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Embedded System Design for Real-time Detection of Asthmatic Diseases Using Lung Sounds in Cepstral Domain

Misha Urooj Khan[1*], Areeba Mobeen[2], Sana Samer[3] and Aqsa Samer[4]

[1] Department of Electronics Engineering, University of Engineering and Technology (UET), Taxila, 47080, Pakistan (Misha.Urooj@students.uettaxila.edu.pk) * Corresponding author
[2] Department of Electronics Engineering, University of Engineering and Technology (UET), Taxila, 47080, Pakistan (18-enc-5@students.uettaxila.edu.pk)
[3] Department of Electronics Engineering, University of Engineering and Technology (UET), Taxila, 47080, Pakistan (18-ENC-16@students.uettaxila.edu.pk)
[4] Department of Electronics Engineering, University of Engineering and Technology (UET), Taxila, 47080, Pakistan (19-ENC-32@students.uettaxila.edu.pk)

Abstract: Bronchial Asthma (BA) and Allergic Bronchopulmonary Aspergillosis Asthma (ABPA) are two of the lethal asthmatic conditions with typical adventitious tones. It is a daunting challenge to detect these diseases from lung sound analytics and by non-invasive methodology. A novel architecture for detection of asthmatic patients is presented here by using machine learning and signal processing. This framework will help the asthma specialist to accurately identify asthmatic and non-asthmatic disease. Normalization and Empirical mode decomposition (EMD)-based techniques are used to denoise and segment the signal. Fusion of cepstral features such as Mel-frequency Cepstral Coefficients (MFCC) and Gammatone Cepstral Coefficients (GTCC) is employed. Feature selection algorithm for fusion is performed through Relieff Algorithm. Improved performance is evidenced by ensembled bagged tree classifier with an accuracy of 97.4% on selected fused features after experimentation on Raspberry pi. This approach for Asthmatic disease detection is quite precise, cost-friendly, easy to operate and non-invasive.

Keywords: Asthma Severity, Feature Extraction, Machine Learning, Non-invasive method, Signal Processing.

I. INTRODUCTION

One of the chronic diseases in our world is Asthmatic illness. In 2016, 339 million patients of this chronic disease have been recorded globally, most of which are children. World Health Organization (WHO) states that about 417,918 asthma patients have died globally per annum [1-3] and 24.8 million disabilities are traceable to asthma in 2016. Inhaled substances and particles causing allergy and irritations to the air passage are the most vital risk agents. According to WHO, deaths caused by asthma have reached the statistics of 1.07% of total deaths in Pakistan [13]. In 2018 Pakistan ranked 47 among the countries where asthma was the leading cause of mortality. If addressed and notified in advance, these fatalities may be shortened to a minimal amount. The challenge arises when there is a shortage or non-availability of improved and credible equipment in hospitals and medical institutions. The diagnostic procedure is a combination of fluoroscopy imaging and lab diagnoses which is not available to many. Auscultation is now the world-famous cheapest method with enhanced and accurate diagnosis's ability for lung diseases.

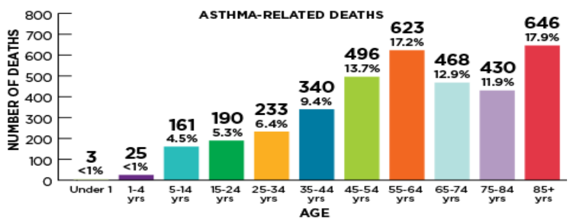

Fig. 1 Age wise morality rate of Asthma.

The objective of this research paper is to analyze lung sounds gathered from various hospitals. The proposed approach describes the characteristics that distinguish effectively between patients with asthma and non-asthma, using reliable low costs facilities. Allergic Bronchopulmonary Aspergillosis Asthma (ABPA) is an infectious disorder that causes aspergillus spores in bronchia to extreme sensitivity. Asthma, recurring lung infiltration, mucoid, eosinophilia, and central bronchiectasis are characteristic of this clinical manifestation. Bronchial Asthma (BA) is a serious chronic illness that swells and narrows the air passages of the lungs. Due to this inflammation, the path of the air contains thick mucus making it difficult to exhale and inhale. The illness is chronic and affects day-to-day work.

