Proc. of the 2nd International Conference on Electrical, Communication and Computer Engineering (ICECCE)
12-13 June 2020, Istanbul, Turkey

Spectral Analysis of Lungs sounds for Classification of Asthma and Pneumonia Wheezing

Syed Zohaib Hassan Naqvi
Department of Electronics Engineering University of Engineering and Technology Taxila
Pakistan
zohaib.naqvi@uettaxila.edu.pk

Misha Arooj
Department of Electronics Engineering University of Engineering and Technology, Taxila
Pakistan
misha.urooj@students.uettaxila.edu.pk

Sumair Aziz
Department of Electronics Engineering, University of Engineering and Technology, Taxila
Pakistan
sumair.aziz@uettaxila.edu.pk

Muhammad Umar Khan
Department of Electronics Engineering, University of Engineering and Technology, Taxila
Pakistan
sa.umarkhan@gmail.com

Mohammad Ahmad Choudhary
Department of Electrical Engineering, University of Engineering and Technology, Taxila
Pakistan
dr.ahmad@uettaxila.edu.pk

Muhammad Nafees.ul.Hassan
Associate Consultant
Department of Anesthesia, ICU and Pain Medicine, Shifa International Hospital, Islamabad, Pakistan
dr.nafees09@yahoo.com

***Abstract*— World Health Organization Statistics declares the pulmonic illness as the class of deadly illness. Wheezing is a key indicator for the diagnosis of pulmonic illnesses like Asthma and pneumonia. In this research article, the identification of wheeze sound in asthma and pneumonia subjects is done from breathing sound. The analysis is performed through signal processing and machine learning practices. Overall, data is acquired from 300 subjects. It includes 100 Asthma, 100 Pneumonia, and 100 Normal subjects This research work proposes a complete design for accurate classification of wheezing signals. It includes pre-processing by normalization, denoising by filtration, segmentation to remove the non-breathing and silent parts, feature extraction from the spectral domain, and classification by support vector machine (SVM) using Matlab 2019b. The system evidenced an accuracy greater than 96%. Further investigation can be done by analyzing the wheezing sound originates in other pulmonic diseases and exploring its role to identify the pulmonary illness.**

Keywords*— *Asthma Wheeze, Lungs Sounds, Pneumonia Wheeze, Support Vector Machine

I. INTRODUCTION

Pulmonic diseases are one of the core causes of death worldwide. asthma and chronic obstructive pulmonary disease (COPD) affected nearly 65,000,000 world's population. Overall, 235 million individuals suffer from asthma and about 3 million people globally die from it each year, making it the third leading cause of death worldwide [1]. Asthma impacts about 10% of the population globally and is a major source of hospitalization for acute illness [2]. Various techniques are devised for the diagnostic of pulmonary issues. It consists of chest imaging, bronchoscopy thoracoscopy, pulmonary artery catheterization, percussion, inception, palpation, breathing patterns, and auscultation [3]. All of the mentioned approaches need a medical expert to treat the illness [4]. A list of developments in medicine and its associated fields for early and appropriate detection of lung diseases has also devised in the last decade. Computed tomography scans, X-rays, and magnetic resonance imaging techniques are remarkable achievements in the analysis of biological information but unaffordable in every health care center. Chemical testing and tissue sampling are alternative procedures for detecting lung abnormalities.

There are many other studies in the literature which exploits sound data modality for the detection of neurological diseases like Parkinson's disease and Alzheimer's disease [5]. These studies provide strong motivation to address the classification of pulmonary abnormalities based on sound data from the lungs. This study comprises wheezing identification in Asthma and Pneumonia which are one of the most lethal pulmonary diseases. In this article, research work is carried on the identification of these pulmonic pathologies by analysis of lung sound (LS). Wheezing has characteristics of sharp pitched whistling sound during inhalation or exhalation. Most often, it can listen during exaltation but in a critical situation, it can be produced during inhalation as well. Inflammations and narrow airways are mainly responsible for this situation. Wheezing may be a symptom of a serious breathing problem that requires diagnosis and treatment [6]. Asthma and chronic pulmonary disease are the most common causes of wheezing. Excessive mucus and narrowing airways produce whistles due to Asthma. It causes breathing problems and hypersensitivity leads to irritants [7]. Pneumonia causes inflammation in alveoli. These alveoli if filled with purulent fluid results in an acute cough with sanies, fever, and hard to breathe. [8].

