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Preliminary Detection of Lung Diseases in Pediatric Population using Soft Computing

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ABSTRACT: ***The investigations from recent studies clearly show the potential of lung sounds in detection of lung abnormalities in human subjects. This paper aims to analyze lung sounds acquired using special electronic stethoscope for detection adventitious sounds arising out of pathological lungs due to various disease like brochities especially in pediatric population. For acquisition and recording of lung sounds, 3M Littmann 3200 model is utilized. After verifying fidelity of electronic stethoscope, the analysis of lung sounds was carried out by various spectral and temporal features. The features extracted were fed to artificial neural network for classification. Various combinations of ANN with different topologies were experimented. The overall accuracy of obtained with one hidden layer GFF is 94.95%.***

Keyword: Lung Diseases; Electronic Stethoscope; Spectral feature; Artificial Neural Network

I. INTRODUCTION

The main aim of this work is to explore the applications of signal processing and soft computing for preliminary detection of lung diseases from human body acoustics. Lung related disorders such as chronic obstructive pulmonary diseases (COPD), Pneumonia and Tuberculosis accounts for 6.4 million deaths globally [1]. In India alone, it causes 11% of all deaths i.e. second after Ischemic heart disease [2]. The above facts directly lead to the conclusions that diseases related to lungs are on the top for mortality, globally as well as in India.

The major difficulties in effective treatment of these diseases arise due to the late diagnosis. In India, people generally have the tendency to avoid visits towards doctors and in the initial phase of disease occurrence, they generally rely on over the counter medicines. In rural India, situations like unavailability of doctors and distant hospitals also lead to reluctance of population to pursue treatment for healthcare except in chronic pain cases. As early diagnosis of these diseases could be lifesaving, it is important to develop a system which is not only a simple and non-invasive, but will also correctly provide road map to the prospective patients for more specific diagnosis and effective treatment.

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Recent advances in human body sounds auscultation and signal processing have opened up new opportunities for the researchers to analyze human body sounds for objective analysis and classification. This research work is an effort in this direction involving study of the different signal processing methods for human body acoustics analysis. These methods can be then utilized in telemedicine applications.

A vast amount of research has been conducted by the early researchers in this field , a brief discussion is presented in next section.

Rational dilation Wavelet transform was utilized for lung sounds classification by S. Ulukaya et al. [3]. Classification was done between normal and adventitious lung sounds. Total 40 adult subjects were taken into consideration and data acquisition was carried out by a system developed atBogazici University Lung Acoustics Laboratory (BU-LAL). The recording system was built in a Jacket which consists of 14 condenser microphones. The study focuses on classification of normal, wheeze and crackle sounds using various statistical features of Wavelets with comparative performance of K-Nearest Neighbor (K-NN) and support vector machine (SVM) for classification. The study shows increase in classification accuracy with the features extracted with high Q-factor Wavelets. The reported classification accuracies for crackles, wheeze and normal lung sounds were 95%, 97% and 93.50% respectively. SVM was reported to outperform K-NN for classification. Although the study reports higher accuracies, the dataset contains only 40 subjects and category wise distribution of subjects was not mentioned in the study. Also, the recording setup (Auscultation Jacket) is costly and may be inconvenient to be used in rural population.

S. A. Taplidou et al. [4] have presented a detailed study on exploration of high order spectral features of Wavelets. Total 21 subjects were used for analysis and the recording of data took placed through condenser microphones. This study actually explores the potential of spectro-temporal technique such as Wavelet transform in analyzing lung sounds associated with COPD and asthma. Total 23 features have been calculated. The statistical assessment of the computed features uncovered the differentiating capability of said feature set i.e. total 22 features contributed in discriminating lung sounds associated with COPD with asthma. This study provides major breakthrough toward feature identification of two important classes of lung sounds (COPD and asthma). However, the authors did not suggest any classification strategy.

