International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Classification of Adventitious Lung Sounds: Wheeze, Crackle using Machine Learning Techniques

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Submitted: 28/04/2023 **Revised**: 26/06/2023 **Accepted**: 08/07/2023

Abstract*:* In the past decade, there has been a significant surge of research interest in automated detection of respiratory disorders using advanced stethoscope technology in both academic and industrial domains. Researchers and practitioners aim to achieve more objective respiratory disease diagnosis by harnessing machine learning models. Pulmonologists frequently observe wheeze and crackle in lung sounds during patient auscultation, and machine learning algorithms have been adopted to mitigate the subjective nature of diagnosis. The project aimed to classify four target classes, namely "none, crackle, wheeze, both," utilizing machine learning techniques, specifically Support Vector Machine (SVM) and Decision Tree (DT) classifiers. The primary goal was to train and test these models to accurately identify respiratory conditions based on temporal lung sound signals. Lung sounds, as temporal signals, are generated during the inhalation and exhalation process. Irregular lung sounds can indicate various respiratory conditions, including inflammation, fluid accumulation, or other abnormalities in the airways or lung tissue. Upon training and testing the SVM and DT classifiers on the dataset, the SVM classifier exhibited superior accuracy compared to the DT classifier. Across all performance metrics, the SVM classifier outperformed the DT classifier, establishing it as the most effective choice for classifying the four target classes. The combination of advanced stethoscope technology and machine learning techniques, particularly SVM classification, presents promising results for automated respiratory disorder detection. This approach has the potential to significantly enhance diagnostic accuracy and objectivity in the field of respiratory medicine, benefiting both patients and healthcare professionals. Further research and development in this area hold promise for substantial advancements in respiratory disease diagnosis and treatment.

Keywords: *Accuracy, Classification, Lung Sound, Machine Learning Techniques, Sound Auscultation*

1. Introduction

Lung is the primary organ in respiration that takes place by the method of gas exchange. In present day pharmaceutical, each cardiac appraisal or respiratory check-up incorporates an sound auscultation amid which one the restorative master tunes in to sounds from the persistent body with distinctive instruments [1]. Lung sounds provide sufficient evidence to evaluate individuals with aspiration disorders and pneumonia. Be that as it may, this traditional strategy endures limitations, for example, if the expert has not practiced much exceptionally, it can lead to basic research. [11]. Concurring to the 2019 Worldwide Burden of Malady Study, COPD was the moment driving cause of passing in India after coronary supply route malady, and discuss contamination was one of the most risk factors for COPD within the nation. Pneumonia was moreover a driving cause of dreariness and mortality in India, especially among children beneath 5 a long time of age. Ordinary lung sounds are the respiratory sounds of solid subjects listened over the chest divider over a certain stream rate and have a recurrence run of 200–600 Hz [27]. Respiratory sounds, particularly irregular sounds, has exceptionally complex constructions with clamor, and positional reliance in step [2]. Finding abnormal breath sounds with a stethoscope is important in the analysis and dealing of breathing infections. However, the accurate identification of breath sounds requires considerable control by the clinician, so learners such as supporters and residents sometimes misidentify breath sounds. Advances in computerized lung sonography have since long attracted a number of analysts, leading to machine learning calculations for lung sound determination [2]. Breath sound is accepted as an objective, direct and non-invasive marker for airway monitoring [17]. Be that as it may, lung sounds may not be adequate to precisely analyze the illness, and other symptomatic tests may be vital the truth is that lung illness can influence individuals of all ages, sexes and foundations. Computerized lung sound investigation, which begun to be found within the writing within the early 1980s, serves as a solid apparatus for the analyze of lung variations from the norm and clutters [3]. Stethoscopes are the foremost common instrument utilized these days to listen and analyze these sounds, but determination based on auscultation is exceptionally subjective and depends incredibly on the individual's possess hearing and involvement [8]. In any case, certain hazard variables such as smoking, introduction to toxins or destructive substances, and a family history of lung malady can increment an individual's chance of creating lung

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malady. The most recent innovation that's endeavouring to fathom this issue is machine learning. Over a long time, different effective calculations were created and presently with the profound learning calculations, mistake rate got to be near to unimportant. Particularly in computer vision and discourse acknowledgment, machine learning is coming to human levels of location [20]. Computer-assisted auscultation (CAA) studies provide a robust and unbiased assessment of lung sounds that can inform clinical choices and potentially advance case management, particularly in resource-poor settings [29].