II. RELATED WORK

Sounds are generated in the lungs due to the blustery flow of the airways. These LS are categorized into two main classes. a) adventitious sounds and b) vesicular sounds. The adventitious and vesicular sounds are also referred to as abnormal and normal sounds. Wheeze, rhonchi, and stridor are few abnormal LS generate because of pulmonic illness. Table I outlines about major attributes of abnormal LS.

TABLE I. CHARACTERISTICS OF ADVENTITIOUS LS [3]

Sr. No	Class	Time Duration	Frequency	Pitch	Timing
1	Wheeze	80-250ms	>100 Hz	>400Hz	Biphasic
2	Rhonchi	>80ms	<200Hz	<200Hz	Biphasic
3	Stridor	>250ms	>150 Hz	>500Hz	Biphasic

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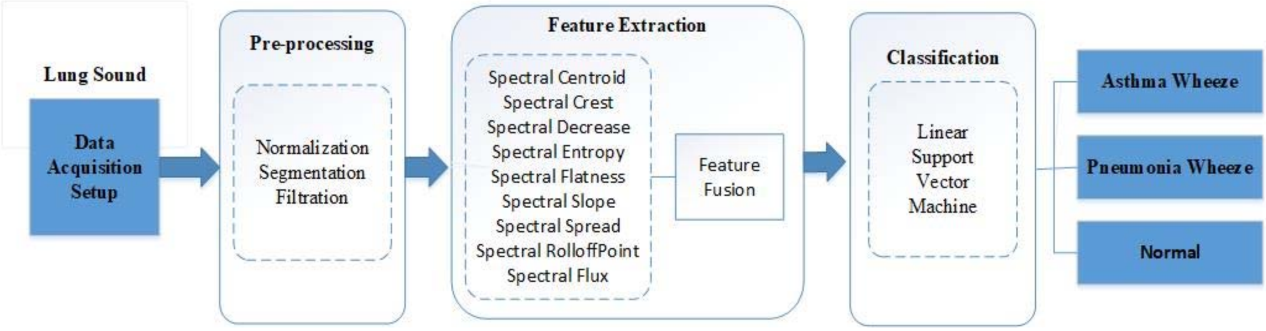


Figure 1: Proposed Methodology of the system

In recent researches, numerous systems have devised but effective and robust system design is a big challenge because of wheezing variability. In [9], the authors presented a comparative study using an intelligent and fine wheeze detection approach implemented by the back-propagation method. In [10], wheeze sounds and their characteristics are analyzed by extracting Mel-frequency spectral coefficients and support vector machine (SVM) kernels. An efficient wheezing detection system is proposed in the research paper [11] which is implemented by using a field-programmable gate array. In the research article [12], the author used an electronic stethoscope to record chest sounds. It mainly focused to distinguish chest sounds into lung and heart sounds via Fast-ICA and MATLAB. In [13], breathing sound signals are classified on spectral bases by using separate filters and peak signal energy. A hardware-based system is proposed in [14] to distinguish lung sounds into ordinary and wheeze class through Mel-Frequency Cepstral Coefficients (MFCC) and Support Vector Machine (SVM). Similarly in [15], a research work presented the implementation of the system on hardware for automatic detection of wheeze in pulmonary sounds and separated them from heart sounds by MFCC and SVM technique. Multiple adventitious sounds were also identified in some researches. In [16], the presence of wheeze and crackle is estimated by using Power Spectrum Density (PSD), Multilayer perceptron (MLP), and genetic algorithm techniques. The design of a wearable system is presented in [17] which monitored breathing sounds by extracting bandwidth and prominent frequency with 90% accuracy. A research study in [18] implemented digital image processing and pattern recognition for wheeze detection with 84.82% accuracy. A pattern recognition system in [19] uses two-layer architecture for the detection of wheezes in the breathing sounds of children due to asthma by using the BU-3173 accelerometer and an amplifier with 98% accuracy. A computerized breathing sound analysis is performed in [20] to explore the association between wheeze and conventional parameters for the lungs. In [21], a wheezing recognition algorithm is developed for infants of 1-2 years with sensitivity and specificity of 71.4% and 88.9% respectively using SVM. In [22], signature wheezes were extracted in the space of spectrogram (WS-SS) and temporary Gaussian regularization with 97.9% accuracy. wheezing is modeled using the hidden Markov model, considering its instantaneous frequency as a hidden state. The hidden state was estimated through the Forward-backward and Viterbi algorithm from a series of observations drawn from STFT in [23]. It is due to the non-stationary and nonlinear nature of lung sounds that most of the researchers analyzed the lung sounds in the time-frequency domain. It helps to get valuable information from the non-stationary signals. It is the reason that in [24] wheeze was detected based on time-frequency analysis on the data acquired by 3M-3200 electronic stethoscope. System performance is validated with clinical observation and experimental outcome. Wheeze is one indication in case of pneumonia and asthma. Different adventitious sound is also focused by the researchers along with wheeze including squawks, stridor and crackles [25].

