An Improved System for Emphysema Recognition Using CNN features extraction and AdaBoost-Decision Tree classifier

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Abstract

In this work, a hybrid model composed of a CNN and a classical machine learning method was proposed to improve the classification of emphysema diseases. Firstly, we have proposed a pre-treatment step based on contrast adjustment in order to improve the performances of the proposed model. Second, we extract the features from the deeper layers of the CNN classifier, then we classify these features with decision tree and AdaBoost algorithm. The proposed model is validated by usinga set of 168 manually annotated ROIs for each CT image, comprising the three classes: normal tissue, centrilobular emphysema, and paraseptal emphysema. The obtained results show that the hybrid model proposed in this work provides the best accuracy in the case of the AdaBoost-Decision Tree classifier.A comparison with CNN, CNN-SVM and CNN-AdaBoost-Decision Tree classifier has been performed. As conclusion, the CNN-AdaBoost-Decision Tree classifier provide the best results with an accuracy of 100%.

Keywords: CNN, features extraction, AdaBoost-Decision Tree

1. Introduction

Emphysema is a type of COPD that affects the air sacs in the lungs, it can be diagnosed based on CT images. There are many emphysema diseases like: Centrilobular emphysema, which is the most common type. This later,it affects the proximal respiratory bronchioles, particularly of the upper zones; Paraseptal emphysema, on the other hand, it affects the peripheral parts of the secondary pulmonary lobule, and is usually located adjacent to the pleural surfaces (including pleural fissures) . Recent studies in the literature have showed shown a growing interest in of using texture analysis methods and machine learning algorithms to identify the emphysema diseases in lung CT images.

For instance, the authors in [1] propose emphysema quantification in CT images by using a texture classification-based system. This classifier fuses pixel posterior probabilities output to predict emphysema severity, while the regions of interest are characterised by using

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Local binary patterns (LBP), joint LBP, and intensity histograms. They then they perform the classification by using the a nearest neighbour classifier method with a histogram dissimilarity measure as distance. They achieved 95.2% classification accuracy. The authors in [3] investigated the performances of local binary patterns. Indeed, they experimented with three different types of LBP and used a support vector machine classifier optimized by an elephant herding optimization algorithm for classification.. In [4] the authors study the connection between the visual score of emphysema and homology-based emphysema quantification (HEQ). Then,they used leave-one-patient-out cross-validation technique to evaluate the accuracy of machine learning and HEQ in predicting the visual score.The difference in the accuracy was assessed using McNemar's test.

In the paper [5], the authors proposed a novel method for emphysema quantification by aggregating a different set of features: statistical features of wavelet transformed image, grey-level co-occurrence matrix(GLCM), first-order texture statistical features, and grey-level run-length matrix(GLRLM). They used a leave-one-out cross-validation technicque to validate the algorithm on the with a CT database, reaching an accuracy of 91.67% accuracy and a sensitivity of 91.89%. They also sensitivity, and obtained the scores of%5.72% and 92.22% in specificity and precision respectively.

In an effort to explore shallow networks,which are more interpretable in the medical imaging domain,anew neural network architecture that uses Radon projections to both classify and represent medical images was proposed in [6]. the proposed model was validated on with five publicly available datasets, a general dataset (namely MNIST), and four medical datasets (namely Emphysema, IDC, IRMA, and Pneumonia).

In the research work presented in [7], a classification strategy based on features extraction using local diagonal extrema pattern (LDEP) and fuzzy particle swarm optimization (FPSO) clustering algorithm allowing to obtain optimal fuzzy partition space for each attribute was presented. The method applied fuzzy PSO to develop input fuzzy space for Fuzzy ID3 and was tested on with the emphysema CT images in order to classify the patient's lung tissue into normal, centrilobular emphysema, and para-septal emphysema.

In this work, we propose to use CNN models to extract features from the training images. The proposed CNN network constructs a hierarchical representation of input images. Deeper layers contain higher-level features, constructed using the lower-level features of from earlier layers. To get a lower-level representation of the images, we use the earlier layer in the network. The CNN proposed model is composed of four convolutional layers and four fully connected layers. The features extracted from the fourth layer are classified by a decision tree with Adaboost algorithm and SVM classifiers.

2. Material and methods

2.1. The convolutional neural network CNN's

The convolutional neural network (CNN, or ConvNet) is one of the most popular algorithms in the field of deep learning, it has been shown to perform well in computer vision tasks such as image classification, object detection, 'objects and neural style transfer[8]. The model proposed in this work have is composed of the following layers (figure 1):

The CNN model has 23 layers including : the input layer, 4 convolution layers, 3 a max-pooling layers and 4 fully connected layers.