The predominance of anomalous lung sounds in India can shift depending on a few variables such as the predominance of respiratory infections, contamination levels and the sum of smoke. India has numerous respiratory illnesses, counting incessant obstructive aspiratory infection (COPD), asthma and tuberculosis. Discuss contamination is additionally a major issue in numerous parts of India, which can decline respiratory maladies and contribute to the advancement of lung maladies. Considering these components, it is likely that irregular lung sounds are more common in India than in many other nations. In any case, the precise predominance depends on a few components, counting the ponder populace and strategies of lung sound evaluation. The recognizable proof and elucidation of anomalous lung sounds is critical for health professionals in India since it can offer assistance within the conclusion and treatment of respiratory maladies. Performing an robotized adventitious lung sound discovery could be a challenging errand since the sound is vulnerable to commotions (heartbeat, motion artifacts, and sound sound) and there's unobtrusive segregation among diverse categories [26]. During breathing, the intake air brings oxygen into the blood and expels carbon dioxide. In the process there are artifacts, noise, sounds too. Respiratory disorders are diagnosed by spirometry and auscultation. Although spirometry is one of the most common pulmonary function tests, it is limited by patient cooperation. As a result, it is prone to errors [19]. Automatic respiratory sound classification is able to distinguish abnormalities in the early period of lung distress and thus improve the efficiency of decision-making. [5]. In a clinical setting, a physician may routinely listen with a stethoscope to detect breathing. However, listening must usually be done in a quiet environment and preferably with the patient in a stationary position, which limits monitoring time and flexibility. Additionally, because respiratory symptoms can occur at home, in public, or even at night, ease of use is limited by how a trained healthcare professional uses the stethoscope [30]. Auscultation, a non-invasive and cost-effective part of physical examination, is essential for the diagnosis of respiratory disorders in children [4]. Analysis of breath sounds (auscultation) is an important part of the diagnosis of lung disease [7]. Lung sounds are classified into three. These are the breath sounds; sound output and random sound. These sounds indicate inflammation, infection, fluid in the lungs, etc., which need to be treated accordingly. This work involves sound classification. By identifying and classifying these sounds, artificial intelligence plays an important role in medical diagnosis. AI algorithms can be based on supervised or unsupervised learning frameworks. In supervised learning, input and output are given to the model [22]. Using Machine Learning these lung sounds are classified in this work. Especially SVM and Decision tree classifier is used to classify the lung sounds.

2. Lung Sounds

2.1 Adventitious Sounds

Abnormal sounds are heard in the anterior lower lung and lateral chest, during inhalation and exhalation. The presence of random noise often indicates a lung disorder [28]. This sound is heard when there is an abnormal or uneven flow of air in the lungs. It can cause wheezing, snoring, asthma, bronchitis, pneumonia. It can be managed wisely with proper diagnosis. In addition, random acoustic components, which are pointers of disease status, provide disease information over their time in the respiratory cycle as well. as their other characteristics (spectrum, time and space).[6] Often, doctors will listen to lung sounds from multiple locations, in turn, to detect lung conditions. Simultaneous hearing in humans is not possible; Therefore, the physician must remember the characteristics of each position and the patient requires many breathing maneuvers [9]. Abnormal sounds, which are associated with respiratory diseases, closely follow ordinary breathing sounds and can be classified as nonstop (>80 ms period) and intermittent sounds. (duration < 25 ms) [18]. Hearing to lung sounds over auscultation is vibrant in inspecting the respiratory system for irregularities [10]. The disadvantage of the methods reported, which is also a delinquent with rapid-term auscultation, is that they are based on distinct respiratory episodes or stages. Breathing passages are usually 1.5 to 3 seconds long, and breathing periods are even rapider [24].