III. PROPOSED METHODOLOGY

This article aims to devise an effective diagnostic scheme to categorize normal, asthma, and pneumonia wheeze from lung sound (LS) analysis. The general proposed methodology for the detection of pulmonic illness is presented in Figure 1.

A. Data Acquisition

Breathing sound data from normal, asthma, and Pneumonia subject is self-collected data gathered from Pakistan Institute of medical sciences Islamabad (PIMS), Pakistan after ethical approval for the research work.

LS acquisition is performed by keeping electronic microphone and mouthpiece near nostrils or by placing a stethoscope on the right lung. The microphone is attached with a small filter and an amplifier so that noise-free and amplified signals can be achieved. Ten samples with 10sec per sample are recorded form each subject. The signals were taken mainly from the nostrils and right lung as it has a larger space area. The complete process is presented in Figure 2.

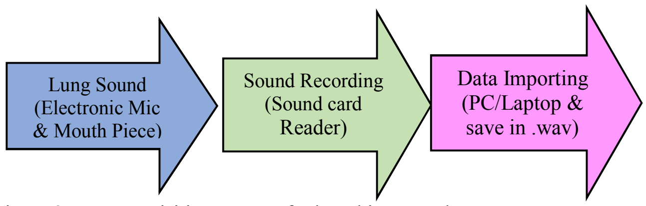


Figure 2: Data acquisition process for breathing sounds

The detail of the acquired data is organized in Table II as presented below.

TABLE II. DETAILS OF ACQUIRED SAMPLES

Sr. No.	Class	Gender*	Age (Years)	No. of Samples
1.	Asthma	40F,60M	12-47	1000
2.	Pneumonia	50F, 50M	28-67	1000
3.	Normal	50F, 50M	27-69	1000

*M: Male, F: Female

B. Preprocessing

It is needed to immaculate LS to extract features and classification. At this stage, normalization, segmentation, and filtration are performed. Time and frequency domain representation of LS signals before pre-processing is shown in Figures 3 and 4 respectively.

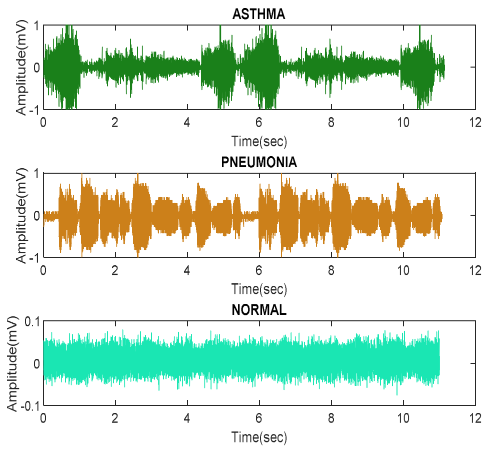


Figure 3: Time Domain representation of LS signals before pre-processing

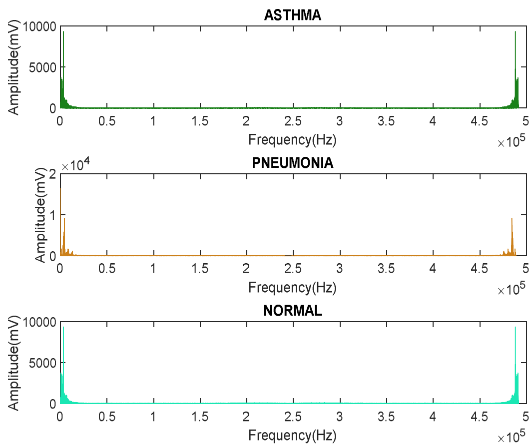


Figure 4: Frequency Domain representation of LS signals before pre-processing

1) Normalization

Normalization is carried out to assess a mean signal level and standard deviation of the recorded signal. It also removes un-necessary artifacts and reduces the time complexity for training and classification [26]. Min-Max method is adopted for the normalization of LS denoted as ‘LS_Nor’. In this method, the minimum value in lung sound signal LS is mapped to 0 and the maximum value in LS is mapped to 1. Mathematically (1),