A study by L.J. Hadjileontiadis [5] proposed classification system based on texture for discriminating squawks and cackles lung sounds. The sole aim of this study was to classify discontinuous lung sounds i.e. Fine Crackles (FC), Coarse Crackles (CC) and Squawks (SQ).

The lacunarity based approach (LAC) resulted in mean accuracy of 100% for FC-CC and FC-SQ group. The mean classification accuracy for CC-SQ group was 99.62% and 100% whereas for FC-CC-SQ group it was 99.75% and 100%. This study needs to be conducted on larger data set to confirm its potentiality. The study did not mention the source of database and recording procedure.

H. E. Elphick et al. [6] discussed the validity and reliability of acoustic analysis of respiratory sounds in infants. Acoustic sensor (Siemens EMT 25C) was employed to record total 102 lung sounds (infant under 18 months) of three categories i.e. wheeze, rattles and crackles. Authors concluded that the conventional stethoscope was unreliable for assessing respiratory sounds in infants because of the poor agreement between stethoscope examination and acoustic analysis, specifically in case of wheeze. Authors had also expressed the need of computerized pattern recognition to improve the diagnostic reliability.

L .J. Hadjileontiadis, and I. T. Rekanos [7] described the method for detection of explosive lung sounds by means of fractal dimension (FD). Lung sounds obtained from auscultation training tapes were utilized. Total 24 lung sounds including fine crackles, coarse crackles and squawks were used for analysis. 100% detection rate was observed with FD analysis for all three categories of lung sound. Although the results are quite impressive, the research gaps still exist due to low number of subjects (24) used in the study.

M. Oud [8] conducted an investigation to analyze internal states of artificial neural network trained to categorize lung sounds. Total 16 recordings, of asthmatic subjects were considered for the study. The features were extracted using principal component analysis subsequently artificial neural network with one hidden layer employing error back propagation was used for categorization. The main aim of internal state analysis (Analysis of weights in hidden layer) was to map the asthmatic lung sounds spectra onto lung function parameter (Flow information FEV_1). The authors have made two conclusions, first that the lung sound spectra is composed of distinct intra-correlated frequency band and secondly the effective pitch shifts towards higher values with increase in airways obstruction.

The major strength of previous work related to lung sounds analysis are as under:

1. Objective Analysis of almost all the categories of adventitious lung sounds in adult population.
2. Utilization of sensor arrays in wearable jackets (Most of the researchers) resulting in convenience of continuous monitoring.

The major weaknesses observed in the previous work related to lung sound analysis are as under:

1. Very few studies on objective analysis of young children's (Pediatric population) adventitious lung sounds.
2. Very few researchers used more than 50 cases for analysis
3. Very few studies for Indian Subjects.
4. The cost of jackets used in major studies is prohibitive for Indian conditions.

Considering above observations there is vast scope for development of signal processing algorithms for lung sounds analysis specially for Indian pediatric population. Next section describes the method adapted in this study for analysis for lung sounds pertaining to pediatric population.

II. RESEARCH METHOD

2.1 Data Acquisition

For acquiring the lung sound data, electronic stethoscope by Littmann model number 3200 was used. The features of stethoscope include wireless connectivity options using Bluetooth with ambient noise reduction. The duration of each recording is sixty seconds in .wav format which is actually sixteen-bit pulse coded modulation with sampling frequency of 4000 Hz. Data acquisition was carried out at private clinics and hospitals, doctor's approval and patient oral consent was taken.

2.2 Sorting and Pre-Processing

Here sorting includes the exclusion of noisy recordings and labeling the sounds accordingly in different category. Total 253 recordings were included after discarding around 40% data. The ratio of adventitious and normal sounds in total sounds is 50%. All the abnormal lung sounds were considered adventitious including harsh, crept and wheeze. Lung sounds for healthy subjects having even cough and cold were categorized as normal.

