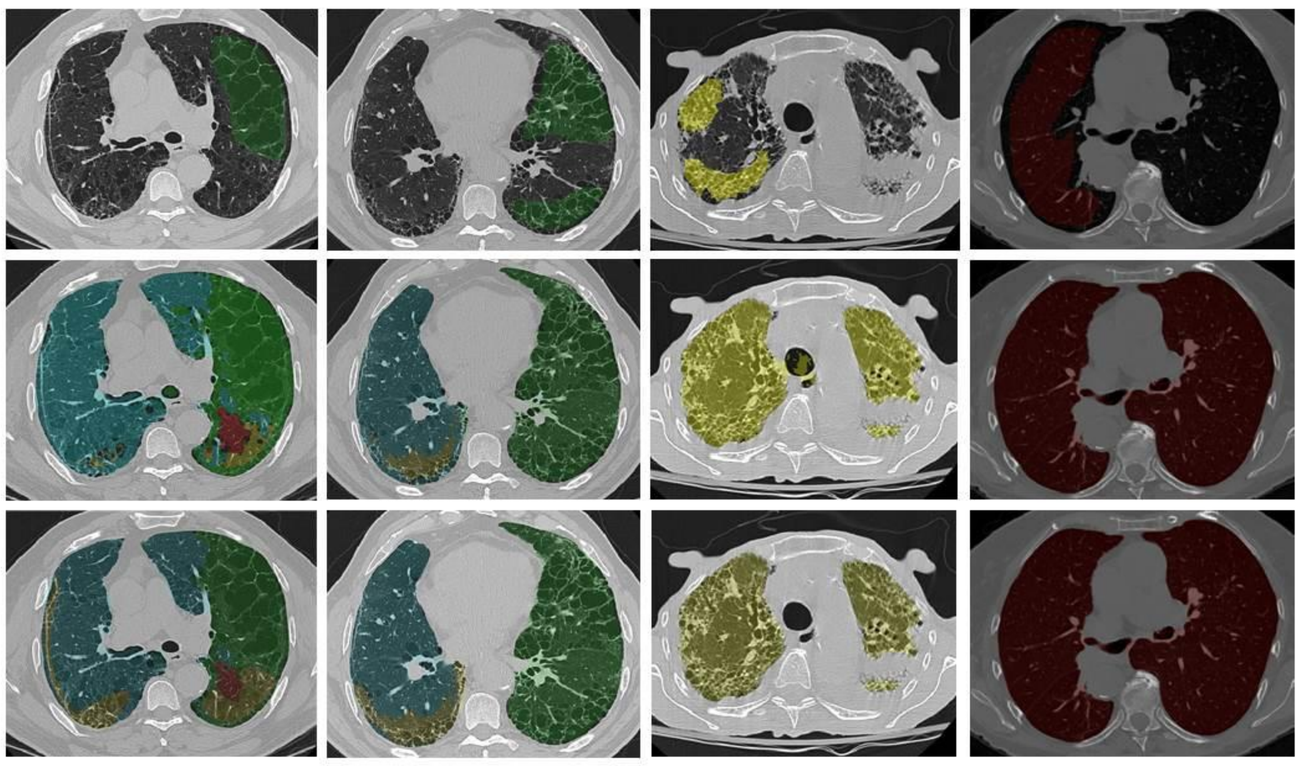


- Constrained unary term
  - Manually labeled pixels are hard-enforced with their original ILD image labels
  - Pixels outside the lung are considered as hard-enforced background
- Constrained pairwise term
  - Message passing can only occur between lung pixels

$$E(\mathbf{x}) = \underbrace{\sum_i \psi_u(x_i)}_{\text{unary term}} + \underbrace{\sum_i \sum_{j \in \mathcal{N}_i} \psi_p(x_i, x_j)}_{\text{pairwise term}}$$



Results



- 92.8% total accuracy
- 7.8 times more labeled pixels
- Multiple diseases can appear on the same slice. Labeling all diseases on slices is crucial for slice-wise disease detection.
- The fully labeled annotation will be publicly shared [5].

References:
[1] Depeursinge, Adrien, et al. "Building a reference multimedia database for interstitial lung diseases." *CMIG 2012*
[2] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012.
[3] Krähenbühl, Philipp, and Vladlen Koltun. "Efficient inference in fully connected CRFs with Gaussian edge potentials." NIPS 2011.
[4] Gao, Mingchen, et al. "Holistic Classification of CT Attenuation Patterns for Interstitial Lung Diseases via Deep Convolutional Neural Networks." MICCAI deep learning workshop 2015.
[5] http://www.research.rutgers.edu/~minggao

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