2.1.1 Wheezes

A continuous, irregular waveform that lasts at least 250 ms and has a distinctly melodic quality is called a sob. Wheezing can be caused by a number of conditions, including swelling of the mucous membranes, external compression, partial obstruction by a tumor or foreign body, and more. Wheezing is usually due to local or diffuse narrowing of the airways or obstruction of the passage from the pharynx to the small airways. Wheezing usually has a visible frequency range above 100 Hz Wheezing is a sign of many different diseases, most of which involve airway obstruction. While persistent obstruction is associated with chronic obstructive pulmonary disease (COPD), such as emphysema (enlarged lungs caused by smoking), chronic bronchitis, and cystic fibrosis, reversible obstruction is the hallmark sign of asthma tendency. Hundreds of publications refer to wheezing each year as an indicator of airway obstruction in infants, to assess the severity of asthma, or to classify asthma attacks. an epidemiological study to give some examples. Due to the clinical importance of this acoustic sign, several objective studies have been conducted on wheezing.[15]. Wheezing auto-detection algorithm uses time-frequency analysis and short-term Fourier transform to identify wheezing parts in recorded lung audio files [14]. Only a stethoscope can detect a slight groan; a loud groan that can be heard with bare ears. Breathing can be shallow or high. Severe wheezing, known as audible wheezing, is heard when the small airways are narrowed by secretions, such as in patients with chronic obstructive pulmonary disease. The high-pitched whistle is known as the sibilant whistle. They are created by the large flow of air through the small gaps created during the exhalation. Wheezing monitoring provides quantitative and non-invasive information on the degree of nocturnal wheezing in children, correlates well with conventional indicators of asthma activity, and can help assess the effectiveness of wheezing. results of treatments. [24].

2.1.2 Crackles

The bursts are irregular in nature and typically last from 1 to 10 milliseconds. Cracks are often caused by rapid opening of small air passages. They are short, loud, muscles sound that can be heard on inhalation and sometimes on exhalation. It has a remarkably wide frequency range, reaching up to 2000 Hz. A crackle can be characterized by total duration, small (short duration) or rough (long duration). The presence of crackles in lung sounds often reflects a pathological process in the lung tissues or airways [13]. The two most common types of cracks are thin and thick. On the other hand, a rough crackle has a low pitch and lasts about 10-6ms, while a smooth crackle has a high pitch and lasts less than 5ms. Coarse Crackle and Fine Crackle are explosive, non-musical sounds with highs and lows respectively [6]. The cracks found in the patient could be a sign of congestive heart failure, carotid sclerosis, interstitial lung disease, alveolar dryness. This happened in Inspiration. The cracks can be early inspiration, mid inspiration, late inspiration or biphasic. It is also known as Crepitations. When the tiny air sacs in the lungs fill with fluid and there is movement of air inside the air sacs, as happens when we breathe, a crackling sound occurs.

