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1. Introduction

Chronic Obstructive Pulmonary Disease (COPD)

慢性阻塞性肺病

Symptom

COPD refers to a group of diseases that cause airflow blockage and breathing-related problems. It includes emphysema and chronic bronchitis.

The third leading cause of mortality in the United States, affecting an estimated 14.7 million diagnosed patients.

The evolution of COPD is slow, therefore it is not diagnosed until the age 40. The active, passive smokers, industrial chemicals and air pollution add great risk for COPD.

There is currently no cure for COPD. The purpose of treatments for COPD is to lower a patient's risk of disease progression and death.

Management of COPD consists of an ongoing process of monitoring and assessing a patient's symptoms and conditions along with interventions.

Test

Commonly used pulmonary function tests for monitoring progression include:

- forced expiratory volume in one second (FEV1)
- forced vital capacity (FVC)
- the FEV1/FVC ratio
- slow vital capacity (SVC)

Radiology examinations (e.g. chest X-ray, cardiac radiography) are often conducted for diagnosis and monitoring purposes.

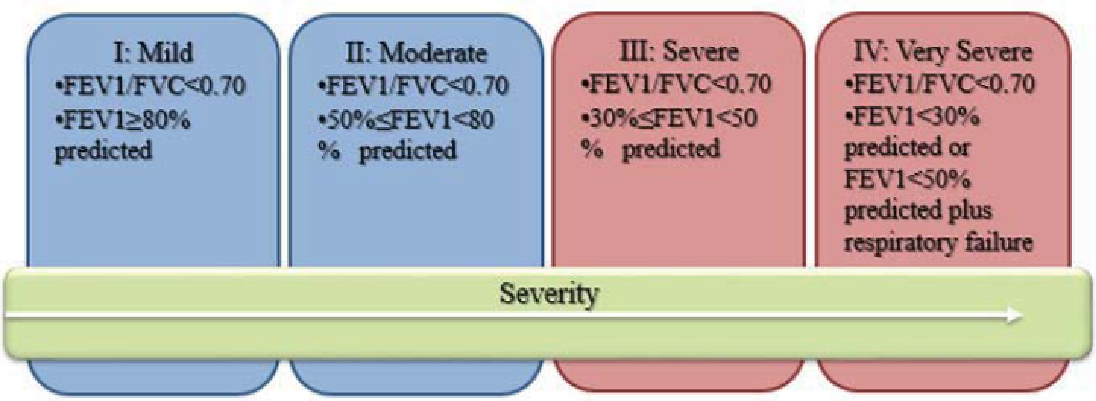


Fig. 2. Four main stages of COPD as identified in the 2001 NHLBI/WHO GOLD workshop.

2. Methods

According to the modality of processed data, methods to prognosis COPD can be categorized into 3 groups:

- electronic medical records
- lung sound signals
- chest CT scans

No public methods using face or pupils as indicators.

Here are results that *Chronic Obstructive Pulmonary Disease* or *COPD* are searched as key words within **Xplore** and **arXiv** databases.

2.1 Electronic medical records

2.1.1 Diagnosis of COPD Based on a Knowledge Graph and Integrated Model

2019

Shandong Normal University

hospital outpatient electronic medical record database

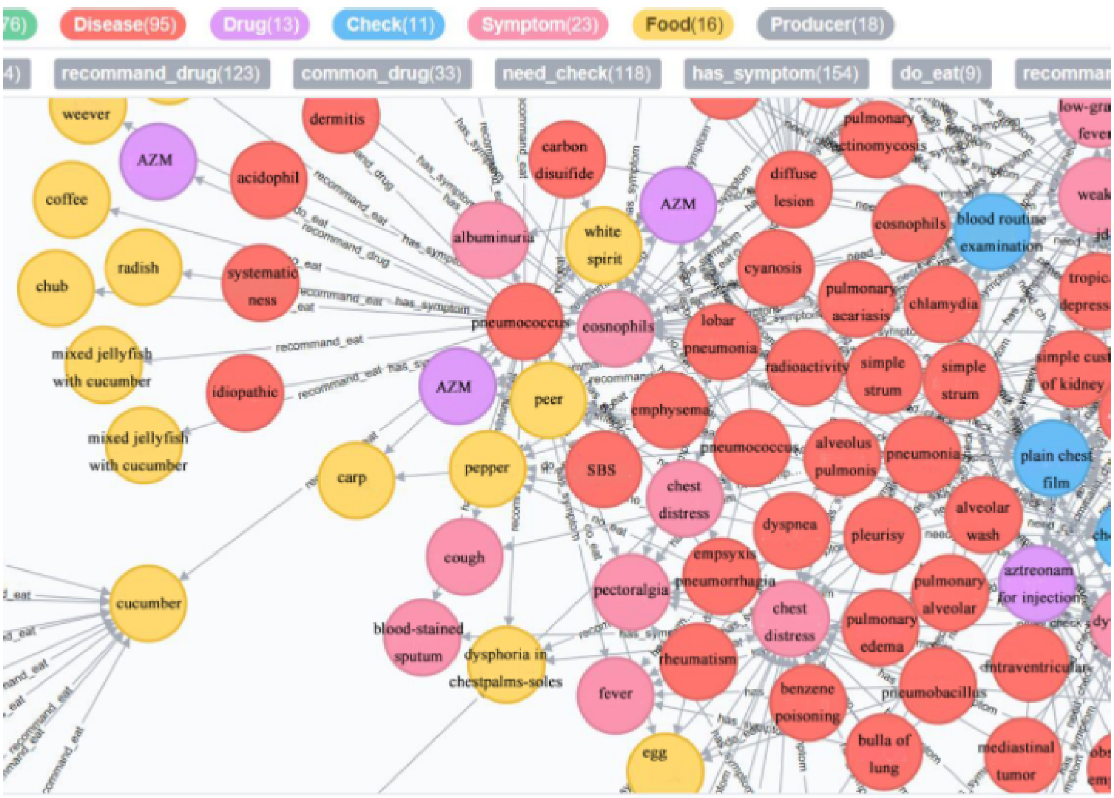


FIGURE 2. Knowledge graph-Partial.

TABLE 1. COPD features table.

