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Optimal chest position of auscultation for chronic obstructive pulmonary disease diagnosis using machine learning

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ABSTRACT

Digital stethoscopes over recent years have gained acceptance among pulmonologists to perform auscultations due to their advantages over traditional stethoscopes. During the previous decade, researchers have prominently contributed to the development of algorithms aimed at enabling objective diagnosis of respiratory sounds and conditions, thereby affording individuals lacking medical expertise the capability to auscultate themselves. However, auscultation requires the personnel to be aware of the optimal chest position to place the device for a reliable diagnosis as well. This study aims to identify the optimal chest position to place a digital stethoscope's diaphragm to objectively diagnose chronic obstructive pulmonary disease (COPD). Lung sound recordings from seven chest positions with data available in the ICBHI 2017 database namely, anterior left (Al), anterior right (Ar), lateral left (Ll), lateral right (Lr), posterior left (Pl), posterior right (Pr) and trachea (Tc), were analyzed in this study. COPD+ and COPD- at diagnosis, each chest position was done objectively using mel frequency cepstral coefficients (MFCC) features and machine learning models namely support vector machine (SVM) and decision tree (DT). The results indicate that the Pr chest position offers superior precision, recall, and F1-score, with a recognition accuracy of 99.7% in COPD screening.

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1. INTRODUCTION

Chronic obstructive pulmonary disease (COPD) is a cluster of diseases that are a global cause of death that causes airflow obstruction. COPD was among the top four leading causes of death in the United States [1]. The alarming fact is that most patients with low pulmonary function are not aware that they have COPD. COPD is caused mainly by air pollutants and the use of tobacco. Early identification of COPD may have an impact on the way the disease progresses and develops. A respiratory disorder like COPD, can affect regular activities like physical movements and hence their social life [2], [3] and cause loss of Memory [4], [5] Patients with COPD may also have other chronic conditions such as arthritis, coronary heart disease, congestive heart failure, stroke, diabetes or asthma [6], [7]. It affects their mental state as well and pushes them into depression or other mental or emotional conditions. Traditionally a spirometry test currently helps diagnose COPD and regular respiratory conditions [8]. With the advent of digital and smart stethoscopes various research continues in the development of algorithms for screening and diagnosis of COPD. This is largely because of the growth of modeling of the respiratory system [9] and a functional hardware of equivalent performance is doable. A standard Littmann 3,200 compared to a prototype made of an electric microphone as the sensor, and an

arduino mega as a controller system both had comparable responses [10]. In addition to this, the automated diagnosis of acute rhinosinusitis (ARS) is a problem for which a definite solution is not available as the system's performance reduces significantly under various complex evaluation conditions [11]. The advancements in affordable micro-electro-acoustic technology (MEA) microphones, implementation of noise cancellation technology while preserving adventitious lung sounds, proven tele-monitoring ability to support during pandemics, the massive impact due to the development of artificial intelligence (AI)-machine learning (ML) on automated screening and diagnosis, the concerns due to the growing need for trained specialists, advent of decentralized diagnosis due to wearable technology, impact of COVID-19 pandemic and the concern over unknown after-effects of treatment, rise in pollution globally, industrial pollutants and automobile on fossil fuel, and falling of trees. The spirometer is considered a golden standard for COPD screening but is not patient-friendly, especially for heart patients, X-rays and ultrasounds suffer from portability issues.

The age of stethoscopes has seen multiple transformations over the centuries, especially in the last decade. State-of-the-art algorithms and systems enable today's stethoscope to be immune to noise and help clinicians perform auscultation seamlessly and receive a self-diagnostic report from the device as well. Recent comparable research attempts to address the same problem statement. The optimal chest positions are used for observation using reinforcement learning which reduces the time of examination [12]. The effect of posture on recorded lung sound intensities in subjects without pulmonary dysfunction helped understand the sensitivity of positioning on diagnosis [13]. Understanding the propagation of sounds from the lung, and modeling sound transmission through the pulmonary system and chest helped validate the understanding [14]. A detailed analysis on an acoustic model of the respiratory tract paved the way for the observation [15].