II. LITERATURE REVIEW

In [1] a total of 4,590 values of Peak expiratory flow (PEF) and Expiratory Volume in one second (FEV1) were registered by the 20 subjects. For PEF, 1,227 readings (26.7%) did not satisfy the criteria set by Burge and co-workers and for 1,501 FEV1 values (32.7%) there was more than 5% difference between the two best values. A survey was conducted in [2] by the Angus Reid Group. Interviews were completed with two groups: normal and patients with asthma. This paper [3] describes what asthma is and how it can be characterized. It showed that cough and dyspnea are major causes of asthma and they can be categorized into ten vital types.. Identification and classification of the three-lung disease were done in [4] with Gray Level Co-occurrence Matrix (GLCM) and extreme learning machine (ELM) for texture characterization and classification from segmented CT images with an accuracy of 86%.

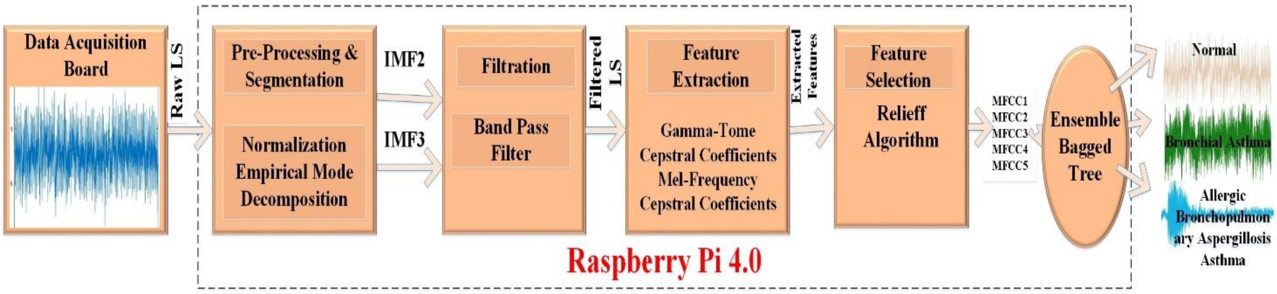

Fig. 2 Embedded System for the detection of asthmatic and non-asthmatic patients.

This paper published in 2014 had 250 lung recordings consisting of 24 input features and one discrete output feature. The Cross-validation method was used to eliminate common errors, after eliminating incomplete data and selecting 15 suitable features, the Random Forest Method gave the accuracy 0.9868, 0.9211, and 0.9652 [5]. The data extraction in [6] was designed in Microsoft Access. The pooled odds ratio (OR) of the prevalence of asthma in immigrants compared to the host population was 0.60 (95% CI 0.45–0.84), and the pooled OR for allergies was 1.01 (95% CI 0.62–1.69). 116 abnormal lung X-ray images were collected in [7]. A median filter was used for noise removal from the input image and its enhancement. Three types of Artificial Neural networks (ANN) were used as classifiers. Feedforward gave an accuracy of 94.8% while the Radial basis function network's accuracy was about 94.82%. In this study, various classification techniques are used to find out the sensitivity, specificity, accuracy of asthma prediction data. The highest accuracy of 98% was achieved through the SVM technique as compared to other present algorithms [8]. Deep Neural Network (DNN) was used to predict asthma severity using data at the National and Hospital level. At a national level, prediction accuracy was 86% and at the hospital level, it was 91.1% on average [9]. A classifier based on a combination of a single-layer Artificial neural network (ANN) and federated learning (FL) was used. During validation of the algorithm, the accuracy was 95.17% for COPD or asthma and 98.7% for healthy subjects [10]. In [11] the occupational population attributable fraction (PAF) was estimated for those conditions for which there were sufficient population-based studies to allow pooled estimates. Asthma (PAF,16%), chronic obstructive pulmonary disease (PAF,14%), chronic bronchitis (PAF, 13%), and community-acquired pneumonia in working-age adults (PAF,10%) were covered.

III. RESEARCH METHODOLOGY

Fig. 2 shows the proposed methodology for the detection of the asthmatic and non-asthmatic patients. An Electret microphone fitted inside the Data Acquisition Board (DAB) records the lung sounds and converts the received analog signal into digital one by saving the raw output in .m4a format. The raw digital signal is then pre-processed through normalization and empirical mode decomposition (EMD) which decomposes the raw signal into its many elements in time domain known as intrinsic mode functions (IMFs). The preprocessed signal is reconstructed by the addition of selected IMFs having no redundant and noisy content. Subsequently, cepstral characteristics are retrieved from these pre-processed signals and integrated to create a concise and accurate portrayal of asthmatic and non-asthmatic auscultation signals. Finally, these features are used to train classification models. An ensemble bagged tree is trained and used to forecast classes with strong differential characteristics of normal and asthma with the help of selected of IMFs.