Feature name	Value	Feature name	Value
f0:Smoke	0,1	f14:Sex	Male,Female
f1:Constipation	0,1	f15:Chest tightness	0,1,2,3,4,5
f2:FEV1/FVC	0-1	f16:Fatigue	0,1
f3:Labor	0,1,2,3,4,5	f17:Cough	0,1,2,3,4,5
f4:Sputum	0,1,2,3,4,5	f18:Chest pain	0,1
f5:Age	0,1,2,3,4,5	f19:Fear of heat	0,1
f6:Acidec	0,1	f20:Fever	0,1
f7:Flustered	0,1	f21:Edema	0,1
f8:mMRC	0,1,2,3,4,5	f22:Itchy throat	0,1
f9:Sleep	0,1,2,3,4,5	f23:Cyanosis	0,1
f10:Booger	0,1	f24:Tongue	0,1
f11:Dry throat	0,1	f25:Energy	0,1,2,3,4,5
f12:Weight	0,1,2,3,4,5	f26:Confidence	0,1,2,3,4,5
f13:Self sweaating	0,1	f27:Yellow complexion	0,1

2.1.2 Mining Sequential Risk Patterns From Large-Scale Clinical Databases for Early Assessment of Chronic Diseases: A Case Study on Chronic Obstructive Pulmonary Disease

IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 21, NO. 2, MARCH 2017 303

Taiwan

diagnostic clinical records, Electronic Medical Records (EMRs)

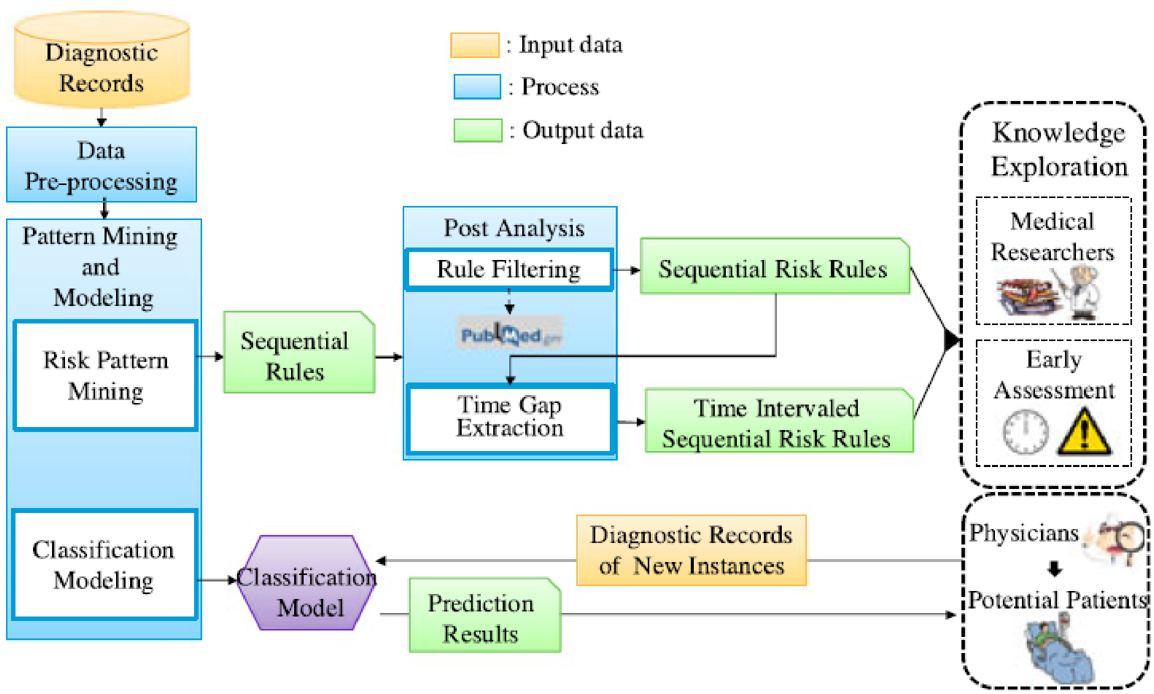


Fig. 1. The proposed framework.

2.1.3 Semi-automatic Construction Method of Chronic Obstructive Pulmonary Disease Knowledge Graph

2019 IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC)

Tsinghua University

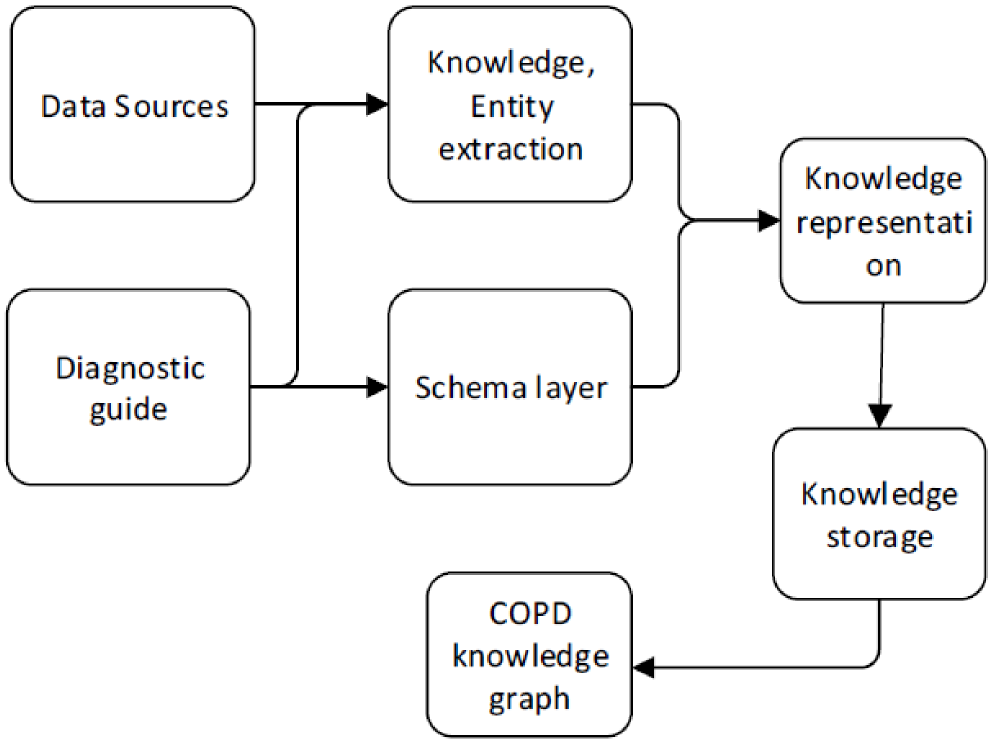


Figure 1. The construction flow chart of the knowledge graph of COPD

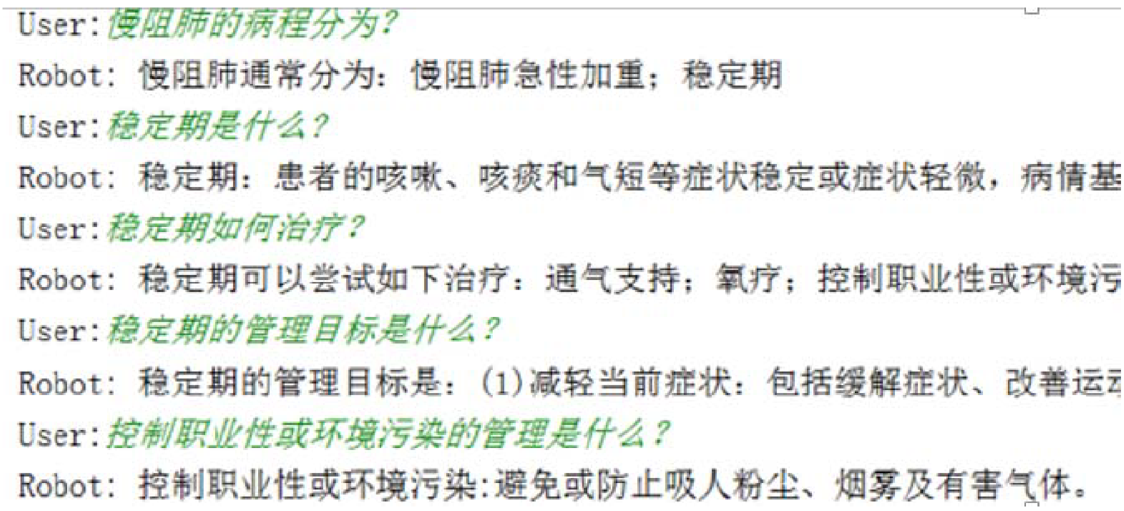


Figure 5. An example of an automatic question and answer system for COPD

2.1.4 Intelligent Syndrome Differentiation of Traditional Chinese Medicine by ANN: A Case Study of Chronic Obstructive Pulmonary Disease

