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A telemedicine tool to detect pulmonary pathology using computerized pulmonary acoustic signal analysis

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ABSTRACT

Background: Detection and monitoring of respiratory related illness is an important aspect in pulmonary medicine. Acoustic signals extracted from the human body are considered in detection of respiratory pathology accurately.
Objectives: The aim of this study is to develop a prototype telemedicine tool to detect respiratory pathology using computerized respiratory sound analysis.
Methods: Around 120 subjects (40 normal, 40 continuous lung sounds (20 wheeze and 20 rhonchi)) and 40 discontinuous lung sounds (20 fine crackles and 20 coarse crackles) were included in this study. The respiratory sounds were segmented into respiratory cycles using fuzzy inference system and then S-transform was applied to these respiratory cycles. From the S-transform matrix, statistical features were extracted. The extracted features were statistically significant with $p < 0.05$. To classify the respiratory pathology KNN, SVM and ELM classifiers were implemented using the statistical features obtained from of the data.
Results: The validation showed that the classification rate for training for ELM classifier with RBF kernel was high compared to the SVM and KNN classifiers. The time taken for training the classifier was also less in ELM compared to SVM and KNN classifiers. The overall mean classification rate for ELM classifier was 98.52%.
Conclusion: The telemedicine software tool was developed using the ELM classifier. The telemedicine tool has performed extraordinary well in detecting the respiratory pathology and it is well validated.

1. Introduction

Electronic Health (eHealth) is a health care related information exchange tool, which uses information and communication technology (ICT). Telemedicine is one such eHealth tool. Telemedicine is of two types namely, asynchronous and synchronous telemedicine. The asynchronous telemedicine is also known as store and forward telemedicine. The synchronous telemedicine is also known as real-time telemedicine. In store and forward telemedicine, data are collected and sent electronically to a medical professional for further analysis and diagnosis. Synchronous telemedicine is real time and interactive and is usually done by videoconference with the audio and visual consultation augmented by distant examination [1]. In recent years a number of studies have highlighted the importance of telemedicine tool for patients with respiratory related illness. Respiratory related illness is currently fourth most common cause of mortality worldwide [2]. It was reported that patients with Asthma using self-monitoring tool at home obtain accurate results compared to that of results collected by medical professional [3]. It was also found that the use of telemedicine tool has not affected the quality of care in patients with Asthma [4]. In another study it was observed that use of self-monitoring tool reduce the frequencies of hospitalization in patients suffering from COPD [5]. It also reduces the cost implications of hospitalization. Another study revealed that the frequency of hospitalization was reduced in patients with COPD due to web-based call centers [6]. The advantages of using telemedicine tools in respiratory related illness include but are not limited to improve access to patients

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Table 1
Related works on breath sound analysis.

Authors/year	Subjects	Sensor	Auscultation points	Feature extraction	Classifier	Outcome
Lu et al. (2008) [10]	RALE database – 68 recordings from various subjects and ASTRA database	Contact accelerometer (EMT-25 C)	Over the chest wall	Spectral and waveform characteristics	Gaussian mixture model (GMM)	91.5% Classification accuracy
Charleston-Villalobos et al. (2011) [11]	27 Subjects in which: 8 – normal, 19 – ILD	25 Microphones	Posterior thoracic surface	Power spectral density (PSD), the eigenvalues of the covariance matrix and both the univariate autoregressive (UAR) and the multivariate autoregressive models (MAR)	Supervised neural network (SNN)	75% for healthy subjects and 93% for patients
Hashemi et al. (2012) [12]	48 Subjects with COPD and asthma	Electronic stethoscope	Over the chest wall	Mel-frequency cepstral coefficients (MFCC)	MLP	Classification accuracy of 92.8% was reported
Serbes et al. (2013) [13]	26 Subjects in which: 13 –normal, 13 – patients (with crackles)	Air coupled electret microphones	14 Auscultation points on the posterior chest	Individual and ensemble features extracted from wavelet transform	SVM, KNN and MLP	Maximum classification accuracy of 96.25–97.50% was reported for Individual and ensemble features
Lei et al. (2014) [14]	65 Subjects in which: 40 – normal, 25 – patients	Microphone	Mouth and nose	Enhanced perceptual and cepstral feature set	SVM and ANN	Overall 98.9% was reported
Palaniappan et al. (2014) [15]	69 Subjects in which: 23 – normal, 23 – AO, 23 – ILD	WISE digital stethoscope	3 Auscultation points: (1) treachea, (2) posterior right lung base, (3) posterior left lung base	AR-coefficients	K-nearest neighbour (KNN)	Classification accuracy of 96.12% was reported
Palaniappan et al. (2014) [16]	RALE database-recordings from various subjects	Contact accelerometer (EMT-25C)	Over the chest wall	Mel-frequency cepstral coefficients (MFCC)	Support vector machine (SVM) and KNN	Classification accuracy for SVM and KNN classifier were 92.19% and 98.26%, respectively
İçer et al. (2014) [17]	60 Subjects in which: 20 – normal, 40 – patients (with crackles and rhonchi)	WelchAllyn electronic stethoscope	6 Auscultation points: (1) posterior right lung upper, (2) posterior left lung upper, (3) posterior right lung middle, (4) posterior left lung middle, (5) posterior right lung base, (6) posterior left lung base	(1) Frequency ratio, (2) instantaneous frequency, (3) eigen values	SVM	Classification accuracy of 90% was reported
Ulukaya et al. (2014) [18]	48 Subjects	Fourteen air-coupled electret microphones (Sony-ECM 44)	Over the chest wall	Perceptual linear prediction features	SVM	Classification accuracy of 95% was reported
Göğüş et al. (2015) [19]	11 Subjects	Sony ECM T-150 microphone	Right and left lung base	Wavelet transform (WT) and wavelet packet transform (WPT) based features	Multi-layer perceptron (MLP)	Classification accuracy of 86.25% was reported for WT and 85.05% was reported for WPT

in remote areas, reduce frequent hospitalization, reduce the cost incurred in traveling to hospital and the doctor's consultation fees and also reduce the shortage of health care professionals. Auscultation is the process of listening to sounds heard over the human body, which gives vital information on the present state of the internal organs. Listening to the respiratory sounds can lead to diagnosis of respiratory pathologies [7]. Auscultation is the basic and primary physical examination done by all medical professionals. Auscultation mainly relies on the hearing perception of the medical professional and it may vary for each individual [8]. Hence it is required to develop a computerized respiratory sound analysis system which can accurately detect the respiratory pathology. Studies on computerized respiratory sound analysis started to appear in the literature in the early 80s [9]. Table 1 lists few recent researches

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