A. Data Collection

Lung sound data is collected from asthmatic patients such as people suffering from Allergic Bronchopulmonary Aspergillosis, and bronchial asthma gathered from the Pakistan Institute of medical sciences Islamabad (PIMS). Non- asthmatic lung sounds data was collected from local universities and colleges. During data collection, a doctor was always with us who helped us in identifying whether the person at hand was an asthmatic or non-asthmatic subject. Signal acquisition is performed by keeping an electronic microphone near the left and then right nostrils. The microphone is attached to an amplifier so that amplified signals can be achieved. A random number of samples were collected from subjects. A single-subject gave at least a 90-sec long signal. The complete process is presented in Fig. 3.

Fig. 3 Data Acquisition process for lung sounds.

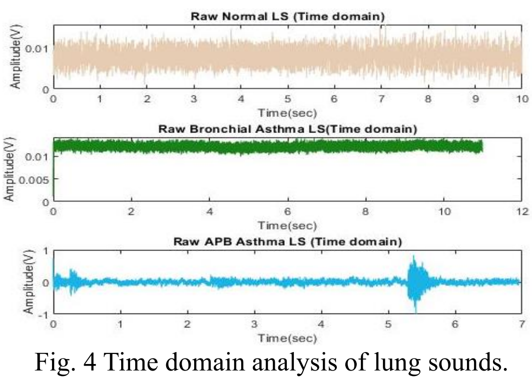

Fig. 4 Time domain analysis of lung sounds.

When time and frequency domain analysis of raw lung sounds (LS) is done, it can be seen that visually it is quite impossible to know which particular segment of the LS contains the useful part, as all three LS have varied amplitudes which will cause increased training time and computational cost. In order to make this signal immaculate for classification and detection of asthmatic patients, it must go through pre-processing steps which are explained in the nest section.

B. Pre-processing and Segmentation

The first and crucial stage in data analysis is pre-processing. It consists of removing the base stroll and high-frequency disturbances, together with other components which can alter the obtained signal. The sound of the heart, muscles, and skin are common disruptions. Raw LS is normalized to remove amplitude variation. EMD is a multi-resolution method adapted to disintegrate a signal into mechanically significant modules. Here Empirical Mode Decomposition (EMD) is used for two main goals. The first one is to eliminate the noise embedded in the raw signal and the second one is to extract the area of interest (AOI) in the signal which is having maximum discriminative characteristics. EMD decomposes the signal into its constituents' elements known as intrinsic mode functions (IMFs) [12]. The frequency range of asthmatic lung sounds constitutes of low-frequency components, so the higher frequency components and noise must be eliminated.

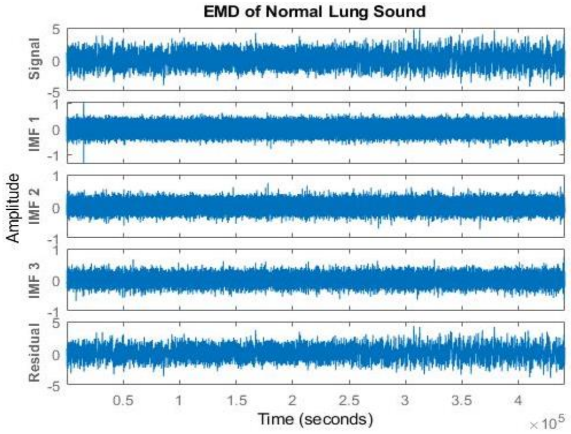

Fig. 5 Empirical Mode Decomposition of Normal lung sound.

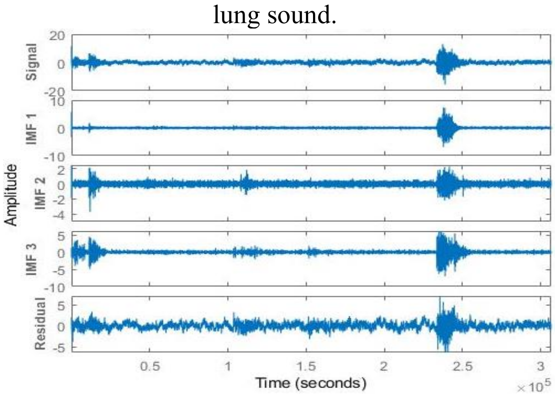

Fig. 6 Empirical Mode Decomposition of APB Asthma lung sound.