2019

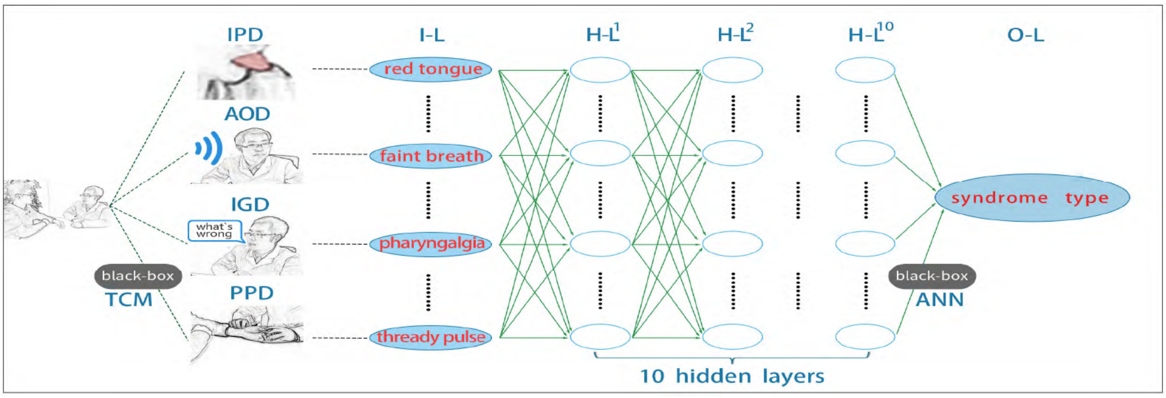


FIGURE 1. The topological architecture of ANN, where'IPD' denotes inspection diagnosis, 'IGD' denotes interrogation diagnosis, 'AOD' denotes auscultation and olfaction diagnosis, 'PPD' denotes palpation diagnosis, 'I-L' denotes input layer, 'H-L' denotes hidden layer, 'O-L' denotes output layer. The similar property of 'black-box' inspire us to merge ANN into TCM.

2.1.5 Predictive Analytics Dashboard for Monitoring Patients in Advanced Stages of COPD

2016 Hawaii International Conference on System Sciences

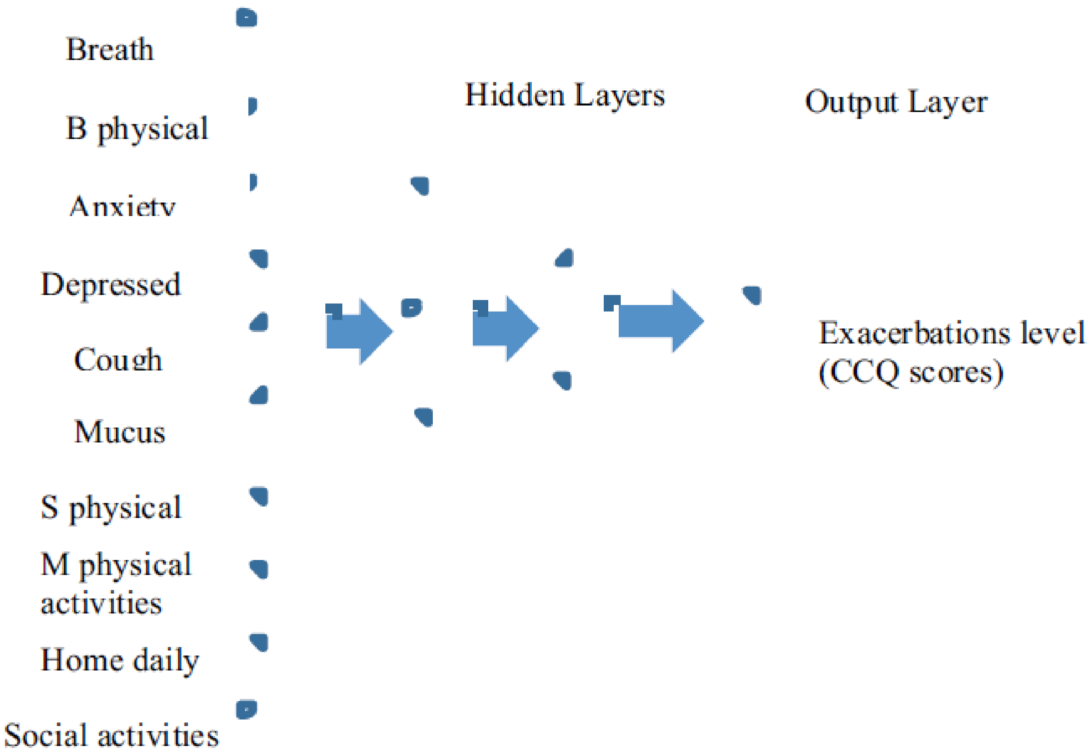
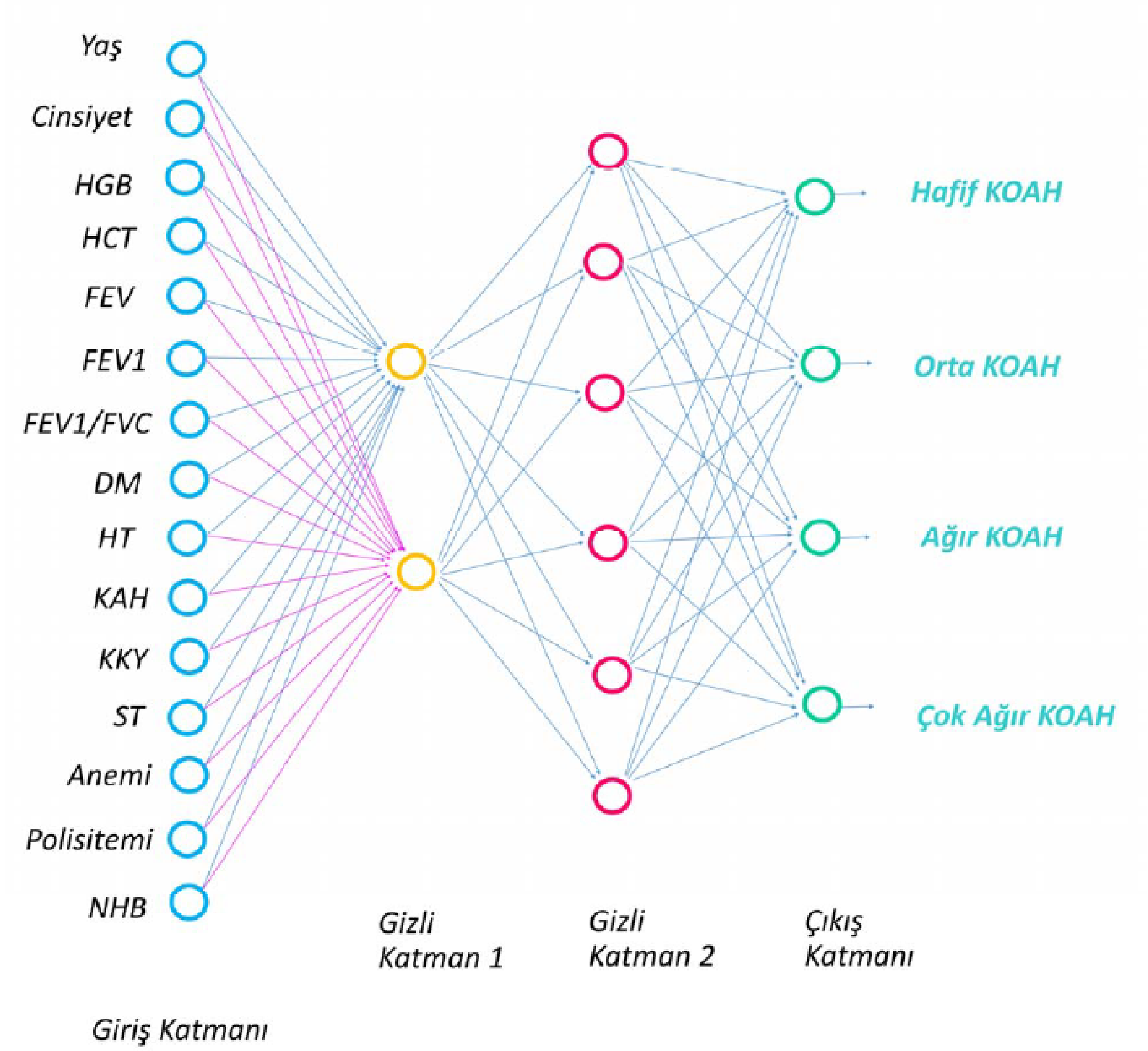