3. Literature Survey

A set of lung sound classification done using several methods and their results are listed. Below are the peer-reviewed works, likely from 2016-2023, that are processed, trained and evaluated tasks are listed briefly. There are 15 articles from IEEE, Springer and so on are evaluated. SVM classification was mainly used in the classification in most of the works, and the ICBHI database was also frequently executed as input. In 2023, Ji Soo Park et al. developed a machine learning model to classify children's breath sounds. Work was performed using the ICBHI database. Set support vector machine models were qualified and analyzed for four classification tasks (normal versus abnormal, cracked versus inactive). wheezing, normal versus heartburn and normal versus wheezing) using K-fold cross-validation (K = 10). The prediction confirmation accuracy (n=90) was 82.22%, 67.74%, 67.80%, and 81.36%, which is comparable between pediatricians and non-pediatricians. In 2020, Bruno Machado Rocha et al. developed the effect of event time on automatic classification of ARS, i.e. how the incident occurred was studied. The second category (the negative category) affects the performance of the classifiers. (2) Method: A series of experiments were conducted from which they mixed the duration of other events in the three missions: crackle versus wheeze versus other (grade 3); crackle compared to others (class 2 crackle); and wheezing vs. others (type 2 wheeze). Four classifiers (linear discriminant analysis, SVM, augmented tree, and CNN) were evaluated in these tasks using a tracing breathing probe database. open access. In the fixed-duration 3-class task, the best classifier achieved 96.9% accuracy, the same classifier achieved an accuracy of 81.8 in the more realistic 3-class task. different durations. In 2019, Renyu Liu et al. used CNN to notice random sounds. The information used in this study consists of two parts: the public record provided by the ICBHI with 126 participants test subjects and our recorded children's listening data, including 222 subjects. The finding act of the CNN used was assessed using our pediatric listening ICBHI database database and their combination. The accuracy obtained was 81.62%.In 2021, Himadri Mukherjee et al. developed a device to detect the breath of patients with respiratory infections. Linear predictive coefficient based functions were used to describe these acoustic slices. By the Multi-Layer Perceptron (MLP) based classifier, in the experience they have achieved the maximum probable accuracy of 99.22% when testing with a publicly available inhalation. audio file (ICBHI17). In 2017, Murat Aykanat et al. had a goal to change a non-invasive technique to classify breath sound noted with an automatic stethoscope, as well as acoustic recording software with many machine learning algorithms. Accuracies obtained for CNN and SVM 86% and 86%. In 2020, Yi Ma et al. implemented and compared using state-of-the-art ICBHI 2017 official challenge materials and their evaluation method. As a result, LungRN NL achieved an efficiency score of 52.26%, which is better than the advanced models by 2.1-12.7%.In 2021, Truc Nguyen et al. used transfer learning to fix discrepancies between recording settings. This will allow to handover information from one dataset to added for detecting lung rupture. The multi-input model is then fitted to the target region of the self-collected lung sound database to classify crackles and normal lung sounds. Experimental results show a significant 9.84% (absolute) improvement in target area F-score performance using multi-input CNN model and learning for crack detection. In 2021,StavrosNtarampirasma et al.proposed a method to automatically detect them using signal processing and pattern recognition algorithms, following the logic of a challenge presented in 2017 in connection with an international conference, to extract information from different classes of breath sounds. The authors designed a suitable set of functions based on wavelet packet analysis that characterizes, Organized on biomedical health informatics. In 2021,Yoonjoo Kim et al. developed a predictive model for breath sound classification by joining pre-trained image feature, lung sound and CNN classification discrimination. It sensed unfamiliar sounds, accuracy 86.5% and area below the ROC curve 0.93.In 2019,XuenHoongKok et al. studied the routine of breath sound copies to automatically regulate a person's respiratory strength. An algorithm wastested against publicly available breath sound databases. A classifier trained on the test data achieved an accuracy of 87.1%,a sensitivity of 86.8%, and a specificity of 93.6%. In 2018, Koki Minami et al. concerned the two main components. First, the one-dimensional transform signal was converted to its two-dimensional time-frequency response using a short-time Fourier transform and a continuous wavelet transform.. Next is the classification of the modified images using a convolutional neural network with a power value of 28 [%], a harmony value of 81 [%], a sensitivity of 54 [%], and a specificity of 42 [%] was done. In 2022, BernaARI et al. aimed to divide a series of lung sounds into four groups using data replication. We obtain and standardize the wave propagation transforms of each pulmonary sound cycle separately, transform the data into test training, and append and classify the training data. SVM and EBT classifiers improved the performance of ELM-W-AE by 4% and 3% respectively, compared to the original structure. In2022, Thanapat Sangkharat et al. worked in just like an Android phone does with Tarsos DSP sound library and Tensorflow Lite. Partial breath samples from the ICHBI data base and online breath research sites were used. Then they used breath sound classification software to perform noise filtering, recordings, spectrogram calculations, and neural network processing. Normal breath sounds were 80°C, crackles were 87°C, and wheezing was 85°C. In 2016, Hendrik Stefan Fischer et al. investigated the relationship between wheeze detection and conventional His LFT parameters.72(65%) infants had wheezing, of which 43(39%) were breathing and 53(48%) had wheezing. In 2016, Rajkumar Palaniappan et al. manually classified lung acoustic signals into three different groups: normal airway obstruction pathologies and parenchymal pathologies. MFCC features were significantly different (p and <0.001). The classification accuracies of SVM and K-named classifiers were 92.19% and 98.26%, respectively.