$$LS\_Nor = LS - min(LS)/max(LS) - min(LS) \qquad (1)$$

2) Segmentation

Segmentation is the division of an entire signal into a smaller segment, parts, or frames. The signal is sectioned into 250 ms frames to remove the non-breathing and silent parts.

3) Filtration

Butterworth bandpass filter of tenth order with a sampling frequency of 44.1 kHz is designed. The scope of the bandpass filter is lies from 250 Hz to 2000 Hz. The filter only transfers the frequencies within a certain specified spectrum and attenuates frequencies outside that specific scope.

The time and frequency domain representation of the preprocessed signal is presented in Figures 5 and 6 respectively.

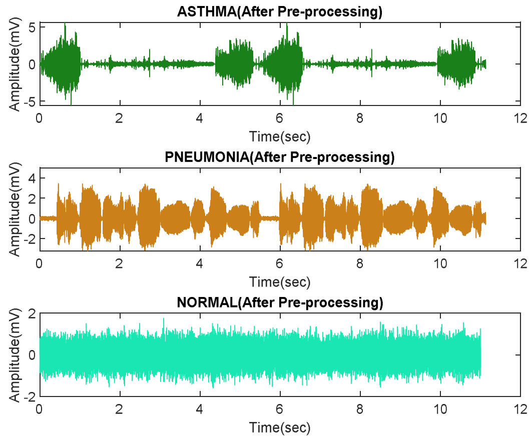


Figure 5: Time Domain representation of processed LS signal

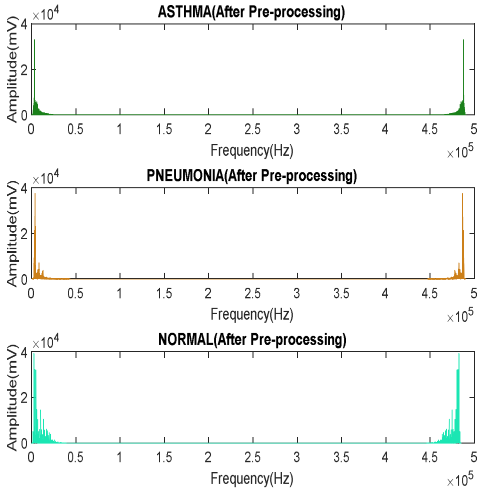


Figure 6: Frequency Domain representation of processed LS signal

C. Feature Extraction

The extraction of features is a technique in which characteristics information is extracted. It is referred to as a feature or characteristics vector. These feature vectors hold important information that helps in classification via machine learning techniques [12]. The following features were extracted from processed signals [27].

1. Spectral Centroid (SCN): Spectral centroid is used in frequency or spectrum characterization during signal processing. It quantifies the spectrum's mass core location. Mathematically,

$$SCN = \sum_{k=BE_1}^{BE_2} f_k SV_k / \sum_{k=BE_1}^{BE_2} SV_k \qquad (2)$$

where ‘BE’ represents band edge, ‘f’ is Frequency, ‘SV’ denotes spectral value and ‘k’ is the number of bins.

2. Spectral Crest (SCR): The spectral crest also known as peak component, provides a method for calculating the signal quality. It is measured as a ratio of a signal's peak value to the RMS of the same signal.

$$SCR = max(SV_k)/\frac{1}{BE_2-BE_1}\sum_{k=BE_1}^{BE_2} SV_k \qquad (3)$$

where 'BE' represents band edge, 'f' is Frequency, 'SV' denotes spectral value and 'k' is the number of bins.

3. Spectral Decrease (SDC): Spectral decrease defines the average spectral slope, and is useful in retrieving low-frequency information

$$SDC = \sum_{k=BE_1}^{BE_2} \frac{SV_k - SV_{BE_1}}{k-1} / \sum_{k=BE_1}^{BE_2} SV_k \quad (4)$$

where 'BE' represents band edge, 'f' is Frequency, 'SV' denotes spectral value and 'k' is the number of bins.