Figure 1: ANN model for predicting the exacerbation level

2.1.6 Chronic Obstructive Pulmonary Disease Classification with Artificial Neural Networks

2015 IEEE

15 variables, 4 COPD disease levels (Mild, Moderate, Severe, Very Severe)



2.1.7 A Combined Classification Algorithm Based on C5.0 and NB to Predict Chronic Obstructive Pulmonary Disease

India

2018 IEEE International Conference on Computational Intelligence and Computing Research

text

a) Dataset.

Real world dataset is collected from a Pulmonologist. During examination of patients, the features of a Patients such as Age, Sex, cough, breathlessness, chest_pain, haemoptysis, wheezing, occupational_hazard, tightness_chest, diabetes, hypertension, smoker, alcohoic, genetic_risk, Have COPD or not are entered in the examination sheet.

2.1.8 Application of Data Analytics to Predict and Analyze COPD Data

Proceedings of the 2nd International conference on Electronics, Communication and Aerospace Technology (ICECA 2018)

India

Forced Expiratory Volume, Forced Vital Capacity, Pulse Rate, the oxygen saturation level

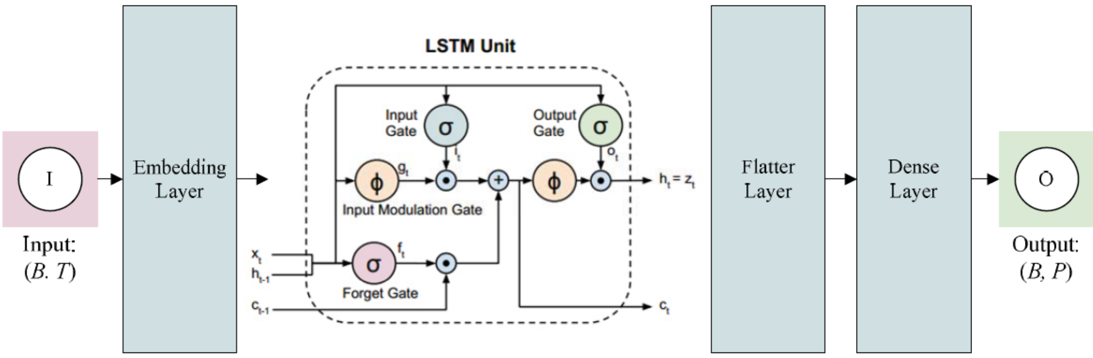
2.1.9 A Deep Learning Approach to Handling Temporal Variation in Chronic Obstructive Pulmonary Disease

Progression

2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)

Harvard Medicine School, Fudan University

Classifying a corpus of free-text clinical notes (i.e., pulmonary notes, radiology reports, cardiology reports) to a COPD stage.



2.1.10 Automatic extraction of personal experiences from patients' blogs: A case study in chronic obstructive pulmonary disease

2013 IEEE Third International Conference on Cloud and Green Computing

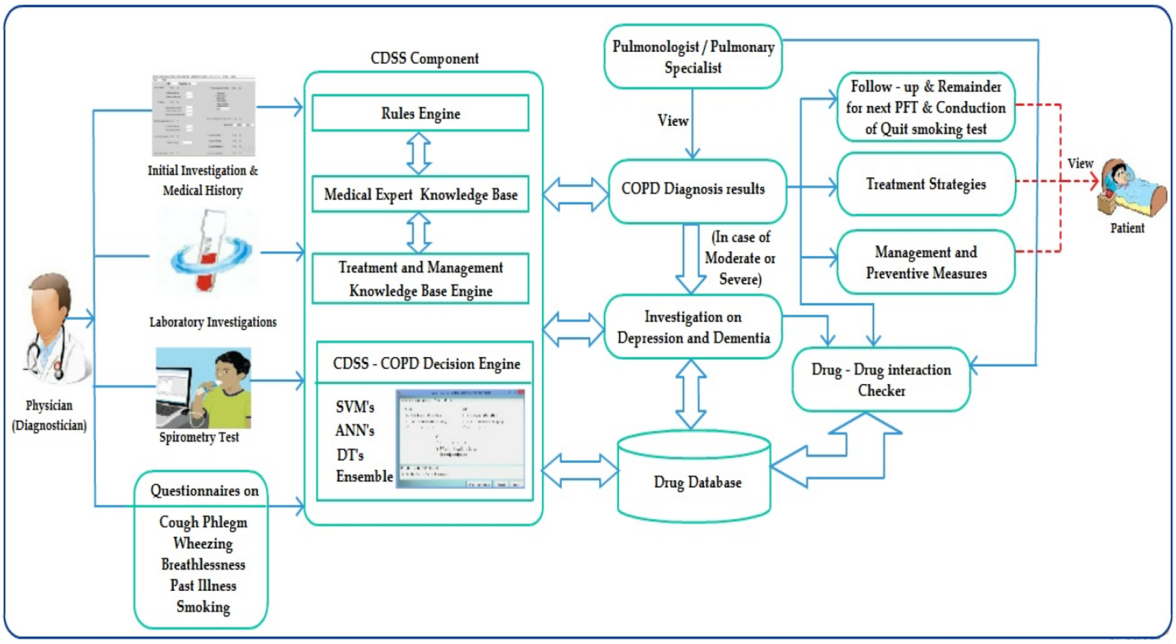
UK

Fig. 1. Annotation site screenshot

2.1.11 Clinical Decision Support System for Chronic Obstructive Pulmonary Disease using Machine Learning Techniques

2017 International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEECCOT) India

Classifier ensemble methods, support vector machine, neural networks, decision trees.