2. PROCEDURE

2.1. Dataset preparation

ICBHI 2017 respiratory database is a widely used source in lung research studies. They contain lung sounds with information on the chest position in which the sounds were acquired [16], [17]. HF_lungV1 and BioCAS databases are other major inclusion of lung sound recordings in the research of lung diagnosis but since it does not hold information on the location of signal acquisition it was not included in this study. In ICBHI 2017, sounds were collected from six chest locations, as shown in Figure 1. The database contains 920 annotated recordings of different lengths -10s to 90s. A total of 5.5 hours of recorded audio of lung sounds containing (COPD+) positive patients and recordings which are (COPD-) negative (all other respiratory sounds). The patients include children, adults, and the elderly.

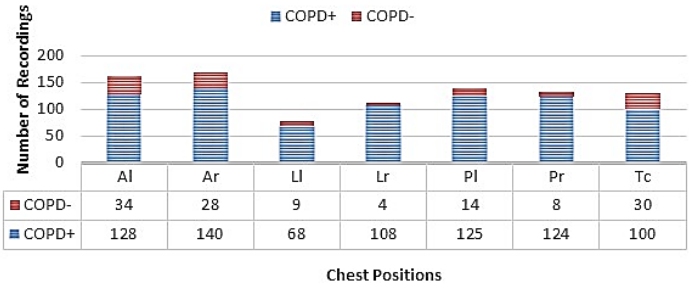

Figure 1. Distribution of data across various chest positions in the ICBHI database for the study

ICBHI database is split into subfolders of seven different datasets for this study namely, anterior left (Al), anterior right (Ar), lateral left (Ll), lateral right (Lr), posterior left (Pl), posterior right (Pr), and trachea (Tc). All data within these subfolders are grouped into COPD+ (all COPD labeled data) and COPD- (healthy, pneumonia, …). A training data set of 70% is taken uniformly across all classes to create the training dataset. 70% of COPD+. 70% of data individually from healthy, pneumonia and other classes to create COPD-. A testing dataset of 30% is taken uniformly across all classes to create the training dataset. 30% of COPD+. 30% of data individually from healthy, pneumonia, and other classes to create COPD-. The datasets are created similarly for varying test ratios of 60:40, 70:30, 80:20, and 90:10 and studied.

2.2. System architecture

COPD+ and COPD- classification is done at all seven chest positions. Mel frequency cepstral coefficients (MFCC) (13 coefficients including energy parameter) are extracted from each training file in an

iterative process to create the feature vectors. A support vector machine (SVM) model with an optimal hyperplane, maximizing the support vector hard and soft margins is found at the end of the training process. Similarly, a DT model is trained as well to validate the study. The models are created for each auscultation position and a comparative study of seven SVM and seven DT models are compared. For the dataset in ICBHI 2017. During training the features are extracted from the lung sound of one chest location and their labels COPD+ and COPD- are used. This is done for each chest location separately to identify in which location is the detection of COPD better as described in Figure 2. During testing the generated labels are compared with the actual test labels and parameters like prediction, recall, F1-score, and recognition accuracy are computed from the confusion matrix generated.

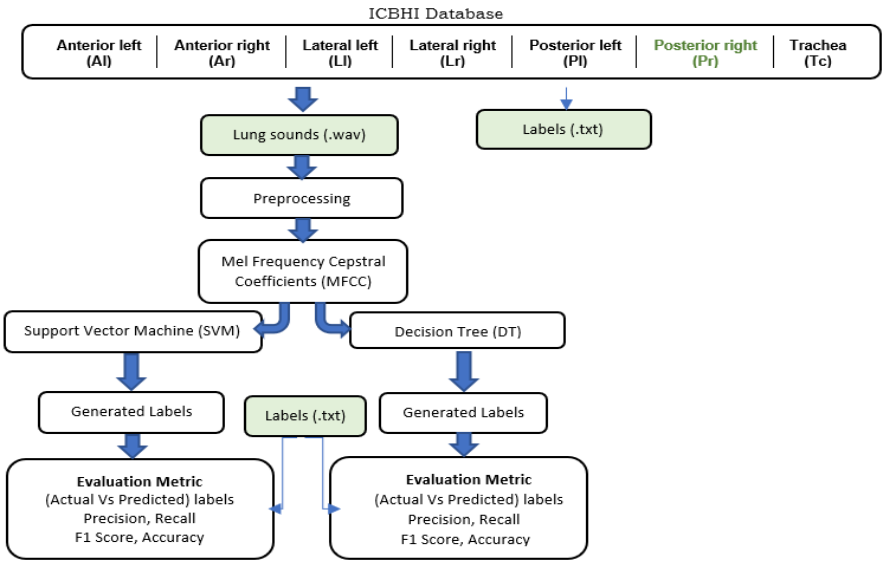

Figure 2. Process flow of the proposed system for diagnosis at the posterior right position (highlighted in green)