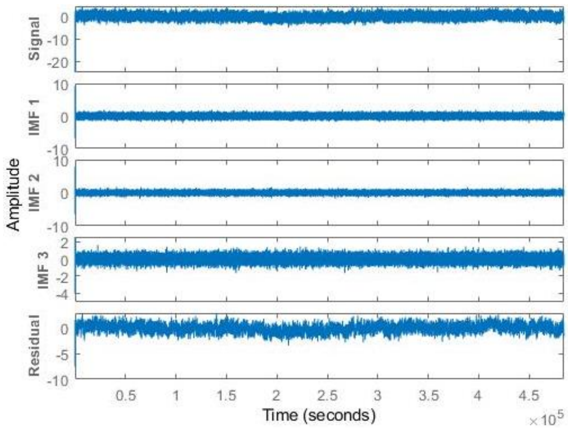

Fig. 7 Empirical Mode Decomposition of Bronchial Asthma lung sound.

With the help of EMD a pre-processed signal is reconstructed using the IMF-2 and IMF-3. Both these signal elements carry low-frequency components. The mean frequency range for bronchial asthma of IMF-2 is 200-1400Hz and IMF-3 is 100-700 Hz. In the case of APB asthma IMF-2 is 200-1600Hz and IMF-3 is 100-500 Hz. For normal IMF-2 is 450-2500Hz and IMF-3 is 100-1kHz. First subplots of Figs. 5~7 show the normalized LS, second, third and fourth subplots show IMF-1, IMF-2 and IMF-3 respectively. Last subplot shows the residual of the normalized LS in time domain.

C. Filtration

In order to extract AOI we used a 10th order Butterworth band pass filter with range of 350 to 1kHz. The region below 300 contains muscle sounds and above 1kHz contains high frequency components which we don't need.

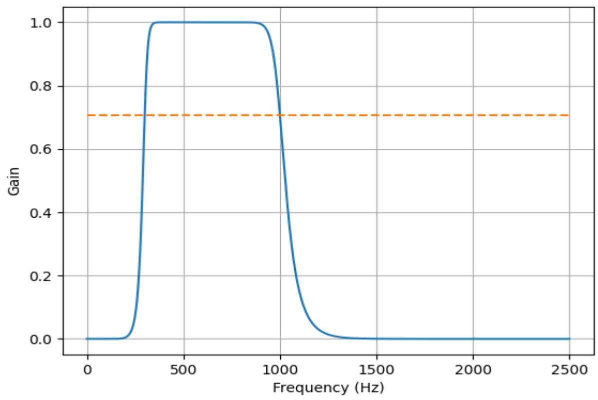

Fig.8 Magnitude response of Bandpass filter.

D. Feature Extraction

Characteristics are the main features that tell a classifier to differentiate between various lung signals. LS by essence is non-stationary. That's why a single characteristic cannot predict the existence of abnormality in any data. 14 mel-frequency cepstral coefficients (MFCCs) and 14 gamma-tone cepstral coefficients (GTCCs) of lung sounds are extracted making a total of 28 cepstral domain features which are shown in Fig. 9~10.

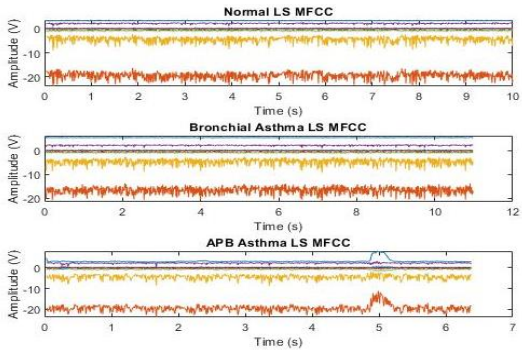

Fig. 9 Extracted MFCC features of lung sounds.

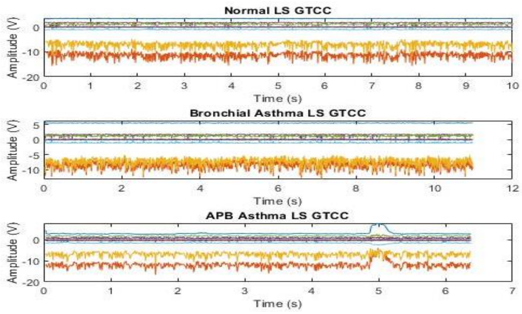

Fig. 10 Extracted GTCC features of lung sounds.

E. Feature Selection

Selected features reduce the number of input variables which leads to minimizing the computing costs of modeling and increases the model efficiency. ReliefF algorithm sorted the features by their ranks in predicting the outcome of predictors. MFCC1-5 carried the highest weights, so we trained our classifier on them to get the best possible results.