2.2 Lung sound signals

2.2.1 TussisWatch: A Smart-Phone System to Identify Cough Episodes as Early Symptoms of Chronic Obstructive Pulmonary Disease and Congestive Heart Failure

University of South Florida

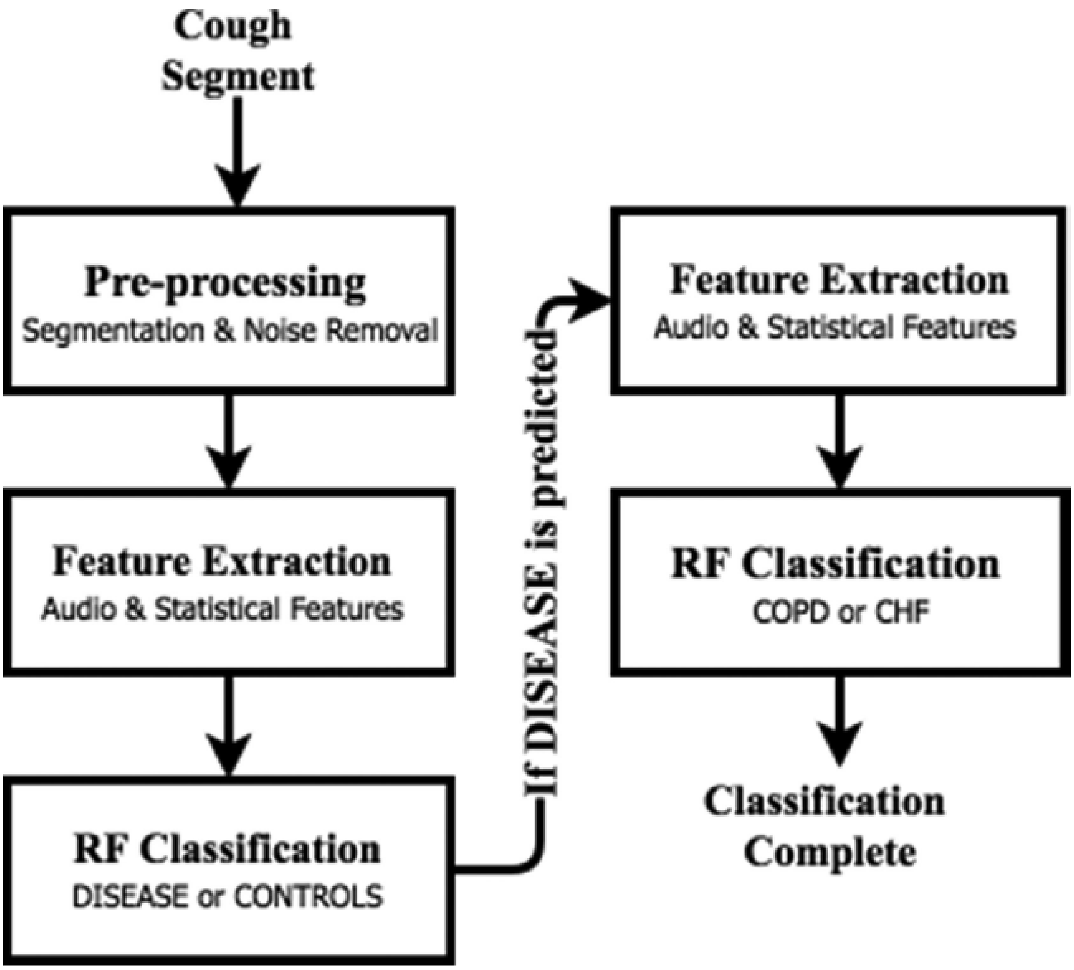


Fig. 1. Work-flow of our two-level cough classification scheme.

2.2.2 Biodata analytics for COPD

IEEE 2016

Portugal

chest sound and multi-channel ECG analysis

2.2.3 Deep Learning on Computerized Analysis of Chronic Obstructive Pulmonary Disease

IEEE Journal of Biomedical and Health Informatics, 2019

Turkey

analyze multichannel lung sounds using statistical features of frequency modulations

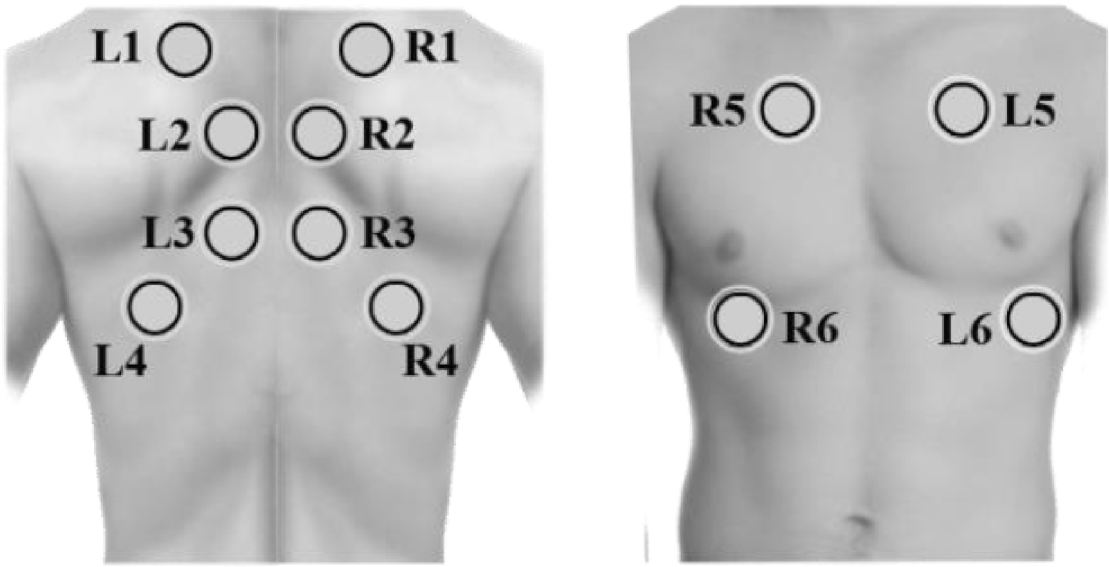
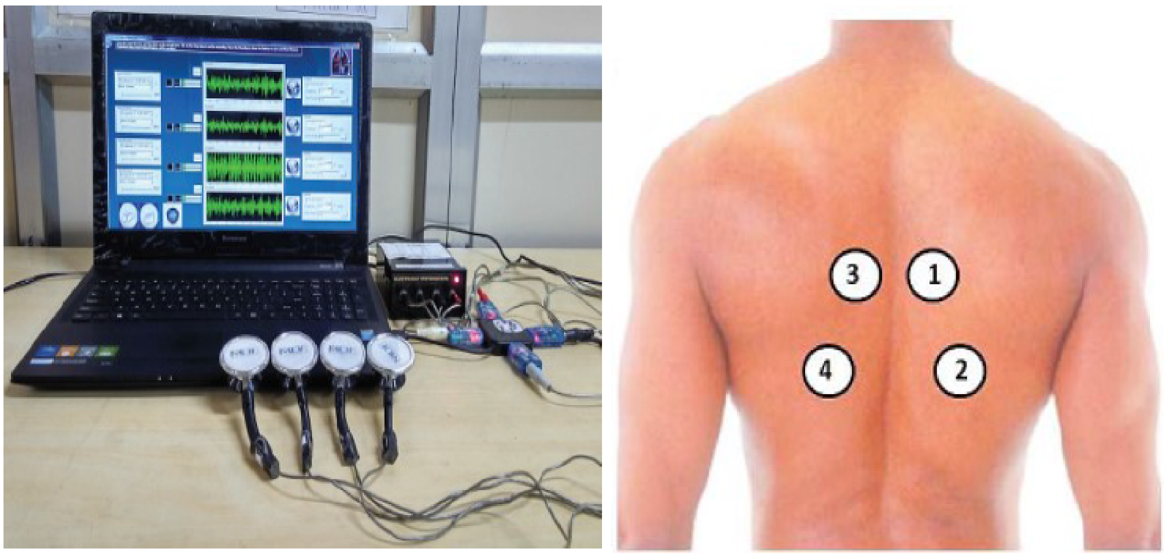