3. METHOD

To facilitate the reproducibility of the work by other researches the following information is presented here. ICBHI database is split into seven folders containing datasets recorded from each chest position. 70% of the data across all folder are grouped to form the training data and simulation. 30% of the data across all folder are grouped to form the testing data. Google colab is used as the platform to built the diagnostic system as shown in Figure 3 and all processing were done in google servers.

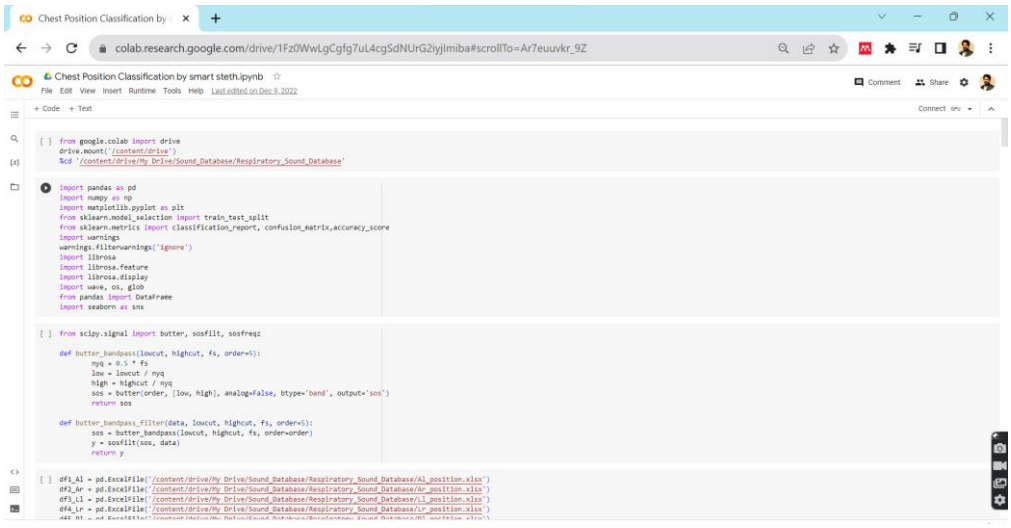

Figure 3. Simulation platform of the work done

3.1. Preprocessing

It is important to ensure that the system studies the distinction in lung sounds alone. Lung adventitious sounds are evident in instances where air flows are present and hence respiratory cycles can be observed [18]. To ensure the same it is important to understand the source of other types of sounds mixed within the signal. It is also important to know the characteristics of lung sounds, to ensure the processed signal contains lung information and ignores other sounds. The reduction of heart sounds in recordings can be achieved using empirical mode decomposition [19] or separated from lung sounds and eliminated using multiple methods as detailed in this review [20]. The signal is down-sampled to 4,000 Hz, ignoring high-frequency sounds (>2,000 Hz) following the sampling theorem. A bandpass filter further filters out signals beyond the range of [50, 1,500] with a filter order of 5 to clean the signal.

3.2. MFCC

Multiple acoustic studies are it in speech recognition, speaker recognition, music information retrieval, and vibration analysis have widely made use of MFCC as its feature extraction technique of study. MFCC qualitatively extracts 'timbre' content from an acoustic signal. This study of lung diagnosis has made use of MFCC as the feature. MFCC as a feature was brought about by Davis and Mermelstein [21] and Moore [22] and is sometimes credited to both [23]. MFCCs are robust time-tested features extracted from acoustic signals for multiple acoustic tasks like music information retrieval, or speech/speaker recognition tasks. If the systems were to be modeled into their source-filter model, the first few coefficients are said to represent the filter information, and higher coefficients are the source. The first few coefficients of MFCC features would represent the underlying unique conditions within the lungs, obstruction, lung sac fluid accumulation, and ignore the source of respiratory sounds. The steps involved in extracting MFCC features from lung sounds as shown in Figure 4.