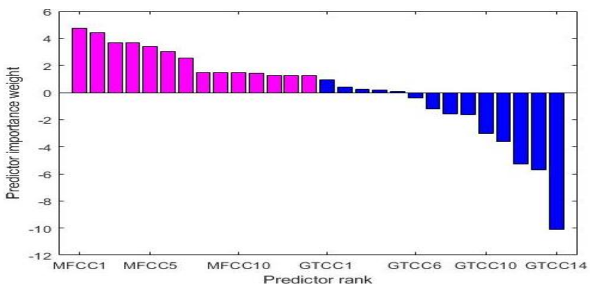

Fig. 11 Feature Selection through ReliefF Algorithm.

F. Classification

For this algorithm, decision tree classifiers are tested to observe the performance of the proposed methodology. Ensemble bagged tree (EBT) gave the highest accuracy i.e., 97.4% with training rate of ~1000 observations per second and misclassification cost of 20. EBT used 853 number of splits, 30 learners and a training time of 17.155 seconds.

IV. RESULTS AND DICUSSION

In this paper, we designed an embedded system for the real-time detection and classification of asthmatic and non-asthmatic patients. We collected the dataset of three classes: normal, bronchial asthma and bronchopulmonary aspergillosis asthma lung sounds by using data acquisition board. The sampling frequency to store the data as .m4a was 8kHz, 8 bits and single channel.

Table 1 Summary of Data Acquisition.

Subjects	Female		Male		Total samples
	Subjects	Samples	Subjects	Samples	
APBA	10	108	9	102	110
BA	15	159	15	160	319
Normal	25	256	25	250	506

Normalization and empirical mode decomposition (EMD) technique is used for the denoising and segmentation of dataset. 14 MFCC and 14 GTCC were given to the feature selection algorithm known as Relieff algorithm. First 5 MFFC's got the highest weights. The Scatter plot in Fig. 9 shows the dispersion and potential effectiveness of the grouping of extracted features.

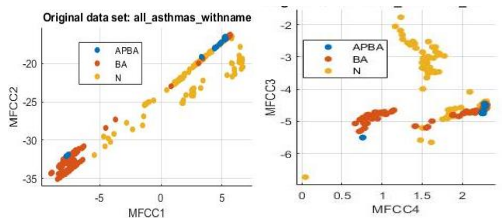

Fig. 12 Scatter Plots of MFCC1-4.

We use these 5 MFFC's to train decision trees with 5 different ensemble methods named as adaboost, bag, subspace discriminant, subspace knn and rusboost. Bagged ensemble tree gave the highest average accuracy of 97.4%. Results are present in Fig. 13 and Table 1~3.

Table 2 Ensemble Bagged Tree Confusion matrix.

Lung Sound		Predicted Class		
		ABPA	BA	Normal
True Class	ABPA	90.5%	0%	9.5%
	BA	0.6%	97.8%	1.6%
	Normal	0.6%	1.6%	97.8%

Normal and Bronchial asthma LS have the highest TRP's i.e., 97.8% and 2.2% FPR. Bronchopulmonary aspergillosis asthma showed the highest FPR of 9.5% and lowest TRP of 90.5%.

Table 3 True Positive Rate (TPR) and False Positive Rates (FPR) of Ensemble Bagged Tree.

Lung Sound	TPR	FPR
ABPA	90.5%	9.5%
BA	97.8%	2.2%
Normal	97.8%	2.2%

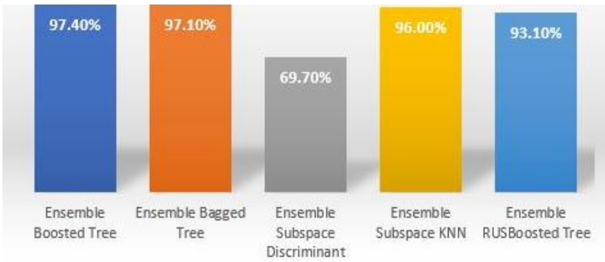

Fig. 13 Accuracy of different decision tree methods.

We performed real-time experiments on Raspberry Pi (Rpi) 4.0 model B having 2 GB RAM and 15W USB-C power supply. Data acquisition board (DAB) was attached with Rpi though USB sound card adapter (7.1 channel) and male to male converter. Electret microphone is attached inside the surgical mask. We accessed the Rpi terminal by connecting the ethernet cable to the laptop whose screen was used to show the Rpi's desktop. This methodology can also perform real-time classification of lung sounds.