Fig. 1. Lung sound auscultation areas at back and chest

2.2.4 Classification of Normal, Asthma and COPD Subjects using Multichannel Lung Sound Signals

International Conference on Communication and Signal Processing, April 3-5, 2018, India

India Institute of Technology



(a) (b)

Fig. 1. (a) 4-channel lung sound signal acquisition system and (b) four different positions over the posterior chest for lung sounds collection.

2.2.5 Rule-based diagnosis of chronic obstructive pulmonary disease with electrocardiogram signal

2018 IEEE

Research on Denoising Algorithm of Thoracic Impedance Data for COPD Diagnosis

Shanghai Jiao Tong University, Renji Hospital

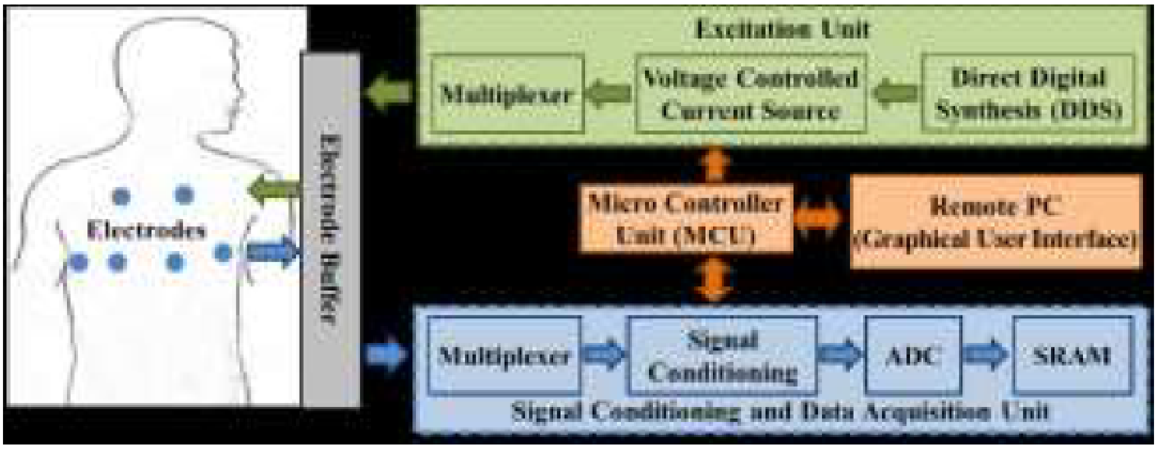


Figure 1. Thoracic Impedance Measurement System

2.3 Chest CT scans

2.3.1 Transfer Learning for Multicenter Classification of Chronic Obstructive Pulmonary Disease

IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 22, NO. 5, SEPTEMBER 2018

Denmark, Netherlands

Chest computed tomography (CT) scans

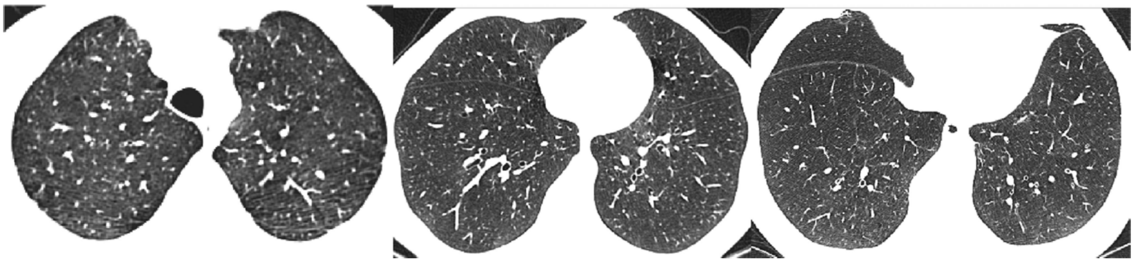


Fig. 3. Examples of slices from the DLCST, COPDGene1 and Frederikshavn datasets.

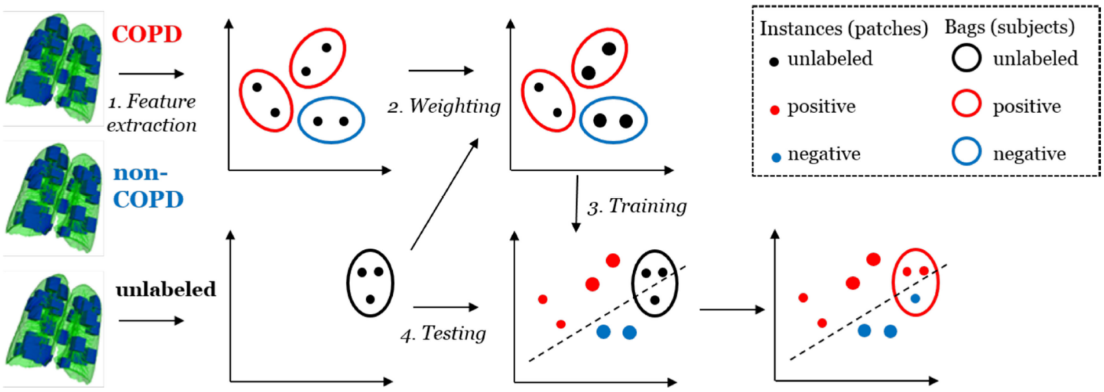


Fig. 1. Overview of the procedure. Step 1 is to represent each scan as a bag of instances (feature vectors). The bag is labeled as COPD (+1) or non-COPD (-1). Step 2 is to weight the training bags by their similarity to the unlabeled test scan. Step 3 is to use the weighted bags to train a classifier. In step 4 this classifier is used to classify the test instances. The instance labels are combined into an overall label for the scan, in this case COPD (+1).

