International Journal in IT & Engineering (IJITE)
Volume 10 Issue 12, Dec 2022 ISSN: 2321-1776 Impact Factor: 7.256
Journal Homepage: http://ijmr.net.in, Email: irjmss@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal

Visual Scoring-Based Learning with Label Proportions for Emphysema Quantification in CT Scans: A Novel Approach for Predicting Regional Extent and Patch-Level Presence

Patil Manjusha Manikrao
(Research Scholar)
Dr. R. Purushotham Naik (Professor)
(Research Supervisor)
Glocal School Of Technology and Computer Science

Abstract

In order to identify and follow up on COPD patients, it is essential to quantify the extent of emphysema. Traditional densitometry was shown to be less accurate than supervised texture classification when it came to measuring emphysema in several trials. Both the current methods rely on laborious human patch annotations or make do with inadequate labels that only show the patient's overall health state, such as healthy or COPD. We demonstrate how an LLP design may detect emphysema in smaller patches and estimate regional extent using visual grading of regional emphysema extent. By comparing the predicted region extent with expert raters, we find an intraclass correlation of 0.72 (0.65-0.78) when applying our method to 195 visually rated CT images. We are unaware of any previous work that has utilized LLP approaches on data from medical imaging.when used on real-world, big, unplanned networks, the approach works wonderfully.

Keywords: Emphysema; with chronic obstructive pulmonary disease (COPD); label proportions (LLP) framework

1. Introduction

The most common lung disease in people around the world, chronic obstructive pulmonary disease (COPD) is characterized by emphysema, a core structural defect. Deterioration of lung tissue and air trapping in affected areas are hallmarks of emphysema. When looking for hereditary correlations with COPD, it is helpful to quantify the amount of emphysema (Kim, 2020).

Standard approaches for CT-based emphysema evaluation include density measurement and image-based scoring by professionals; chest CT scans can reveal emphysema. While this does offer an objective emphysema measurement, it is not immune to noise and cannot differentiate between different kinds of emphysema. Despite its usefulness in determining emphysema subtype and extent, visual scoring is laborious and prone to inter-observer variability. In order to forecast the subtype and severity of emphysema, a new machine learning method relied on expert annotations of CT patches (Park, et al 2020). Because region-based visual grading is more clinically relevant and takes less time than annotating patches, it is a more practical way to acquire big data sets.

Using visual rating of regional emphysema extent, we learn emphysema patterns and use them to

identify CT scan patches in this work. Each of the six sections of the both lungs—the upper, middle, and lower sections—is given a percentage interval that indicates the degree of emphysema in this visual scoring system.

As an example of learning with label proportions (LLP), we consider this learning problem. LLP is an innovative learning environment that applies proportional labeling. Bags of instances are the focus of both MIL and LLP; for example, a CT scan's patch collection; and the goal is to use known bag labels to forecast the labels of unknown instances, MIL uses binary bag labels, such as COPD versus no-COPD, to make decisions (Tran, et al., 2020). Instance labels can be better understood with bag percentage labels as opposed to binary bag labels, and LLP approaches aim to make better use of this additional information to boost efficiency. A number of LLP approaches have been put up,

2. Methodology

This study adopts a texture-analysis approach to characterize emphysema patterns in chest CT scans, building on the work of Cheplygina et al. (2014). The goal is to predict chronic obstructive pulmonary disease (COPD) by analyzing visual patterns in lung texture using convolutional neural networks (CNNs).

2.1Texture Analysis Using Multi-Scale Filters

In Cluster Model Selection (CMS), machine learning predicts binary labels for each picture patch to learn emphysema patterns. Filter responses define a high-dimensional feature space for each patch. Emphysema severity is labeled on each lung patch "bag" sample. Learning from label proportions (LLP) classifies each patch into an emphysema or non-emphysema cluster.

2.2Cluster Model Selection (CMS)

In Cluster Model Selection (CMS), machine learning predicts binary labels for each picture patch to learn emphysema patterns. Filter responses define a high-dimensional feature space for each patch. Emphysema severity is labeled on each lung patch "bag" sample. Learning from label proportions (LLP) classifies each patch into an emphysema or non-emphysema cluster.

CMS clusters the data and labels each cluster as emphysema-positive or negative. Clusters are utilized to estimate patch and lung region labels. The model optimises the bag loss function, which compares anticipated cluster labels to emphysema extent labels..

.

2.3Interval Bag Loss Function

The cluster labeling procedure is improved using an interval bag loss function. This function minimizes the difference between predicted emphysema extent and genuine interval labels by keeping predicted labels within a range. The loss function penalizes projected values outside the anticipated range, making clustering and label assignment resistant to data noise and variability.

