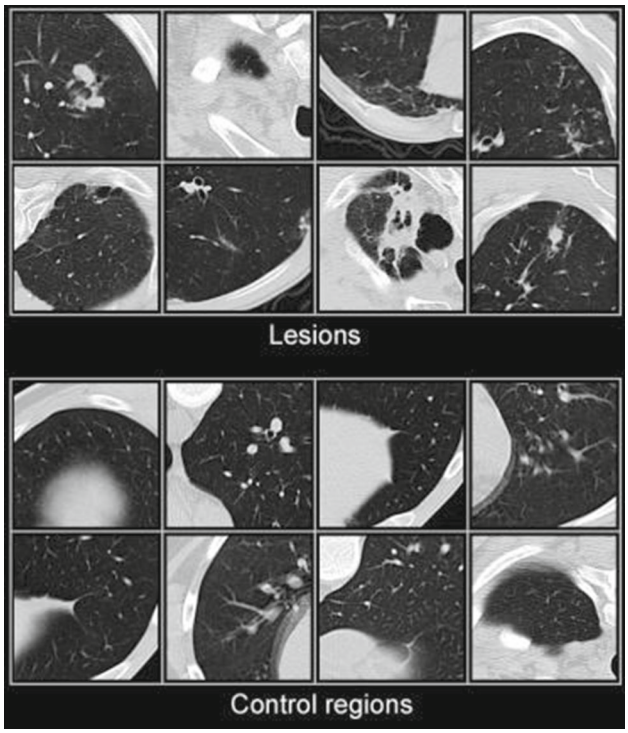

Fig. 1 Examples of lung lesions and control CT image regions

Conventional methods. Conventional methods of image classification were based on a typical procedure which includes calculation of image descriptors, reducing feature space by Principal Component Analysis (PCA) method and supplying the relevant principal components into a Linear model and Random Forest (RF) classifier. The commonly known histograms of Local Binary Patterns (LBP) as well as 2D version of extended multi-sort, six-dimensional co-occurrence matrices [1] which fuse the intensity, gradient magnitude, and anisotropy image properties were used as image descriptors. In addition, we calculated also the commonly known Histograms of Oriented Gradients and Banks of Filters suggested in [2].

Deep learning methods. The GoogLeNet CNN was trained using Nvidia Deep Learning GPU Training System (DIGITS) interface. DIGITS integrates the popular Caffe deep learning framework which supports GPU acceleration using cuDNN to massively reduce training time. The training was performed on a personal computer equipped with Intel i7-6700 K CPU and dedicated GPU of Nvidia TITAN X type with 3072 CUDA Cores and 12 Gb of GDDR5 onboard memory. The network training parameters were set to the following values: Number of epochs = 120, Activation function = ReLu, Batch size (minimum size to place network in GPU memory) = 64, Number of iterations = 220,000, Solver type = SGD Caffe solver. No image data augmentation procedures applied to extend the training set.

Results

ROC curves presenting the results of classification of CT image ROIs using both conventional and deep learning methods are presented in Fig. 2. As it can be seen from the figure, conventional methods provide relatively low classification performance with Area Under Curves (AUC) values of 0.811 for Histograms of Oriented Gradients, 0.834 for Filter Banks, 0.849 for LBP features, and finally 0.874 for extended co-occurrence matrices.

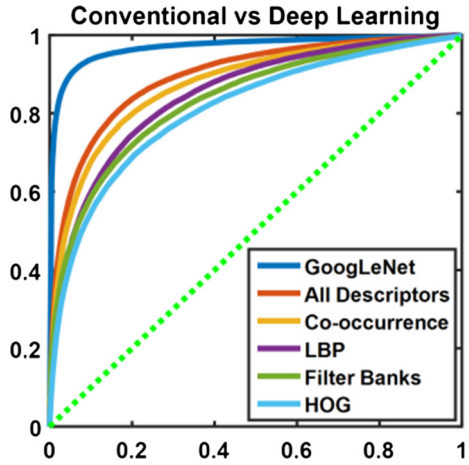

Fig. 2 ROC curves for classification of image ROIs using conventional and deep learning methods

Combining all above image descriptors into one table, entering it into PCA and performing classification using the relevant output principal components provides even better classification quality (see brown ROC curve labeled by "All Descriptors" in Fig. 2) with AUC = 0.895. Nevertheless, the deep learning approach employing the GoogLeNet provides substantially better results (dark blue curve) with AUC value as high as 0.969. For instance, such a high AUC value can provide the following particular result: if we have decided to keep the sensitivity on a practically acceptable level of 0.7 (vertical axis), the corresponding rate of false positive categorizations of ROIs (horizontal axis) would be as low as 0.0079 which corresponds to only about 8 wrong categorizations per 1000 predictions.

Conclusion

Deep learning methods and convolutional neural networks appear to be a powerful tool for detecting lesions in lung CT images. On a dataset containing 149,273 ROIs sampled from CT images of 338 tuberculosis patients it outperforms conventional technique based on feature extraction and classification with area under ROC-curve of 0.969 against 0.895 respectively.