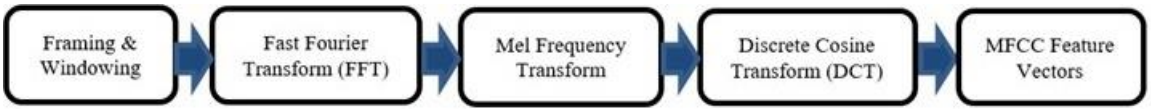

Figure 4. Steps involved in extracting MFCC features from lung sounds

MFCC coefficients the first 13 coefficients are generally the best representation of the model. The electrical output of the electret microphone of a digital stethoscope is preprocessed and the lung sound obtained is stacked in the database which is fed into the algorithms for further processing. The MFCC coefficients extraction algorithm from an audio file is understood and implemented in this paper [24]. Since the nature of the signal is non-stationary standard FFT techniques cannot to applied to this time-varying signal. So, the signal is broken down using a mathematical window and FFT is analyzed within each frame. Mel scale is a perceptual scale of the human ear to frequency. It models the non-linear behavior of the human ear to frequency and amplitude. Taking the DCT brings the signal back to a domain called a cepstral domain where the que-frequencies components are processed to extract as coefficients of the MFC algorithm. are analyzed. MFCC typically extracts the first 13 parameters, which contain information about the filter, and high-frequency bins, which contain information about excitation, are ignored as they do not have information on the mechanical deformation or acoustical changes of the lung. The energy parameter represents the average power of the cepstral signal. The first-order coefficient reflects the distribution of spectral energy between low and high frequencies. A broader study is also possible using multiple feature parameters (126 parameters) as described [25] which can be furthered in this study.

3.3. SVM

SVM algorithm, each feature vector of COPD+ and COPD- clusters at a different point in an n-dimensional space, where n is the number of features. The classification of the feature vectors is then performed by finding a hyperplane that can differentiate between the different classes [26], [27]. When the data has four or more dimensions, the support vector classifier (SVC) uses a hyperplane to perform the classification [28], [29] as shown in Figure 5. SVM uses Kernel tricks to systematically find SVC in higher dimensions to make it mathematical possible [30]. Previous studies have demonstrated the radial basis function (RBF) to be the optimal kernel for the study. The RBF is a way to handle overlapping data and functions and is used to find the SVC in infinite dimensions, which means it cannot be visualized directly.

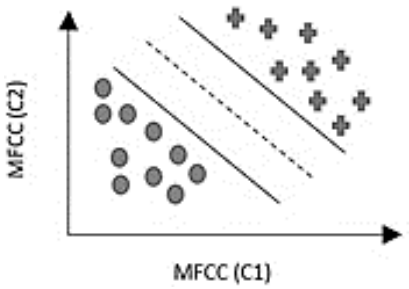

Figure 5. SVM demonstrated with linear kernel COPD+ (o), COPD- (+) on a 2D MFCC feature space

3.4. DT

The DT, which is utilized in the application of lung sound classification tasks in the screening of COPD is a non-parametric supervised learning algorithm. Its tree structure consists of a root node representing the lung sound features, branches, internal nodes, and leaf nodes and is grouped based on the similarities within the features. The leaf nodes represent all the possible categorical similar groups within the dataset. The learning involves creating a tree-like model of lung sound classification decisions and their possible structures. The objective is to find the optimal point of division within the tree that will allow for the diagnosis of COPD into COPD+ and COPD-class labels. This is iteratively repeated in a top-down, recursive manner until the classification process is complete. The more complex the DT depends on the features that have similar traits to group into homogenous sets. Several leaves can be specified and smaller trees give a clear broad classification of the lung sounds, but if a larger tree is grown it becomes increasingly difficult to maintain this clarity of classification due to overfitting. To avoid this, DTs prefer smaller trees as demonstrated in our data below. Pruning is used to clip off branches that are less significant to our classification and hence reduce overfitting. The classifier is evaluated as elaborated in the next sections of the paper.