2.4Feature Weight Optimization

Greedy heuristics address cluster labeling complexity. Start labeling with all clusters as non-emphysema (zero). Clusters are iteratively labeled emphysema (one) if they improve bag label predictions. This iterative procedure ends when no improvements are made.

2.5 Greedy Heuristic for Labeling

To address the complexity of labeling clusters, a greedy heuristic is employed. The labeling process begins with all clusters labeled as non-emphysema (zero). Then, clusters are iteratively labeled as emphysema (one) based on their contribution to improving the overall accuracy of bag label predictions. This iterative process stops when no further improvements are achieved.

2.6 Evaluation

The model is tested on 973 photos. Learning a low-dimensional embedding that differentiates emphysema and non-emphysema regions helps classify unseen test images. Clustering and feature weighting optimizations strengthen the CNN model to collect key emphysema features from texture analysis.

3. Results

The Danish Lung Cancer Screening Trial uses low-dose computed tomography images to examine this strategy. Two raters visually score emphysema patients using the approach stated in.

Two raters visually rated each lung for emphysema and awarded each area a label from 0 to 100% based on the following criteria: 1-5%, 6-25%, 26-50%, 51-75%, and 76-100%. A train dataset had 193 scans, A validate dataset contained 195 scans, and A test dataset contained 195 scans. The lack of visual scores led to the exclusion of several scans. In order to match the size of lobules (10-25 mm), a crucial hallmark of emphysema, patches of 21×21×21 mm^3 were taken from each area of the lungs **(Veit, Belongie, & Karaletsos, 2017).**

The model training was divided into two steps:

1. Several models were trained on A_train, with parameters selected based on A_validate performance.
2. Selected parameters were used to train on the combined A_train ∪ A_validate dataset, with performance evaluated on A_test.

3.1Choosing Parameters

We judged each model's performance on A_validate by calculating intraclass correlation (ICC) and mean absolute error (MAE). For this set of parameters, we used k=[5,10,15,20,25,30], which yielded 36 models. All locations saw a stabilization of the MAE around 0.01 at k≥20, with the top regions exhibiting the largest ICC. The ICC for the top regions on the right and left are shown in Table 1.1.

Table 1.1. Intraclass correlation for parameter selection.

Region	Number of clusters	Raters	ICC (CI)
Right upper	20	R1/R2 Avg/CMS	$0.83(0.79-0.87)$ $0.62(0.53-0.70)$
Left upper	15	R1/R2 Avg/CMS	$0.78(0.72-0.83)$ $0.53(0.43-0.63)$

3.2Region Prediction

The models were retrained using the selected parameters from the combined A_train ∪ A_validate dataset. In Table 1.2, we can see the results of evaluating performance on the A_test by calculating the ICC. The ICC improved in the upper right corner when the larger dataset was employed, but it deteriorated in the upper left corner. In the left region, overfitting was seen, which contradicts the results from A_validate.

Table 1.2 Concordance Between Rater Assessments and Model Predictions on Atest.

Region	Raters	ICC on A_test
Right Upper	R1/CMS	$0.82(0.76-0.86)$
	R1/R2	$0.71(0.63-0.77)$
	R2/CMS	$0.58(0.48-0.66)$
	Avg/CMS	$0.67(0.59-0.74)$
Left Upper	R1/R2	$0.81(0.75-0.85)$
	R1/CMS	$0.38(0.25-0.49)$
	R2/CMS	$0.31(0.18-0.43)$
	Avg/CMS	$0.36(0.23-0.48)$

3.3Reduced Data Set for Training

We redo the experiment using patches that had emphysema exclusively to look at the skewed data

issue (where more than 70% of occurrences do not have emphysema). We used A_validate and A_test to assess performance after training on a stripped-down version of A_train. Tables 1.3 and 1.4 summarize the results. The ICC values, especially in the top right corner, were higher after training on the decreased data.

Table 1.3 Intraclass Correlation for Reduced Training Data

Region	Number of Clusters	Raters	ICC (Cl)
Right Upper	30	R1/R2	$0.83(0.79-0.87)$
		Avg/CMS	$0.73(0.65-0.79)$
Left Upper	20	R1/R2	$0.78(0.72-0.83)$
		Avg/CMS	$0.56(0.46-0.65)$

Table 1.4. The degree to which Atest model predictions utilizing sparse training data agree with those of raters. ICC is provided with 95% confidence intervals.