1	'input'	Image Input	64x64x1 images
2	''	Convolution	8 5x5 convolutions
3	''	Batch Normalization	Batch normalization
4	''	ReLUReLU	
5	''	Max Pooling	2x2 max pooling
6	''	Convolution	16 5x5 convolutions
7	''	Batch Normalization	Batch normalization
8	''	ReLUReLU	
9	''	Max Pooling	2x2 max pooling
10	''	Convolution	32 5x5 convolutions
11	''	Batch Normalization	Batch normalization
12	''	ReLUReLU	
13	''	Max Pooling	2x2 max pooling
14	''	Convolution	64 5x5 convolutions
15	''	Batch Normalization	Batch normalization
16	''	ReLUReLU	
17	''	Max Pooling	2x2 max pooling
18	''	Fully Connected	32 fully connected layer
19	''	Fully Connected	16 fully connected layer
20	''	Fully Connected	8 fully connected layer
21	''	Fully Connected	3 fully connected layer
22	''	Softmaxsoftmax	
23	''	Classification	Output

Figure 1: The architecture of the CNN model

2.2. AdaBoost-Decision Tree classifier

Boosting is an ensemble learning technique that attempts to create a strong classifier from several weak classifiers. This is done through an iterative approach by building an initial model, then creating a second model that attempts to correct and learn from the mistakes of the first one. Models are added until the training set is predicted perfectly, or a maximum number of models is reached.The weak models are generated using machine learning (ML) algorithms with different distributions, as each iteration generates a new weak prediction rule. Boosting technique basically works on for reducing the bias error which arises when models are not able to identify relevant trends in the data. This happens by evaluating the difference between the predicted value and the actual value. To find weak learners, we apply ML algorithms with a different distribution. As each time base learning algorithm is applied, it generates a new weak prediction rule. This is an iterative process. After many iterations, the boosting algorithm combines these weak rules into a single strong prediction rule. AdaBoost,or Adaptive Boosting, is the most popular boosting technique. it was originally called AdaBoost.M1 in a paper authored by Yoav Freund and Robert. ,recently Recently it can be referred to as discrete AdaBoost because it is more commonly used for classification than regression. Rather than being an independent model, AdaBoost can be applied on top of any classifier to learn from its limitations and develop a more accurate model, being the "best out-of-the-box classifier". The most suited and therefore most common algorithm used with AdaBoost is decision trees with one level, or what's frequently called decision stumps. Decision Trees are a non-parametric supervised learning method used for classification and regression. It aims to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.Decision Stumps is a weak classification model with a simple tree structure consisting of one split, which can also be considered as a one-level decision tree. They have one internal node (the root) which is immediately connected to the terminal nodes (its leaves). A decision stump makes a prediction on the basis based on of the value of just a single input feature. AdaBoost works by emphasising difficult to classify instances and leaving those already well handled.For a base classifier with a larger classification error, a smaller weight is assigned to weaken its role in voting; .for For the base classifier with a better classification effect, it is given higher weight to strengthen its role in voting. In this work, the features extracted from the fourth fully connected layer (the 21st layer) are classified with AdaBoost-Decision Tree classifier.

3. Results and discussion

3.1. Description of the data

The database used in this work contains 115 high-resolution CT (HRCT) slices in addition to168 square patches manually annotated in a subset of the slices.CT images we reacquired using a General Electric scanner (LightSpeed QX/i; GE Medical Systems, Milwaukee, WI, USA)with four detector rows and using the following settings:0.78 x 0.78 mmin-plane resolution, 1.25 mmslice thickness, 140 kVtube voltage, and 200 mAs tube current. The slices were reconstructed by using a high-spatial-resolution (bone) algorithm.the The study group CT scanned for collecting the data comprises 39 subjects (9 never-smokers, 10 smokers, and

20 smokers with COPD). Readers can See see [1] and [2] for more details. The additional 168 square patches measure 61 x 61-pixels and are from present three different classes: NT (59 observations), CLE (50 observations), and PSE (59 observations). The normal tissue (NT) patches were annotated in never smokers, and the CLE and PSE ROIs were annotated in healthy smokers and smokers with COPD

3.2. Pre-processing with contrast adjustment

As the first step, we have used the contrast adjustment as pre-treatment. The figure 2 presents an example of normal tissue(NT), centrilobular emphysema (CE), and paraseptal emphysema(PSE) before and after contrast adjustment.

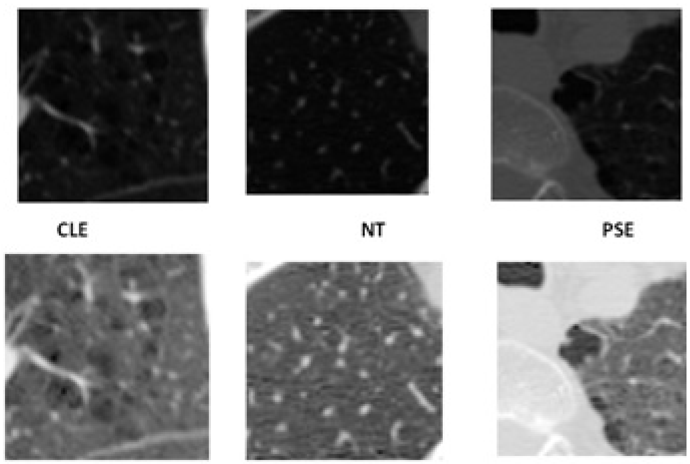

Figure 2: example of normal tissue(NT), centrilobular emphysema (CE), and paraseptal emphysema(PSE) before and after contrast adjustment

figure 3, We compare the accuracy of three models: CNN, CNN-SVM, and CNN-AdaBoost-Decision Tree without and with contrast adjustment. :