Fig. 14 Embedded System for Detection of Asthmatic Diseases.

Positive Predictive Values (PPV) and False Discovery Rates (FDR) of EBT are given in Fig. 15. PPV is the proportion of correctly categorized observations per expected class. FDR is the percentage per expected class of wrongly labelled findings. Normal class shows the shows the highest PPV rate with 97.8% and bronchopulmonary aspergillosis asthma shows the highest FDR of 13.0%.

Fig. 15 Accuracy of decision trees on different kind of ensemble methods.

V. CONCLUSION

In this research paper real-time classification of asthma and non-asthma patients is done by using analysis of lung sounds. EMD–EBT based model is proposed in this paper. Total samples for normal were 506, for bronchial asthma 319 and for bronchopulmonary aspergillosis asthma 110. Extracted features, 14 mel-frequency cepstral coefficients (MFCC) and 14 gamma-tone cepstral coefficients (GTCC) of lung sounds are checked through relieff algorithm to see their maximum weights. Using 5 MFCC's selected by relieff algorithm are combined with ensemble bagged tree classifier achieved maximum average accuracy of 97.1% after 10 successive experiments on Raspberry pi 4.0 model B. When this system is tested on various cross-validation methods, there is no noticeable improvement in system accuracy. It shows improved device effectiveness even in the 5-fold cross-validation, which decreases the device's computation time. Our future aim is to propose a hardware framework for the detection of asthmatic disorders by wheezing sounds.

REFERENCES

[1] L. P. C. T. C Leroyer, "Comparison of serial monitoring of peak expiratory flow and FEV1 in the diagnosis of occupational asthma," *PunMed*, vol. 158, no. 3, pp. 827-32, 1998.

[2] P. E. A. G. P. D. S. Z. K R Chapman, "Control of asthma in Canada: failure to achieve guideline targets," *PubMed*, pp. 35-40, 2001.

[3] W. M. v. Aalderen, "Childhood Asthma: Diagnosis and Treatment," *PubMed*, vol. 2, no. 1, p. 10, 2012.

[4] R. L. B. RamalhoI*, P. P. R. FilhoI, F. N. S. d. MedeirosII and P. C. CortezII, "Lung disease detection using feature extraction and extreme learning machine," *Revista Brasileira de Engenharia Biomédica*, vol. 20, no. 3, pp. 1517-3151, 2014.

[5] M. L. m. Z. Taha Samad-Soltani, "Intelligent Diagnosis of Asthma Using Machine Learning Algorithms," *International Journal of Sciences: Basic and Applied Research (IJSBAR)*, vol. 4, no. 12, p. 10, 2014.

[6] E. U. M. P. J. M. A. J. W. Báltica Cabieses1, "A systematic review on the development of asthma and allergic diseases in relation to international immigration: the leading role of the environment confirmed," *PLoS One*, vol. 9, no. 8, p. 20, 2014.

[7] S. Khobragade, A. Tiwari, C. Patil and V. Narke, "Automatic detection of major lung diseases using Chest Radiographs and classification by feed-forward artificial neural network," *1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, Delhi, 2016.

[8] M. K. S. M. Princy, "Survey on Asthma Prediction Using Classification Technique," 2016.

[9] L. G. C. Almir Badnjevic, "An Expert Diagnostic System to Automatically Identify Asthma and Chronic Obstructive Pulmonary Disease in Clinical Settings," *Scientific Reports*, vol. 8, pp. 116-45, 2018.

[10] I. A.-M. J. R. B. K. J. C. D. F. D. M. N. M. R. N. N. C. J. R. T. S. K. T. D. V. C. A. R. Paul D Blanc, "The Occupational Burden of Nonmalignant Respiratory Diseases. An Official American Thoracic Society and European Respiratory Society Statement," *Am J Respir Crit Care Med*, vol. 199, no. 11, p. 1312-1334, 2019.

[11] B. B. K. A. H. D. T. O. L. K. T. S. L. S. C. J. Hee HI, "Development of Machine Learning for Asthmatic and Healthy Voluntary Cough Sounds: A Proof of Concept Study," *Applied Sciences*, vol. 9, no. 14, p. 2833, 2019.

[12] S. Z. H. Naqvi, M. Arooj, S. Aziz and M. U. Khan, "Spectral Analysis of Lungs sounds for Classification of Asthma and Pneumonia Wheezing," *ICECCE*, Istanbul, 2020.