Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network

Andreas Christe[1], Marios Anthimopoulos[2], Stergios Christodoulidis[2], Lukas Ebner[1], Stavroula Mougiakakou[2]
[1] Department of Radiology, lnselspital, Bern University Hospital, University of Bern, Switzerland
[2] University of Bern, ARTORG Center for Biomedical Engineering Research Diabetes Technology Research Group Murtenstrasse 50, CH-3008 Bern

Purpose: Deep learning techniques have recently achieved impressive results in a variety of computer vision problems, raising expectations that they might be applied in other domains, such as medical image analysis. We propose and evaluate a convolutional neural network (CNN), designed for the classification of interstitial lung disease (ILD) patterns.
Materials and methods: The proposed network consists of 5 convolutional layers with 2×2 kernels and LeakyReLU activations, followed by average pooling with size equal to the size of the final feature maps and three dense layers. The last dense layer has 7 outputs, equivalent to the classes considered: healthy, ground glass opacity (GGO), micronodules, consolidation, reticulation, honeycombing and a combination of GGO/reticulation (Fig. 1). To train and evaluate the CNN, we used a dataset of 14696 image patches, derived by 120 CT scans from different scanners and hospitals (Fig. 2). A comparative analysis proved the effectiveness of the proposed CNN against previous methods in a challenging dataset.
Results: The classification performance (~85.5%) demonstrated the potential of CNNs in analyzing lung patterns. Pattern-sensitivities reached from 99% (consolidation) to 69% (honeycombing). The individual "true positive" and "false negative" results for each pattern is demonstrated in Fig. 3.
Conclusion: The CNN showed very promising results in lung pattern recognition outperforming many state-of-the-art methods. Future work includes, extending the CNN to three-dimensional data provided by CT volume scans.
Clinical Relevance: Integrating the proposed method into a CAD system helps providing a differential diagnosis for ILDs as a supportive tool for radiologists.

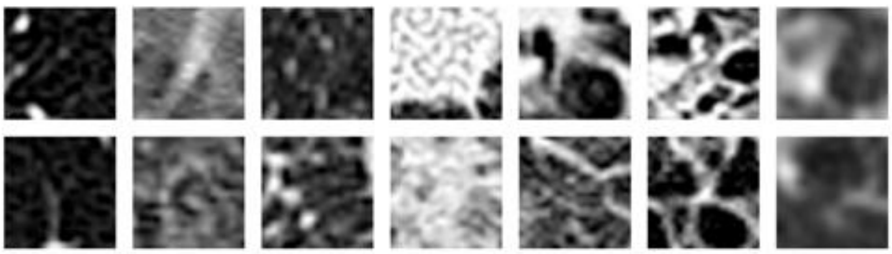


Fig 1. Examples of healthy tissue and typical ILD patterns from left to right: healthy, GGO, micronodules, consolidation, reticulation, honeycombing, combination of GGO and reticulation.

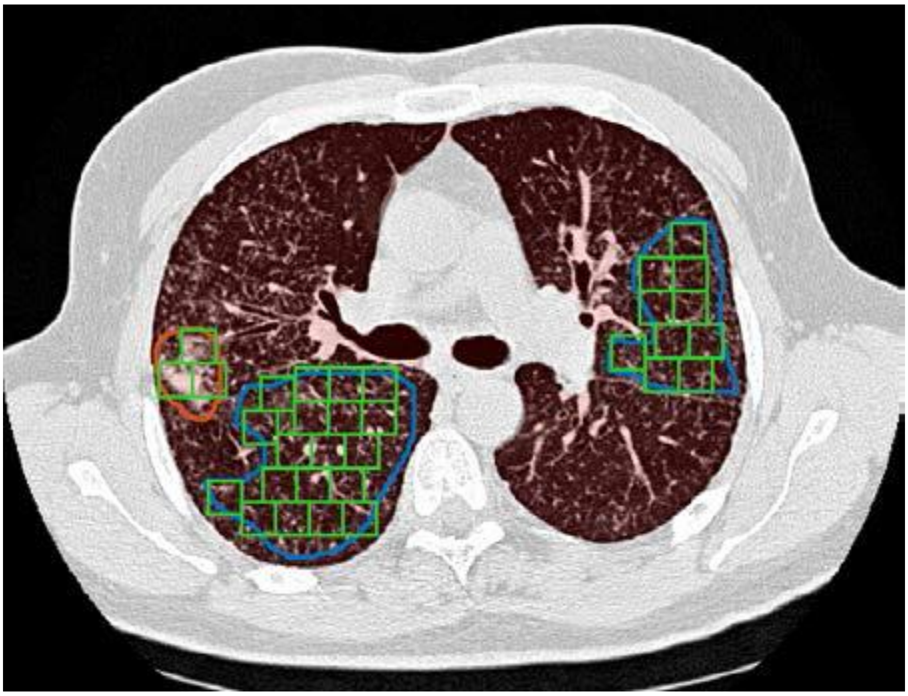
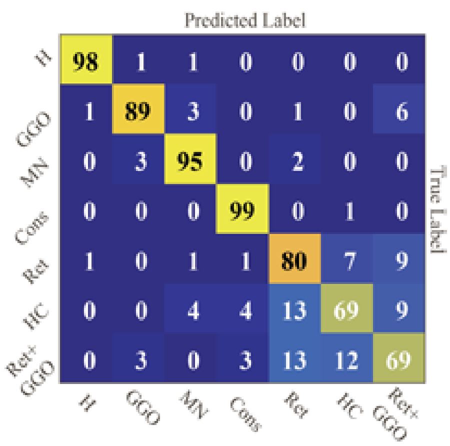


Fig 2. Example of generating image patches through the annotations of a CT slice. The lung field is displayed with transparent red. The polygons are the ground truth areas with considered pathologies. The patches have 100% overlap with the lung, at least 80% overlap with the ground truth and 0% overlap with each other.



Confusion matrices of CNN. The entry in the i^{th} row and j^{th} column corresponds to the percentage of samples from class i that were classified as class j. H: healthy tissue; MN: micronodules; GGO: ground glass opacity; Cons: consolidation; Ret: reticulation, HC: honeycombing.