In preprocessing step, the dc component was removed followed by filtration. Various filters were experimented in Matlab'Fdatool' and finally seventh order Chebyshev IIR filter was chosen with lower cutoff frequency of 100 Hz. The response of chosen filter is shown in figure 1. After filtration, Amplitude normalization of carried out. The last preprocessing task was segmentation. The main aim of segmentation was to extract breath cycles from lung sounds. Here in this work manual segmentation was carried out using 'wavedit' software. Figure 2 shows the lung sounds before and after filtration.

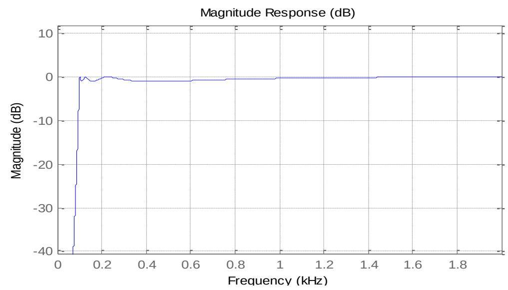

Figure 1. Frequency Response of Chebyshev Type 1 High Pass Filter

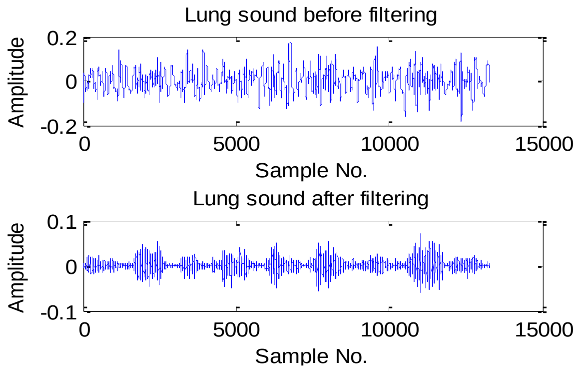

Figure 2. Lung Sound of Abnormal Subject before and after Filtering

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2.3 Feature Extraction

Due to similarity in time domain shape of lung sounds of both categories, it was decided to opt for frequency domain features. There is tremendous amount of research pertaining to automatic speech recognition which involves frequency domain features [9-10]. Here in this paper, these frequency domain features have been explored for classification of both category of lung sounds. The brief description of each explored frequency domain feature is given in the next paragraph.

1. *Spectral Centroid*

$$SC = \frac{\sum_{k=1}^{L} kX(k)}{\sum_{k=1}^{L} X(k)} \tag{1}$$

Considering spectrum as geometrical shape, SC represents its center of gravity.

2. *Spectral Crest Factor*

$$S.Cr(n) = \frac{\max_{0\le k\le \frac{k}{2}-1} |X(k,n)|}{\sum_{k=0}^{\frac{k}{2}-1} |X(k,n)|} \tag{2}$$

To know the concentration and distribution of frequencythis factor is useful.

3. *Spectral Decrease*

$$S.Dec = \frac{\sum_{k=1}^{\frac{k}{2}-1} \frac{1}{k}\left(|X(k)| - |X(0)|\right)}{\sum_{k=1}^{\frac{k}{2}-1} |X(k)|} \tag{3}$$

To know the rate of fall of frequencies in a spectrum , this factor is useful.

4. *Spectral Flatness*

$$S.F = \frac{\sqrt{\prod_{k=0}^{\frac{k}{2}-1} |X(k)|}}{\frac{2}{k}\sum_{k=0}^{\frac{k}{2}-1} |X(k)|} \tag{4}$$

The ratio of geometric to arithmetic mean is given by spectral flatness.

5. *Spectral Flux*

To know the average difference between consecutive short time Fourier transform frames spectral flux is useful parameter. It is defined as

$$S.F(n) = \frac{\sqrt{\sum_{k=0}^{\frac{k}{2}-1} \left(|X(k,n)| - |X(k,n-1)|\right)^2}}{\frac{k}{2}} \tag{5}$$

Spectral Kurtosis

To know the rapid fluctuations in spectrum, spectral kurtosis is very useful. It is given as

$$S.K = \frac{2\sum_{k=0}^{\frac{k}{2}-1} \left(|X(k)| - \mu|x|\right)^2}{k\sigma^4 |x|} \tag{6}$$

6. *Spectral Roll off*

To measure the concentration of frequency spectrum it is useful parameter, given as

$$\sum_{k=1}^{m} X_i(k) = C\sum_{k=1}^{F_L} X_i(k) \tag{7}$$

Here 'C' indicates the roll off factor.