4 RESULTS AND DISCUSSION

The ICBHI database is divided based on lung sound recordings taken from different chest positions. Recordings from each chest location are segregated based on their labels COPD+ or COPD- classes. The confusion matrix of COPD+ and COPD- consistently shows good performance of diagonal values (true positive and false negative) for different ratios of lung sound data as shown in Table 1. Precision analysis of the classes by the models consistently shows diagnosis at the posterior right with the highest precision as shown in Tables 2 and 3 and illustrated in the radar plots in Figures 6 and 7. Recall analysis of the classes by the models consistently shows diagnosis at the posterior right providing the highest recall as shown in Tables 4 and 5 and illustrated in the radar plots in Figures 8 and 9. F1-score analysis of the classes by the models consistently shows diagnosis at the posterior right providing the highest F1-score as shown in Tables 6 and 7 and Figures 10 and 11. Recognition Accuracy in the classification of COPD+ and COPD- classes by trained models of SVM and DT consistently shows diagnosis at the posterior right providing the highest accuracy as illustrated in Figure 12.

Table 1. Confusion matrix demonstrating the classification performance (COPD+, COPD-) evaluation of MFCC-SVM model-source stethoscope position-posterior right

	Train-test ratio 60-40		Train-test ratio 70-30		Train-test ratio 80-20		Train-test ratio 90-10	
True Predicted	COPD+	COPD-	COPD+	COPD-	COPD+	COPD-	COPD+	COPD-
COPD+	3,128	74	2,392	9	1,595	5	798	1
COPD-	0	3195	0	2395	0	1595	0	795

Precision is the ratio of true positive values to all positive values predicted by a model with a range of 0 to 1: $\frac{\mathrm{TP}}{(\mathrm{TP+FP})}$. Recall is the ratio of true positive values to true positives and false negatives combined as positive by a model, with a range of 0 to 1: $\frac{TP}{(\mathrm{TP+FN})}$. F1-score is the harmonic mean of precision and recall, with a range of 0 to 1: $\frac{2*(\mathrm{precision}*\mathrm{recall})}{(\mathrm{precision+recall})}$. Recognition accuracy is the ratio of true values out of the total values with a range of 0–1: $\frac{(\mathrm{TP+TN})}{(\mathrm{TP+TN+FP+FN})}$.

Table 2. Precision analysis on detection of COPD+ and COPD- at all chest locations using SVM

Train-test CLASS	Anterior left (Al)	Anterior right (Ar)	Lateral left (Ll)	Lateral right (Lr)	Posterior left (Pl)	Posterior right (Pr)	Trachea (Tc)
COPD+	0.955	0.925	0.9925	1	0.96	1	0.995
COPD-	0.905	0.7175	0.767	0.807	0.765	0.995	0.9

Table 3. Precision analysis on detection of COPD+ and COPD- at all chest locations using DT

Train-test CLASS	Anterior left (Al)	Anterior right (Ar)	Lateral left (Ll)	Lateral right (Lr)	Posterior left (Pl)	Posterior right (Pr)	Trachea (Tc)
COPD+	0.915	0.9125	0.9775	0.9975	0.9475	1	0.91
COPD-	0.907	0.735	0.717	0.800	0.687	0.962	0.772

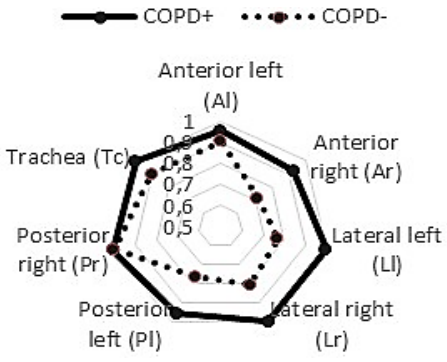

Figure 6. Radar plot of precision analysis using SVM

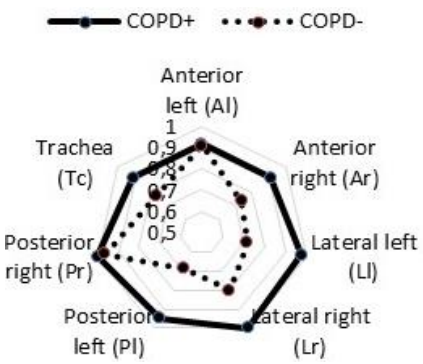

Figure 7. Radar plot of precision analysis using DT

Table 4. Recall analysis on detection of COPD+ and COPD- at all chest locations using SVM

Train-test CLASS	Anterior left (Al)	Anterior right (Ar)	Lateral left (Ll)	Lateral right (Lr)	Posterior left (Pl)	Posterior right (Pr)	Trachea (Tc)
COPD+	0.890	0.605	0.687	0.687	0.697	0.995	0.890
COPD-	0.960	0.957	0.997	1	0.972	1	0.995