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Emphysema detection and classification using a multi-scale deep convolutional neural network

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Keywords Computed tomography · Emphysema · Tissue classification · Convolutional neural networks

Purpose

Chronic Obstructive Pulmonary Disease (COPD) is the fourth leading cause of death worldwide and leads to two main phenotypes: chronic bronchitis and emphysema. Densitometric analysis in CT is widely accepted measurement of emphysema, however it may not be able to classify it into subtypes. Others methods based on texture information have been proposed to carry out an emphysema classification. Texture patterns lead to six distinct types of emphysematous tissue: normal tissue (NT), paraseptal (PS), panlobular (PL) and mild, moderate and severe centrilobular (CL1, CL2, CL3) emphysema. In this article we propose and validate an emphysema pattern classification tool in CT images based on a Multi-scale Convolutional Neural Network (M-CNN).

Methods

The proposed methodology is based on labeling two-dimensional ROIs sliding through all the segmented parenchyma in the corresponding axial slices. The definition of the physical extent of these ROIs is critical to achieve a successful classification. After carrying out different experiments, it has been corroborated the optimal ROI size proposed previously by other authors [1]—24.18×24.18 mm^2.

Benchmark classification method

We will benchmark our proposed methodology against state-of-the-art work that is based on emphysema classification using local intensity distributions functions, estimated by Kernel Density Estimation (KDE), and subsequently classified by KNN classifier [2]. The authors showed that emphysema discrimination can be performed using intensity distributions, obtaining always even better results than when using more complex features.

Multi-scale Convolutional Neural Network Architecture

In this work we propose a Multi-scale Convolutional Neural Network (M-CNN) that may be able to learn the optimal features of the input data not only at the single original image scale level but also at other levels. In this way the input of the proposed methodology is composed of a multi-scale representation at different scale levels of the image to be classified. The scaled versions correspond to Gaussian filtered versions according to the following equation: $I_\sigma = I * G_\sigma$, $\sigma = \{0, 0.3, 0.8\}$.

The proposed M-CNN architecture is shown in Fig. 1, and it is composed of 4 convolutional and 3 max-pooling layers. The input of the network is a $31 \times 31 \times 3$ image patch, where reflects the three different scale representations, which is firstly convolved with a bank of 32 filters with a kernel size of 3×3 to capture local information. The first layers learn low-level features of the input. After applying the ReLU transformation, $f(x) = \max(0, x)$, to this first layer, we apply a max-pooling layer with a receptive filed size of 2×2 where we will half the feature dimensionality. These layers are followed by a succession of convolutional and max-pooling layers, where features will be distributed from lowest to highest abstraction level hierarchy. The resulting extracted features are introduced into a 3 dense fully-connected layers composed of 64, 112 and 6 neurons respectively, since 6 is the number of considered classes.

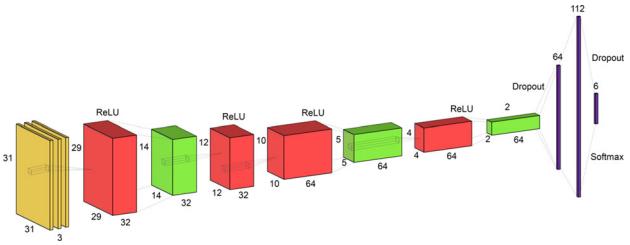

Fig. 1 Proposed M-CNN architecture for emphysema classification with 4 convolutional (red), 3 pooling (green) and 3 fully connected (purple) layers

Training is done through Stochastic Gradient Descent method updated with Nesternov momentum to minimize the categorical cross-entropy.

Overfitting prevention

In this work we apply 4 different techniques to reduce the overfitting: L2 regularization of the loss function, data augmentation using different spatial transformations over the training data set, early stopping where the training is stopped before overfitting begins and finally dropout by randomly dropping units with a given probability ($p = 0.5$) during training.

Results

The training and validation dataset for the proposed algorithm has been selected from a subset of 267 CT scans from the COPDGene study, where experienced pulmonologist have manually selected regions providing a total of 1337 tissue samples, corresponding to 6 tissue classes: NT (370 samples), PS (184), PL (148), CL1 (170), CL2 (287) and CL3 (178). We perform data augmentation on all samples by rotating (90°, −90° and 180°), flipping (along X and Y axes) and combining both transformations during training.

Evaluation

Architecture's hyperparameters selection and evaluation of the proposed and reference classification methods are based on a train-validation-test scheme jointly with a tenfold cross validation scheme.

Multi-scale convolutional network

An evaluation has been made to prove that introducing a multi-scale representation of the image can improve the performance. As shown in Table 1, Multi-scale CNN (M-CNN) obtained a greater global classification accuracy when compared to the mono-scale version of the architecture.