4. Spectral Entropy (SEN): A signal's spectral entropy is a function of the distribution of its spectral power. It gives information about the signal's irregularity, complexity, or amount of disorder.

$$SEN = -\sum_{m=1}^{N} PD(m) log_2 PD(m) \quad (5)$$

where 'PD' represents the probability distribution of Lung Sound.

5. Spectral Flatness(SFL): It is the measure of the ratio of arithmetic and the geometric mean of a signal powers spectrum.

$$SFL = \left(\pi_{k=BE_1}^{BE_2}\right)^{\frac{1}{BE_2 - BE_1}} \Big/ \frac{1}{BE_2 - BE_1} \sum_{k=BE_1}^{BE_2} SV_k \quad (6)$$

where 'BE' represents band edge, 'f' is Frequency, 'SV' denotes spectral value and 'k' is the number of bins.

6. Spectral Flux (SFL): Spectral flux is the spectral modification variable for two consecutive frames and is calculated through short spectral frames as the square discrepancy between the magnitudes, with values of -1 to 1 of the continuum of both the two successive frames [29].

$$SFL = \left(\sum_{k=BE_1}^{BE_2} |SV_k(t) - SV_k(t-1)|^P\right)^{1/P} \quad (7)$$

where P represents the norm type, 'BE' represents band edge, 'f' is Frequency, 'SV' denotes spectral value and 'k' is the number of bins.

7. Spectral Roll Off (SRO): The spectral roll-off is defined as the frequency in the power spectrum of the signal below which 85% of the spectral magnitude is situated.

$$SRO = \sum_{k=BE_1}^{i} SV_k = \kappa \sum_{k=BE_1}^{BE_2} SV_k \quad (8)$$

where 'κ' is the percentage of the total energy contained between 'BE_1'and 'BE_i' and can be set via Thresholding.

8. Spectral slope (SSL): Spectral slope is a function of wavelength dependency on the reflectance. It is a calculation of how quickly the spectrum of an audio sound swings towards the high frequencies, measured using a linear regression

$$SSL = \sum_{k=BE_1}^{BE_2} (f_k - \mu_f)(SV_k - \mu_s) / \sum_{k=BE_1}^{BE_2} f_k - {\mu_f}^2 \quad (9)$$

where 'f_k' represents frequency in Hz to every bin 'k', 'μ_f' is the mean frequency, 'SV_k' is the spectral value at bin 'k' and 'μ_s' is the mean spectral value.

9. Spectral Spread (SSP): The spectral distribution reflects the usual frequency gap around its centroid, and is related to the bandwidth. Noise signals have a wide spectral range when contrasted with other natural signals.

$$SSP = \sqrt{\sum_{k=BE_1}^{BE_2} (f_k - SCN)^2 \, f_k SV_k / \sum_{k=BE_1}^{BE_2} SV_k} \quad (10)$$

where 'f_k' represents frequency in Hz to every bin 'k', 'μ_f' is the mean frequency, 'SV_k' is the spectral value at bin 'k', '*SCN*' is the spectral centroid and 'BE' represents band edge.

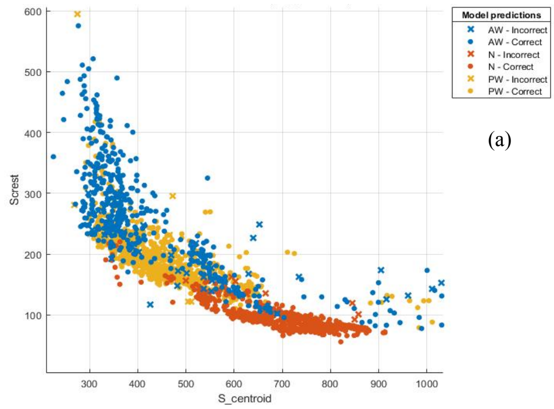
D. Classification

After going through pre-processing and feature extraction different techniques are used to classify the wheezing signals into normal, asthma, or pneumonia wheeze from breathing sound. Support Vector Machine (SVM) [28-38] is mainly used for classification. Experimentation is also made with other classifiers including Linear discriminant (LD), Kernel Naïve Bayes (KNB), Fine Tree (FT), Gaussian Naive Bayes (GNB) [39], Fine KNN (FKNN) [40], Bagged Tree (BT) and Subspace KNN (SKNN) used in various diagnostic systems.