Table 5. Precision analysis on detection of COPD+ and COPD- at all chest locations using DT

Train-Test CLASS	Anterior left (Al)	Anterior right (Ar)	Lateral left (Ll)	Lateral right (Lr)	Posterior left (Pl)	Posterior right (Pr)	Trachea (Tc)
COPD+	0.897	0.650	0.467	0.687	0.550	0.957	0.710
COPD-	0.915	0.937	0.992	1	0.972	1	0.932

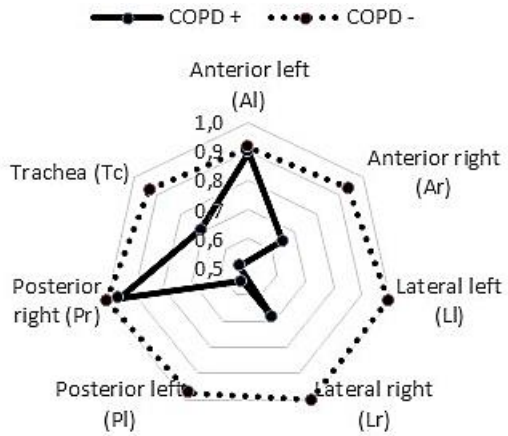

Figure 8. Radar plot of recall analysis using SVM

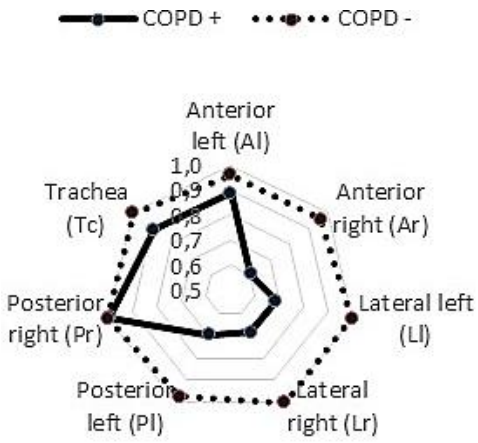

Figure 9. Radar plot of recall analysis using DT

Table 6. F1-score analysis on detection of COPD+ and COPD- at all chest locations using SVM

Train-test CLASS	Anterior left (Al)	Anterior right (Ar)	Lateral left (Ll)	Lateral right (Lr)	Posterior left (Pl)	Posterior right (Pr)	Trachea (Tc)
COPD+	0.918	0.723	0.805	0.768	0.805	0.998	0.940
COPD-	0.928	0.818	0.863	0.880	0.858	0.998	0.945

Table 7. F1-score analysis on detection of COPD+ and COPD- at all chest locations using DT

Train-test CLASS	Anterior left (Al)	Anterior right (Ar)	Lateral left (Ll)	Lateral right (Lr)	Posterior left (Pl)	Posterior right (Pr)	Trachea (Tc)
COPD+	0.903	0.748	0.625	0.780	0.685	0.978	0.795
COPD-	0.910	0.820	0.783	0.878	0.808	0.980	0.840