7. *Spectral Skewness*

To measure how symmetric a distribution is , spectral skewness is calculated. It is given by:

$$S.Skw = \frac{2\sum_{k=0}^{\frac{k}{2}-1} \left(|X(k)| - \mu|x|\right)^3}{k\sigma^3 |x|} \tag{8}$$

8. *Spectral Slope*

To calculate the slope of spectral shape, following formula is used

$$S.Slp = \frac{\sum_{k=0}^{\frac{k}{2}-1} (k-\mu_k)\left(|X(k)| - \mu|x|\right)}{\sum_{k=0}^{\frac{k}{2}-1} (k-\mu_k)^2} \tag{9}$$

9. *Spectral Spread*

To know the spread of frequency over a specified range, spectral spread is calculated. Here frequency ranges from zero to maximum that is half of the sampling frequency. Generally, it is normalized in the range of zero to one.

$$SS = \frac{\sum_{k=1}^{L} (k-C)^2 x(k)}{\sum_{k=1}^{f_L} X(k)} \tag{10}$$

All the above computations were performed on MATLAB with audio processing toolbox [11]. For the feature matrix of 126 x 10, for both normal and adventitious classes, it was observed that the linear separability was lacking. So, to have efficient classification among the larger dimension data, it was decided to proceed with various artificial neural networks. In next section, the analysis and results related to performance of various ANNs have been presented.

III. RESULTS AND ANALYSIS

All the classification algorithms have been employed from Neuro Solutions 5.07 version (ND Inc. USA)

Various ANNs like Multilayer Perceptron (MLP), Modular Neural networks (MNN) and Generalized feed forward (GFF)neural networks have been explored for task of classification.

The flow for using ANNs for classification is as under:

First of all, the classifiers were employed sequentially with varying the corresponding network topologies. Here network topology includes Processing elements PEs, transfer functions and learning rules. To test the performance of each network with particular topology performance measures like Mean Square Error MSE , Minimum Absolute Error and Correlation Coefficient have been obtained. Taking the lead from obtained conclusion in the first step, the best performing neural network in terms of above said performance measures was selected. Table 1 and 2 shows the performance of MLP, GFF and MNN on basis of standard performance measure mentioned earlier. It is evident from tables that GFF is performing well compared to other two networks. So, it has been decided to go with GFF. Now next task is to experiment with GFF with varying topologies in terms of transfer function and learning rules. The comparative performances with various transfer function and learning rules are tabulated in Table 3 and 4.

Table 1. Comparison of MSE in Training, Cross Validation and Testing

Classifier Network	**Train**	**Cross Validate**	**Test**
Multilayer Perceptron	0.0037	0.2109	0.1093
Generalized Feed Forward	**0.0236**	**0.1598**	**0.0885**
Modular Neural Network	0.0037	0.2109	0.1235

Table 2. Comparison of performance measures for MLP, GFF, MNN

Classifier Network	**Category**	**MAE**	**CC**	**CA**
MLP	Healthy	0.0013	0.7564	85.714
	Pathological	0.0012	0.7604	82.692
GFF	Healthy	**0.0004**	**0.8015**	**90.909**
	Pathological	**0.0018**	**0.8008**	**91.228**
MNN	Healthy	0.0044	0.7271	76.470
	Pathological	0.0054	0.7233	92.000