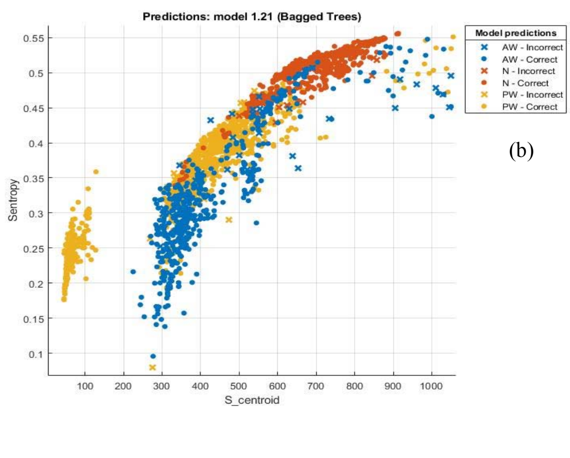
IV. Results and Discussion

This paper presents the role of spectral analysis to differentiate between the wheezing of asthma, pneumonia, and normal subjects. Respiratory signals are acquired by an electret microphone or a stethoscope, making it low-cost, and convenient to use.

In the Pre-processing stage, normalization is carried out via the min-max technique to transform the whole dataset of the same amplitude. After it, Segmentation is made to sectioned the signal into the 250ms frame to extract the breathing signal with wheeze and discarding the silence part of the breath. Filtration is applied to remove the unwanted frequency. Wheeze sound lies is frequency range greater than 100 Hz of breathing signal. As its frequency varies in asthma and pneumonia illness so the region of interest (ROI) in each LS signal is selected from 250Hz to 2000. Bandpass filter ensured the LS sound extraction of 250 Hz – 2KHz. Nine different features in the spectral domain were extracted in this research. The Scatter plot in Figure 7 demonstrates the possible efficacy of these features in classification. The scattering of selected features evidenced its effectiveness to provide better outcomes at the classification stage.



(a)



(b)

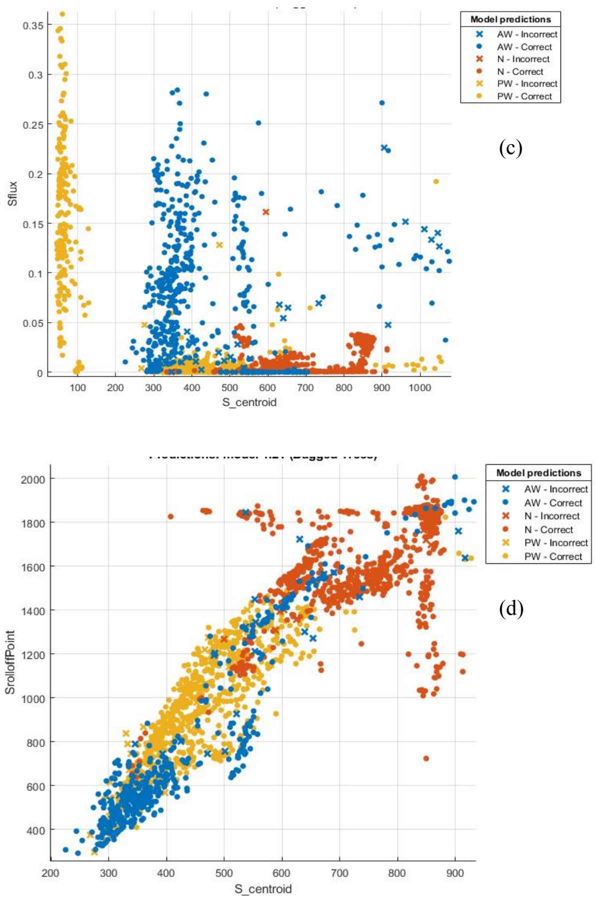


Figure 7: Scatter Plots of Some Extracted Features (a) Spectral crest and Spectral centroid (b) Spectral entropy and Spectral centroid (c) Spectral flux and Spectral centroid (d) Spectral roll of point and Spectral centroid

