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DEEP LEARNING FOR COPD ANALYSIS USING LUNG SOUNDS

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1. Introduction

Deep Learning (DL) algorithms have become popular with the detailed analyzing capabilities with many hidden layers in recent years. The size of hidden layer in the classifier models is completely correlated with the analyzing capability of the proposed models. Multiple hidden layers and neuron size in the hidden layers enhance the analyzing capability of the models, whereas increasing the training time [2]. When using lots of hidden layers provides enhancing analyzing capabilities by assessing different presentations of the input, on the other hand it costs much training time. The idea of reducing the training time for the DL algorithms is the main focus point of recent researches. Although the DL is a neural network structure which has many hidden layers, they differ in consequence of performing variant back-propagation procedures during the training and the definition of the classification parameters (including weight and biases) in pre-training. While the input weights and the hidden node parameters are randomly defined for neural network model, the DL algorithm pre-defines the weights and biases using unsupervised learning models including Restricted Boltzmann Machines (RBM) [9], Sparse autoencoders [8], and Extreme Learning Machines (ELM) Autoencoders [6].

The DL algorithms differ with the unsupervised learning phase and the feature learning models in the training process. The Deep Belief Networks (DBN) is frequently used for training considering the capabilities of accessing the global minimum and high classification performances with fast greedy layer-wise pre-training of the layers [8]. The DBN has two stage classification. The input weights and the hidden layer biases are defined using RBM in the first stage, the pre-defined parameters are optimized unfolding them into neural network model with the same structure at the second stage [8–10]. The main point of the DBN is fast training speed causing pre-defining the parameters before optimization and enabling the global minimum with small number of iterations for optimization [10].

The DBN was applied to classify various biomedical signals for asthma disease diagnosis models [7], diagnosis of the coronary artery disease [2], arryhthmia classification [3] and brain activity detection [4]. In this study, Hilbert-Huang Transform (HHT) was applied to the lung sounds from RespiratoryDatabase@TR and the statistical features were calculated from the different modulations of the HHT. The statistical features were fed into the DBN to classify the lung sounds from Chronic Obstructive Pulmonary Disease (COPD) and healthy subjects.

2. Materials and method

2.1. **Classifier.** The DBN algorithm performs RBM to pre-define the classification parameters using unsupervised ways to address the deficiency of training time on deep models with multiple hidden layers. The DBN performs layer-by-layer top-down directed learning operations and defines generative weights. The generative weights represents the relationship between adjacent layers, how the parameters in a layer rely on the parameters in the adjacent layer above. Upper layers of the DBN provide to represent more abstract features where as the lower layers of the DBN learn simple features. Each RBM in the DBN model generates different presentation of the input data [10]. Energy function (1) and probability function (2) of the DBN model are :

$$E(v,h) = \sum_i f_i(v,h) = \quad bv \quad ch \quad Wvh, \tag{1}$$

$$P(v,h) = \frac{1}{Z} e^{-E(v,h)}, \tag{2}$$

v is input layer vector, h is hidden layer vector. b and c represent for biases of the DBN model for visible and hidden layer, respectively. Z is normalization constant for the RBM distribution, W is the weights for pre-training phase of the model.

2.2. Database. RespiratoryDatabase@TR is a unique multimedia respiratory database which has 12-channel lung sounds, chest X-rays, 4-channel heart sounds, spirometry metrics from subjects with the COPD and healthy subjects [5]. It generates a wide analysing potentiality for the COPD and asthma diseases using computerized signal analysis and machine learning approaches. 12-channel lung sounds with 15s duration from 30 subjects (15 COPD+15 Healthy) were utilized in the analysis.

2.3. Hilbert-Huang transform. HHT is an adaptable and efficient transformation method to overcome the non-linearity and non-stationarity signal problems. The HHT enables extracting time-frequency-energy characteristics of the signal [11].

The HHT is a two step transformation including Empirical Mode Decomposition(EMD) and Hilbert Transform (HT), consecutively. The EMD extracts Intrinsic Mode Functions (IMFs) which are the ortogonal basis frequency modulations of the signals without leaving the time domain.The formulation of the EMD process is:

$$X(t) = \sum_{j=1}^{n} IMF_j + r_n, \tag{3}$$

r_n is the residual signal, X represent the input signal and n is the number of the sifted IMFs. The HT is applied to the sifted IMF modulations for counting instantaneous frequency characteristics [1, 11]. Analytical function of the HT for an $x(t)$ is formulated as follows:

$$x(t) = \Re \left\{ \sum_{i=1}^{n} a_i(t) e^{jW_i(t)dt} \right\}. \tag{4}$$

3. Experimental results

The HHT is applied to the 12-channel lung sounds. The HHT-based statistical features including standard deviation, mean, median, maximum, minimum, variance, mode, correlation coefficient, kurtosis, moment, cumulant, and energy for each IMFs were calculated as dataset. It was fed into the DBN model with 2 hidden layers (340-580 neurons). The DBN was iterated for 50 epochs. The learning rate was selected as 2 and the sigmoid activation function was utilized as the output function for the DBN model. The statistical metrics such as accuracy, sensitivity, and selectivity were calculated from the contingency table of classification to estimate differences in distribution of lung sounds from the COPD patients and healthy subjects using 6-fold cross validation technique. The achieved results are presented in Table 1 considering the IMF-based feature sets and the entire feature set.

The proposed DBN model has achieved high results for each IMF feature set and entire feature set expect IMF1. IMF1 is the first modulation which has still noise, that is why it is the lowest

Table 1. The classification performances (%) of the DBN

	Accuracy	Sensitivity	Specificity
IMF1	33.61	28.89	38.33
IMF2	62.78	66.67	58.89
IMF3	50.83	53.33	48.33
IMF4	47.50	54.44	40.56
IMF5	38.06	36.67	39.44
All	70.28	67.22	73.33
SFFS	90.83	94.44	87.22

responsible feature for the classifier. The DBN has separated the lung sounds from the COPD and healthy lung sounds with classification performance rates of 70.28%, 67.22%, and 73.33% for accuracy, sensitivity, and specificity, respectively. The sequential forward feature selection (SFFS) algorithm is performed on the DBN classifier model and has increased the classification performance rates to 90.83%, 94.44%, and 87.22% for accuracy, sensitivity and specificity.

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