2.3.2 Automated Classification Using End-to-end Deep Learning

IEEE 2018

Singapore and China

classify Chest X-Ray images into one of 14 primary classes of lung diseases

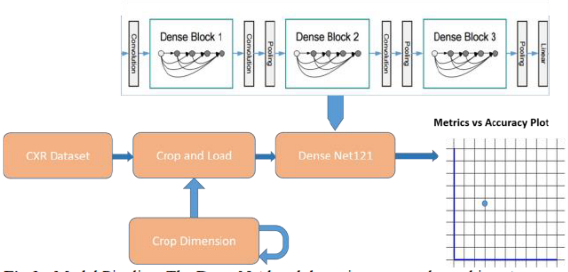


Fig.3 : Model Pipeline. The DenseNet breakdown is an example, and is not implicative of the usage of just 3 dense blocks

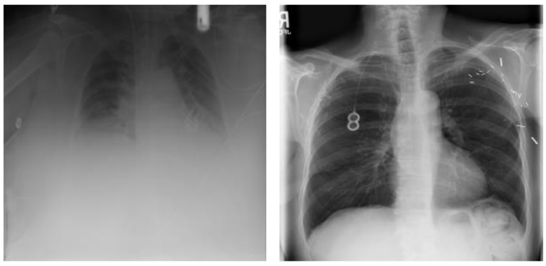


Fig. 4: Comparison of an image with Low SNR (left) to one with a high SNR (right)

2.3.3 Assessing Lung Volumetric Variation to Detect and Stage COPD

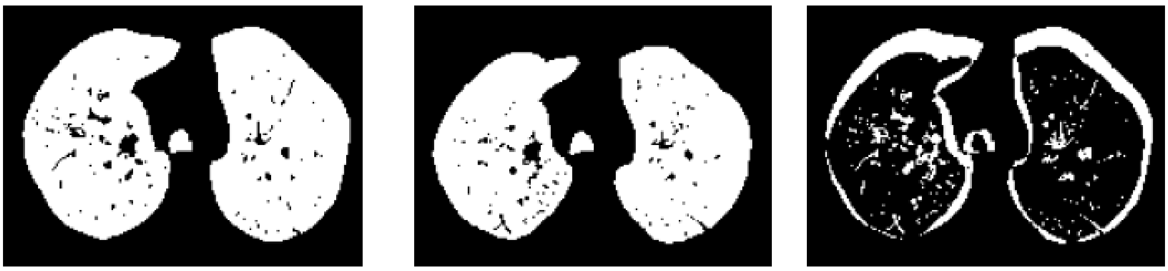
2011 IEEE

find volumetric changes of the lungs from inspiration and expiration.

Bayesian classifier

a b c

Fig. 3: *a. Lung area at inspiration in a healthy subject. b. Lung area at expiration. c. Difference between inspiration and expiration.*



a b c

Fig. 4: *a. Lung area at inspiration in a patient subject. b. Lung area at expiration. c. Difference between inspiration and expiration.*

2.3.4 Classification of COPD with Multiple Instance Learning

arXiv 2017

The Netherlands, Denmark

COPD can be quantified by classifying patches of computed tomography images, and combining patch labels into an overall diagnosis for the image.

2.3.5 Automatic emphysema detection using weakly labeled HRCT lung images

arXiv 2017

Denmark

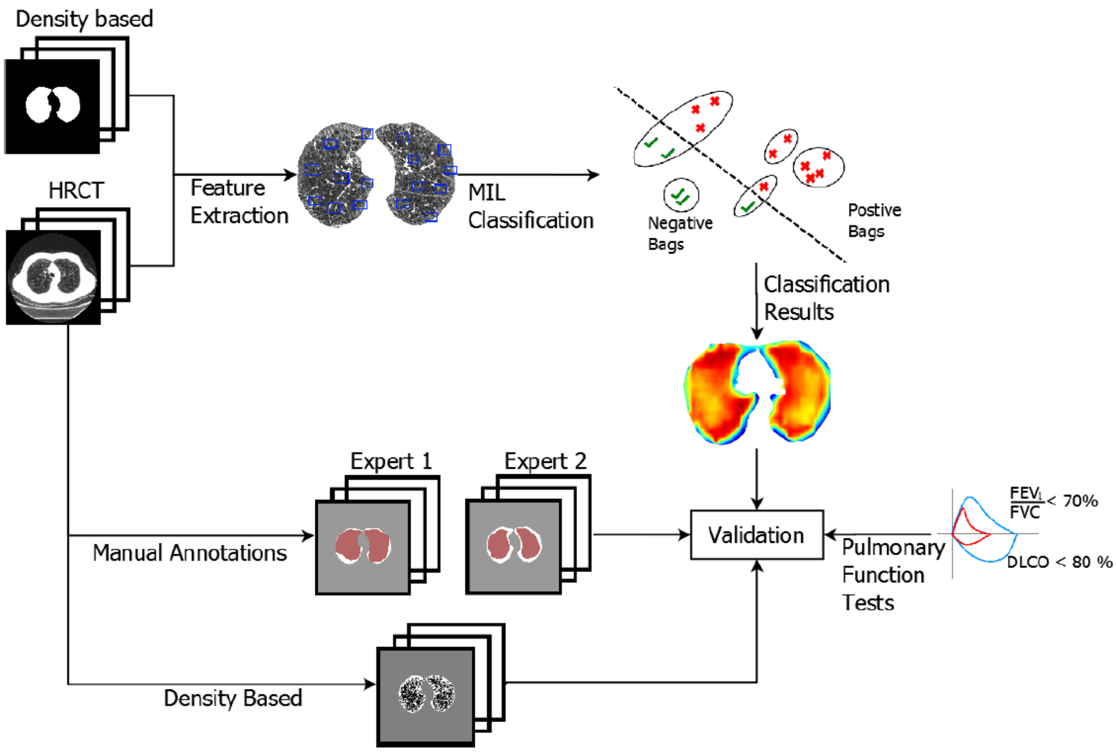


Figure 1. Summary of the methodology. Texture features are extracted from the lung parenchyma. Two different MIL classifiers are trained and are tested on previously unseen scans. The results are evaluated against manual annotations performed by two radiologists, a density based analysis, and pulmonary function tests.