From figure 3 we can see clearly that the accuracy increases in the case of the three models when we use the contrast adjustment. The CNN model was trained with two optimizer algorithms: Adam (adaptive moment estimation) and Stochastic gradient descent with momentum (SGDM).

The obtained results are presented in table 1 2.

From table 12, we can see clearly that the hybrid model proposed in this work provides the best accuracy in the case when using of the AdaBoost-Decision Tree classifier. For the CNN classifier trained with the function SGDM optimiser, we obtained an accuracy of $67,9\%$. The accuracy was increased to $76,2\%$ when we have used the contrast adjustment pre-treatment. For the CNN and SVM models, the accuracy was increased in comparison with CNN only. We achieved an accuracy of $81,5\%$ with contrast enhancement. For the CNN classifier trained with the function ADAM, we obtained an accuracy of $67,9\%$. The accuracy was increased to $77,4\%$ by applying contrast enhancement When we have used

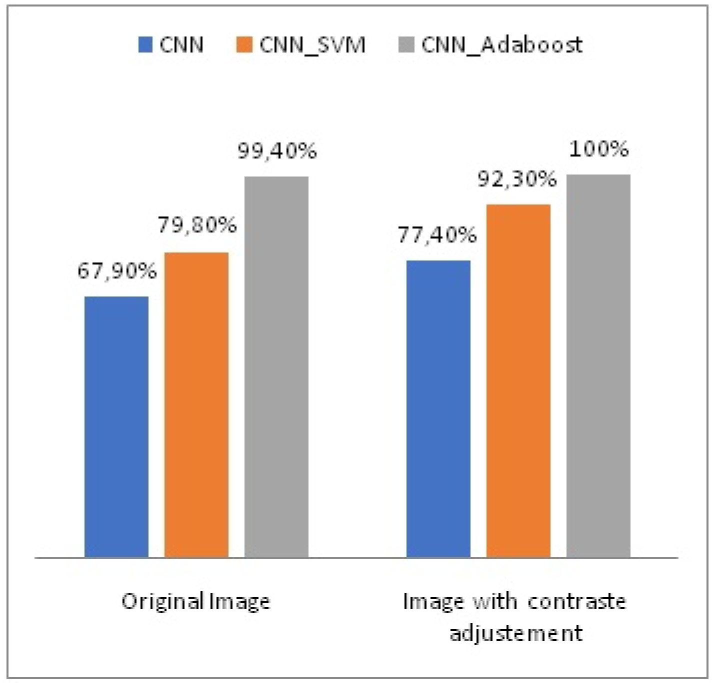

Figure 3: the accuracy of three models: CNN, CNN-SVM, and CNN-AdaBoost-Decision Tree without and with contrast adjustment

Table 1: Sensitivity and accuracy of CNN, CNN-SVM, and CNN-Adaboost classifiers (ADAM)

Classifier	**CLE**	**NT**	**PSE**	**ACCURACY**
CNN	68	54,2	81,4	67,9
CNN-CA	82	64,4	86,4	77,4
CNN-SVM	74	66,1	98,3	79,8
CNN-SVM-CA	92	88,1	96,6	92,3
CNN-AdaBoost	100	98,3	100	99,4
CNN-AdaBoost-CA	100	100	100	100

Table 2: Sensitivity and accuracy of CNN, CNN-SVM, and CNN-Adaboost classifiers (SGDM)

Classifier	**CLE**	**NT**	**PSE**	**ACCURACY**
CNN	70	42,4	91,5	67,9
CNN-CA	80	64,4	84,7	76,2
CNN-SVM	72	69,5	98,3	80,4
CNN-SVM-CA	90	61	94,9	81,5
CNN-AdaBoost	100	100	100	100
CNN-AdaBoost-CA	100	100	100	100

the contrast adjustment pre-treatment. For the CNN and SVM models, the accuracy was increased in comparison with CNN. We achieve an accuracy of $92,3\%$.

4. Conclusion

In this paper, a hybrid model based on CNN features extraction and AdaBoost-Decision Tree classifier has been proposed and evaluated on for the detection of the emphysema diseases recognition from CT lung images. Experiments show that the pre-treatement step have increased the accuracy. A comparison with CNN, CNN-SVM and CNN-AdaBoost-Decision Tree classifier has been performed. In conclusion, the CNN-AdaBoost-Decision Tree classifier provides the best results.

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