Table 1 Differences in the classification accuracy between the mono-scale and multi-scale versions of the proposed method

Architecture	Accuracy [mean (SD)]
Mono-scale CNN	0.819 (0.027)
Multi-scale CNN	0.891 (0.035)

Analysis of the method's performance

Table 2 provides a comparison of the proposed M-CNN with the benchmark method (KDE-KNN) in the same emphysema classification problem. All methods were implemented by the authors and the same dataset and evaluation methodology were used. The results prove the superior performance of the proposed M-CNN that outperforms by 21% with respect to KDE-KNN the global accuracy.

Table 2 Comparison of the proposed method (M-CNN) with the reference methodology (KDE-KNN)

Method	Accuracy [mean (SD)]	95% CI [LL, UL]
KDE-KNN	0.679 (0.035)	[0.656, 0.702]
M-CNN	0.891 (0.035)	[0.866, 0.913]

Full lung classification

We also performed full-lung classification of CT scans with different stage of disease severity. The classification was carried out at a fixed sampling grid with spacing 5 × 5 pixels in each axial image slice. The rest of the voxels were classified using nearest-neighbor interpolation. The results obtained for the methods in a full lung CT image are shown in Fig. 2. It has been visually confirmed by experts that the proposed M-CNN method yields a better performance in full-lung classification.

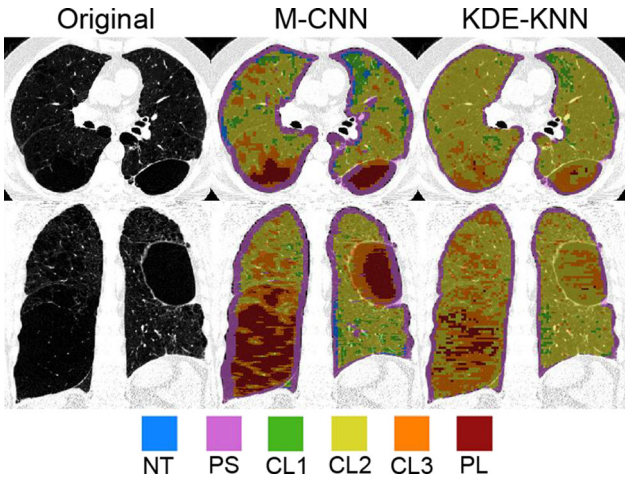

Fig. 2 Full lung classification results for a severe disease case. From left-to-right: original image, classification results for M-CNN and KDE-KNN

Conclusion

In this work we propose a Multi-scale Convolutional Neural Network for emphysema classification in CT images considering 6 different classes, including normal tissue and 5 emphysema subtypes. A new architecture has been designed to capture local texture features of the lung tissue in different scales. The classification accuracy of the proposed approach is 89.1% and it has been evaluated in a large dataset composed by 1337 tissue samples and through visual clinical validation in complete lungs.

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Computer-aided prediction of overall survival of patients with rheumatoid arthritis-associated interstitial lung disease based on deep learning

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Keywords Computer-aided diagnosis · Deep learning · Interstitial lung diseases · Survival analysis

Purpose

The use of machine learning has recently attracted the attention of researchers in the medical imaging field. In particular, deep learning has shown remarkable ability to derive radiomic features automatically from medical images.

Rheumatoid arthritis (RA) is the most common connective-tissue disease that develops inflammatory synovitis. The RA affects approximately 1% of the population of the United States [1]. One of the major extra-articular manifestations of RA is the interstitial lung disease (ILD). Approximately 5–10% of patients with RA also suffer from clinically significant ILD.

The purpose of this study was to investigate the effect of image-based features derived by deep learning, called deep radiomic features, for the prediction of the overall survival of patients with the RA-ILD. The deep radiomic features are extracted from CT images by use of a deep convolutional neural network (DCNN). To the best of our knowledge, this is the first study that used DCNN-extracted regions of ILD of RA-ILD patients for deriving radiomic biomarkers to predict survival after a diagnosis of RA-ILD.

Methods

In this study, we first trained a DCNN with manually extracted regions of interest (ROIs) that had been labeled with five types of ILD disease patterns. The trained DCNN was applied to a test set for classifying each point of the lung tissue in terms of the six disease patterns. We extracted deep radiomic features as the feature vector from the last convolutional layer. We then assessed the performance of these deep radiomic features in the prediction of survival of the patients with RA-ILD.

Subjects

A total of 104 patients with a diagnosis of RA and ILD and who underwent chest CT were identified retrospectively as potential candidates for this study. After reviewing their medical records, patients who had been diagnosed with RA-ILD based on clinical and radiological findings or through surgical lung biopsy were included in this study. Patients with history of any cancers involving the lungs, and patients with a history of lung resection except surgical biopsy, were excluded. An experienced observer (C.W., an internist with 15 years of experience in pulmonary disease diagnosis and treatment) extracted 7329 ROIs from the CT images of all patients, and labeled them as having one of the following five ILD patterns: normal, consolidated, ground-glass opacity, reticular, or honeycombing patterns (Fig. 1a).