2.3.6 Subject2Vec: Generative-Discriminative Approach from a Set of Image Patches to a Vector

arXiv 2018

University of Pittsburgh, University of British Columbia, Carnegie Mellon University

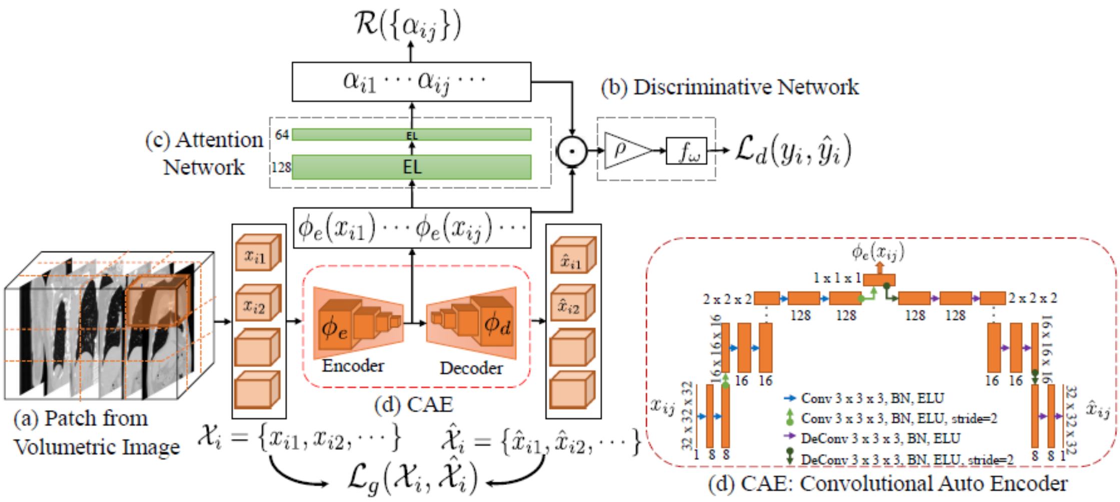


Fig. 1. (a) A subject is represented as a set of 3d image patches, (b) Discriminative Network: aggregates local features to form a fixed length representation for the subject and predicts the disease severity ($\hat{y}_i$), (c) Attention Network: focuses attention on critical patches to provide interpretability. (d) Convolutional Auto Encoder (Generative Network): prevents redundancy of latent features.

2.3.7 Automatic Airway Segmentation in chest CT using Convolutional Neural Networks

arXiv 2018

The Netherlands, Denmark

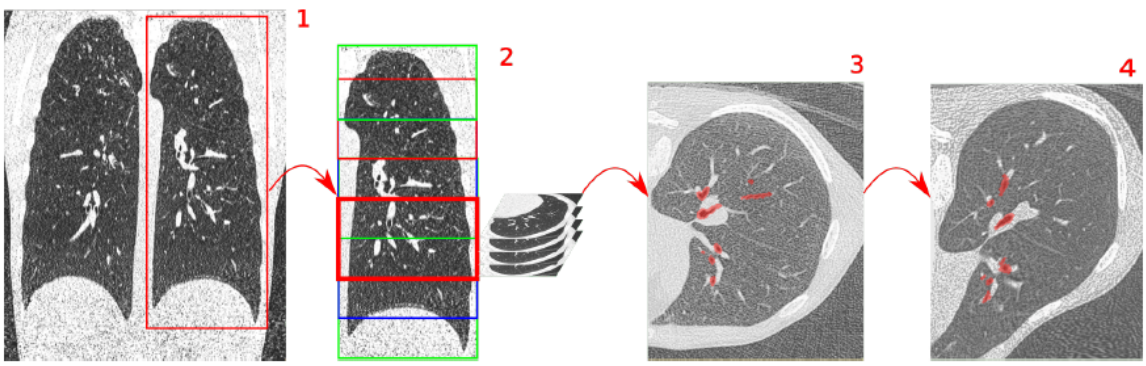
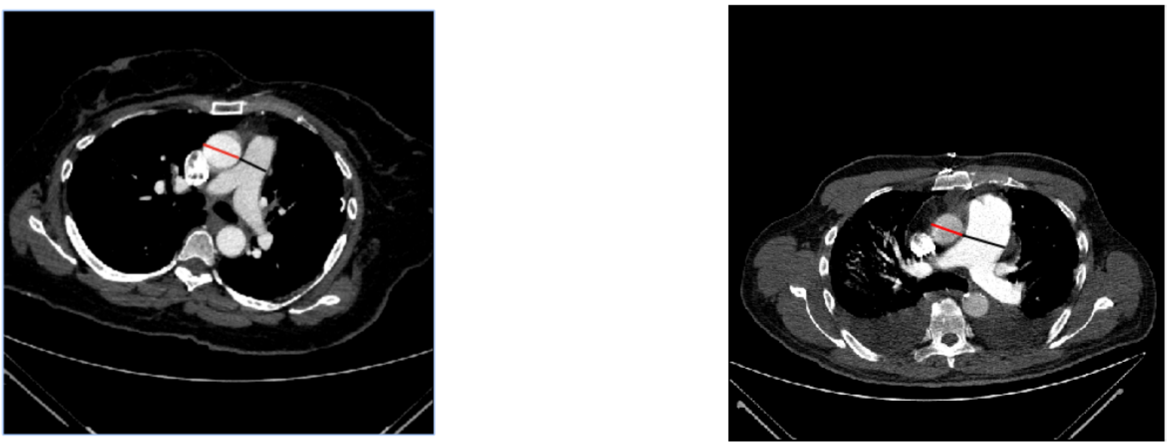


Fig. 1: Preprocessing pipeline of input images to the network. 1: crop CTs. 2: Extract 3D images patches by sliding-window. 3,4: Apply data augmentation (elastic deformations) to the input patch, which is fed to the network.

2.3.8 PHT-BOT:DEEP-LEARNING BASED SYSTEM FOR AUTOMATIC RISK STRATIFICATION OF COPD PATIENTS ASED UPON SIGNS OF PULMONARY HYPERTENSION

arXiv 2019



(a) Case with a PA to Ao ratio < 1.

(b) Case with a PA to Ao ratio > 1.

Figure 2: Sample of the system visual results. The measurements are shown in red and black for the Ao and PA, respectively.

2.3.9 Adversarial regression training for visualizing the progression of chronic obstructive pulmonary disease with chest x-rays

arXiv 2019

University of Utah

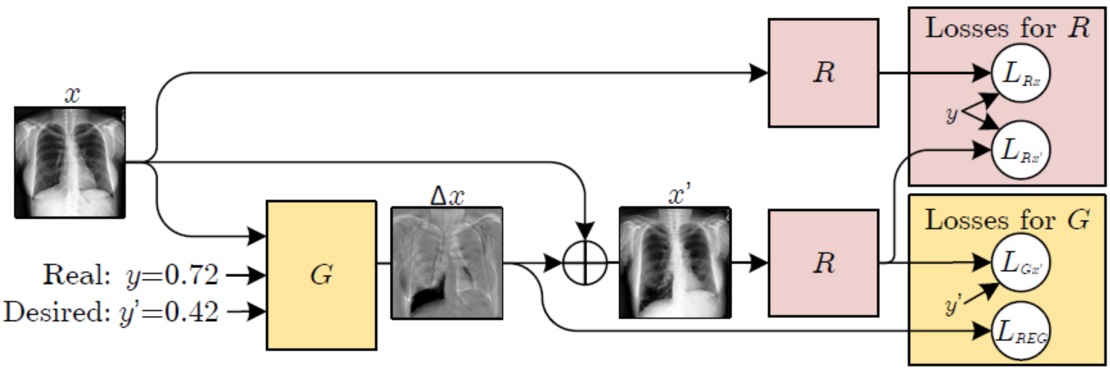


Fig. 1. Overall model architecture for training with the proposed adversarial loss. The losses L_{Rx}, $L_{Rx'}$ and $L_{Gx'}$ are $L1$ regression losses, and L_{REG} is an $L1$ norm penalty.