Region	Raters	ICC on A_{test}	
		A_{train}	A_{combined}
	$0.82(0.76-0.86)$	$0.82(0.76-0.86)$	
Right upper R1/CMS	R2/CMS	$0.64(0.52-0.69)$	$0.68(0.60-0.75)$
	Avg/CMS	$0.66(0.57-0.71)$	$0.69(0.61-0.75)$
		$0.72(0.65-0.78)$	
	R1/R2	$0.81(0.75-0.85)$	$0.81(0.75-0.85)$
Left upper	R1/CMS	$0.45(0.33-0.56)$	$0.59(0.49-0.67)$
	R2/CMS	$0.45(0.33-0.55)$	$0.60(0.50-0.68)$
	Avg/CMS	$0.47(0.36-0.58)$	$0.63(0.53-0.70)$

3.4Patch Prediction

The forecasts for the patches were examined visually (Figure 1.1). When the forecasts matched the raters' observations, non-emphysema patches exhibited minimal tissue damage, but emphysema patches indicated extensive area damage. Overestimation occurred when bigger expected extents were associated with predicted emphysema patches situated in areas with minimal tissue damage.

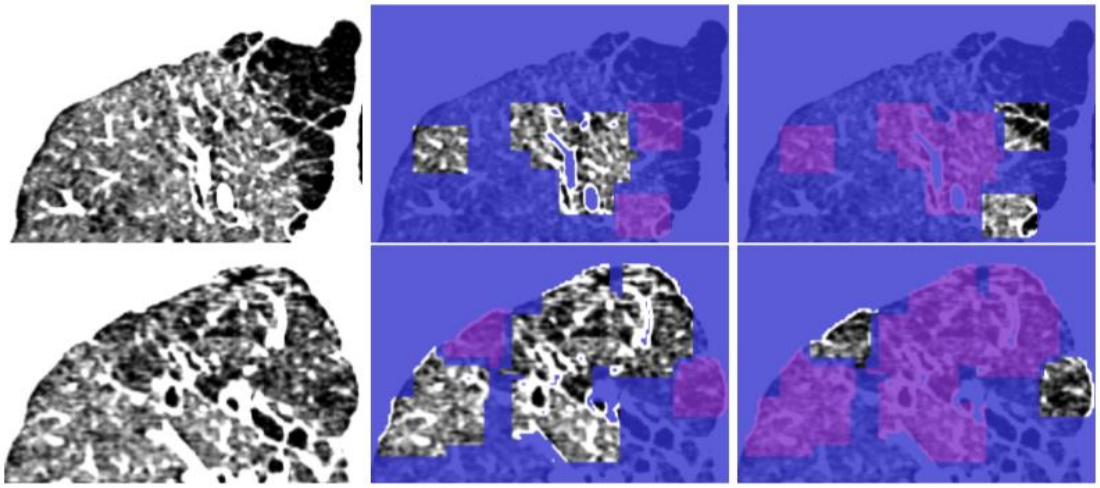

Fig.1.1 Upper right area patch forecast.

4Conclusion

We conclude that visual grading of emphysema extent can effectively train a learning-based system (LLP) to predict the presence and degree of emphysema in specific lung areas. The results show that emphysema bag training on balanced data sets increases prediction performance. Overfitting and poor rater agreement in areas with low emphysema prevalence are two difficulties that need to be addressed. To improve the modeling of emphysema progression, future research should investigate the best combinations of training data and the feasibility of continuous severity grading. The method's clinical usefulness could be improved by adding emphysema sub-type predictions.

Reference

"Kim, W. (2020). *Genome-wide Study of Emphysema Progression and Gene-by-smoking Interaction of Chronic Obstructive Pulmonary Disease* (Doctoral dissertation, The Johns Hopkins University).

Park, J., Hobbs, B. D., Crapo, J. D., Make, B. J., Regan, E. A., Humphries, S., ... & COPDGene Investigators. (2020). Subtyping COPD by using visual and quantitative CT imaging features. *Chest*, *157*(1), 47-60.

Tran, H. D., Bak, S., Xiang, W., & Johnson, T. T. (2020, July). Verification of deep convolutional neural networks using imagestars. In *International conference on computer aided verification* (pp. 18-42). Cham: Springer International Publishing.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

Jones, I., & Wheadon, C. (2015). Peer assessment using comparative and absolute judgement. *Studies in Educational Evaluation*, *47*, 93-101.

Cheplygina, V., Sørensen, L., Tax, D. M., Pedersen, J. H., Loog, M., & De Bruijne, M. (2014, August). Classification of COPD with multiple instance learning. In *2014 22nd International Conference on pattern recognition* (pp. 1508-1513). IEEE."

DECLARATION

I as an author of this paper / article, hereby declare that paper submitted by me for publication in the journal is completely my own genuine paper. If any issue regarding copyright/ patent/ other real author arises. The publisher will not be legally responsible. If any of such matters occur publisher may remove my content from the journal website/ updates. I have resubmitted this paper for the publication, for any publication matters or any information intentionally hidden by me or otherwise, I shall be legally responsible.

Name: Patil Manjusha Manikrao