Table 3. Comparison of different TFs for GFF

Transfer Function	**MSE**		**MAE**		**CC**		**CA**	
	Healthy	Pathological	Healthy	Pathological	Healthy	Pathological	Healthy	Pathological
Tanh	**0.061**	**0.063**	**0.154**	**0.156**	**0.866**	**0.861**	**94.545**	**91.304**
Sigmoid	0.185	0.189	0.353	0.355	0.520	0.505	82.978	61.111
Linear Tan	0.108	0.108	0.222	0.224	0.756	0.756	89.285	80.000
Linear Sig.	0.123	0.127	0.278	0.284	0.712	0.700	82.352	78.000
Soft Max	0.137	0.130	0.295	0.281	0.666	0.686	88.888	76.785

Table 4. Comparison of GFF for various learning rules

Learning Rule	**MSE**		**MAE**		**CC**		**CA**	
	Healthy	Pathological	Healthy	Pathological	Healthy	Pathological	Healthy	Pathological
Stp	0.070	0.072	0.154	0.158	0.850	0.846	93.617	85.185
Mom	0.061	0.063	0.154	0.156	0.866	0.861	94.545	91.304
Conj.Grad	**0.062**	**0.057**	**0.133**	**0.131**	**0.881**	**0.886**	**97.959**	**92.307**
LM	0.172	0.158	0.233	0.220	0.711	0.696	98.000	70.588
Delta Bar Delta	0.158	0.156	0.197	0.194	0.718	0.738	84.313	88.000

By looking at the obtained performances (Table 3) of transfer function (TF), it is clear that the *tanh* is outperforming others TFs. This result is obvious and expected by considering the high degree of non-linearity in the data. After fixing *tanh* as transfer function, the next step is to decide the learning rules. So, the same process was repeated for GFF with *tanh* as transfer function with varying learning rules. Table 4 shows the performances of various learning rules in terms of standard performance measures. Here Conjugate Gradient is outperforming its other counterparts. So finally, the GFF Neural Network with one hidden layer containing eight processing elements is selected. For hidden layer and output layer both, *tanh*and *conjugate gradient* is selected as transfer function and learning rule respectively.

Figure 3 shows the sensitivity bar plot of selected neural network for vector containing 10 features. From figure 3 it is evident that, all the features are well performing except spectral roll off and spectral flux.

The accuracy of the classification ANN was found to be 94.95%, with specificity of 98% and sensitivity of 91.9%.

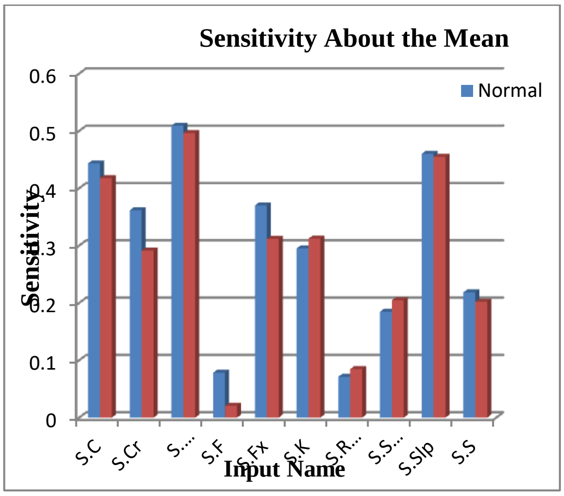

Fig. 5.16:

Figure 3. GFF Sensitivity for various features

IV. CONCLUSION

To conclude, this study leads to the development of novel approach to diagnose pathological and adventitious lung sounds in child having lung abnormality. Acquired data using electronic stethoscope was used for further analysis using features obtained from time and frequency domain characteristics. Three artificial neural networks i.e multilayer perceptron, generalized feed forward and modular neural network were tested with different network topologies. Form the obtained results it is evident that, generalized feed forward neural network with one hidden layer outperforms other two networks. After experimentation with various learning rules, transfer functions and number of processing elements in hidden layer, it has been observed that six processing elements are performing well with respect to MSE with *tahh*and CG as transfer function and learning rule. The accuracy achieved with this approach is 95.1%, which is encouraging for future studies involving soft computing approach in preliminary diagnosis of pathological and adventitious lung sounds using spectral features. The methodology presented here could be extended to sub-classify various adventitious and pathological lung sounds.

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