Investigation and analysis are performed on diverse classification methods to attain a better and accurate outcome. It includes Linear discriminant (LD), Kernel Naïve Bayes (KNB), Fine Tree (FT), Gaussian Naive Bayes (GNB), Fine KNN (FKNN), Bagge Tree (BT) and Subspace KNN (SKNN) and Supports Vector Machine (SVM). The results are presented in Figure 8. It shows the good outcome of the SVM method. Further investigation is made on different kernels of SVM using the same spectral features. These kernel includes SVM linear (L_SVM), Quadratic SVM (Q_SVM), Cubic SVM (C_SVM), Fine Gaussian SVM (FG_SVM), Medium Gaussian SVM (MG_SVM) and Coarse Gaussian SVM (CG_SVM). The accuracy achieved by these kernels is demonstrated in Figure 9. Linear SVM outperformed with 96.70% accuracy. Cross-validation (CV) is a resampling procedure used to evaluate machine learning models on a limited data sample. The cross-validation of the proposed system is carried out on the 5-fold and 10-fold technique. The accuracy achieved in both CV is 96.7% and 96.4%. It depicts that system performance is fine even with the 5-fold technique which reduces the time complexity of the system significantly. Figure 10 demonstrates the confusion matrix of Linear SVM. It can be observed that there is 4% false detection of asthma wheeze (AW) in pneumonia wheeze (PW) signals, 1% false detection of normal signals (N) in pneumonia wheeze (PW) signals and 3% false detection of pneumonia wheeze (PW) in asthma wheeze (AW) signals.

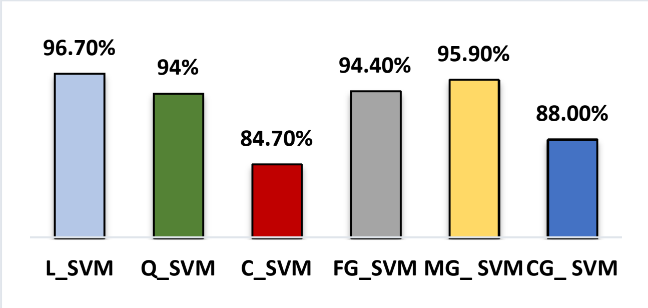


Figure 8: Accuracy of the system on different kernels of SVM

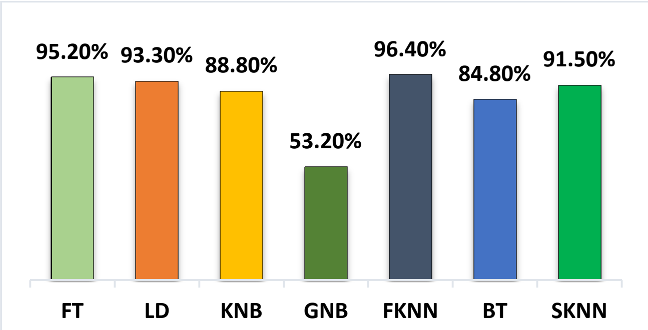


Figure 9: Accuracy of the system on different classifiers

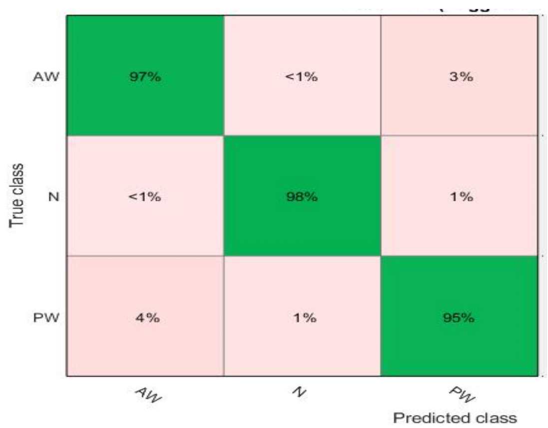


Figure 10: Confusion Matrix of Processed Data

V. Conclusion and Future Work

In this article, a technique is proposed to perform the identification of normal, asthma, and pneumonia wheeze. The designed system provided system accuracy of 96.7% on spectral analysis of the LS signal. It depicts that wheeze caries significant information that can be helpful in the diagnostics of pulmonary diseases. No significant variation in system accuracy is observed when the system is tested on different CV techniques. It evidences better system efficacy even on the 5-fold CV which will reduce the time complexity of the system. Future work can include the implementation of the proposed system on hardware and analysis of wheezing sound produces in other pulmonic abnormalities and investigating its role in the identification of pulmonary disease

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