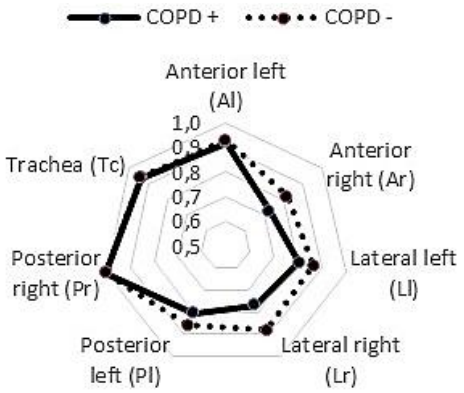

Figure 10. Radar plot of F1-score analysis using SVM

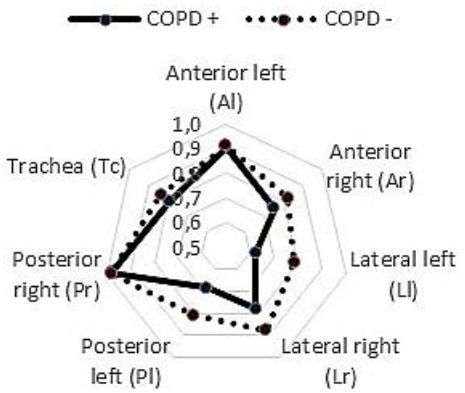

Figure 11. Radar plot of F1-score analysis using DT

Consistency in the performance of COPD diagnosis at the posterior right is evident by observing classification ability both with SVM and DT as shown in Figure 12. The trachea also shows higher performance which could be due to the free unobstructed air passage pathway in the anatomical structure. The study shows consistency of results for various ratios of data as well as demonstrated in the results. Posterior right (Pr) is observed to be the optimal position for COPD diagnosis with 99.605% accuracy in diagnosis using a SVM and 96.665% for the DT system.

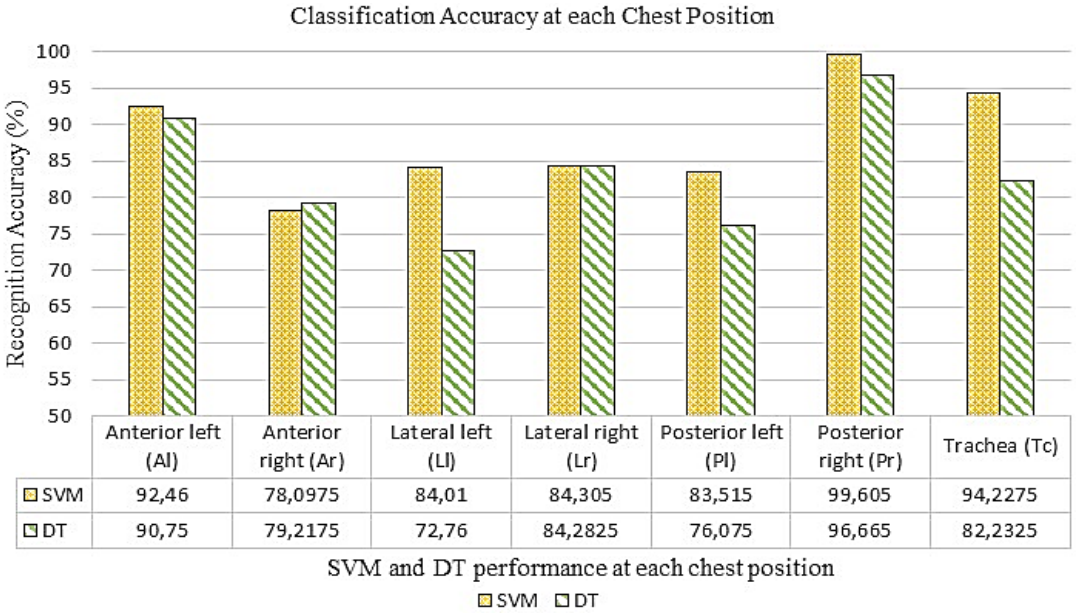

Figure 12. Recognition accuracy of COPD at different chest locations using SVM and DT

5. CONCLUSION

This study concludes that for an objective diagnosis of COPD using a digital stethoscope the posterior right chest position, is proven to be the optimal position for auscultation. This is justified in terms of precision, recall, F1-score, and recognition accuracy in comparison with all other standard clinical chest positions. Novelty in the study is the observation to identify the chest position better suited for objective diagnosis creating a new paradigm of 'clinical practices' for a digital stethoscope. The conclusions are limited to the data available in the benchmark database ICBHI 2017.

6. FUTURE SCOPE

The demand for automated stethoscope-based diagnosis is growing, especially in underserved rural areas, driven by escalating air pollution and deforestation, major COPD contributors, and a lack of global policy addressing this issue. To tackle these challenges, smart stethoscopes must autonomously identify ideal chest areas for precise diagnosis, diverging from traditional methods. Research is imperative to establish clinical approaches for self-diagnostic systems and adapt practices based on their strengths. With healthcare's shift towards decentralization and direct-to-patient diagnostics, user-friendly devices are crucial for market success. Research needs to focus on two categories: (i) aiding healthcare professionals in diagnosis and (ii) direct patient use or untrained assistance devices, offering effective solutions. Additionally, exploring specialized techniques for optimizing stethoscope placement in detecting other respiratory disorders holds promise. In summary, this study emphasizes the need for research on optimal digital stethoscope placement, broadening their applications in respiratory health diagnosis.

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