4. Methodology

4.1 Machine Learning Techniques

Machine learning techniques are mainly used for classification, prediction and regression. This allows the computer system to examine the data and improve its performance in classification and regression tasks. In this work, SVM and decision tree classifiers are used to classify breath sounds from the breath sound database. The SVM classifier is likely to meet the desired classification performance.

4.1.1 SVM Classifier

SVM is a distance-founded supervised learning classifier used to solve sorting and regression problems. The foremost purpose of SVM is to distinguish between two specific classes and classify the target class very accurately according to training this model using labeled data. SVM chooses extreme vectors and points to help create hyperplanes. Hyperplanes help classify information into different categories. So this model offers good performance . The advantages are that it can be applied to both linear and nonlinear data, has a high level of accuracy, can model complex decision boundaries, and can handle many independent variables[16]. Through the exercise time, the SVM shapes the model, plots the choice limits of each class, and requires the hyperplane that discretes the different courses. Growing the hyperplane border to increase the distance between courses improves the classification exactness [23].

4.1.2 Decision Tree

Decision tree is used in case of classification and regression. It is a tree-based classifier. As the work is a multiclass classification surely Decision tree plays a major role in classifying the data provided. Decision tree is a supervised learning technique in which the data are labelled previously before the classification begins. The raw data is aligned to this algorithm and so this classifier classifies the data to which category the input belongs to. This classifier deals with Decision nodes and the Leaf nodes. The decision node takes a perfect responsibility to provide the desired Target classes successfully after the flow of tree classification process. The leaf node flows to the decision node until the target class is reached. Here the Lung sounds are classified into four target classes as “none, crackle, wheezes, both”.

4.2 Preprocessing Feature Extraction

Correlation is a function of how similar two signals are and how long they remain similar when one is shifted relative to the other. Note that the respiratory cycle contains enough information to perform its intended function. The results of applying the FFT were used to determine the power spectrum of the dataset [12]. MFCC is the most commonly used property to characterize the spectral shape of sound. MFCC is used to improve the classification process for feature extraction. The code was a Python function extract_feature(X, sample_rate) that extracts MFCC (Mel-Frequency Cepstral Coefficients) features of an audio signal X at a given sample rate. This function uses General Ledger to calculate MFCC. The number of calculated MFCC coefficients is 50 (n_mfcc=50). In general, this function extracts a 100-dimensional feature vector of a given audio signal, consisting of the mean and standard deviation of 50 MFCC coefficients. The process looks like this: The dataset is initialized as an empty list containing the extracted functions and d in the data.Iterate over each element of the input data. Then function a calls the function with the current data and variable sr[0] as arguments and assigns the result to variable a. Dataset.append(a) appends a list of datasets to the expert function. Then data=np.asarray(dataset) converts the dataset list to a NumPy array. The dataset was reformatted to convert the NumPy array to a 2D array with 6898 rows and a flattened shape based on the original shape of the extracted features. Label=np.asarray(label) converts another variable's label to a NumPy array. In general, this preprocessing step encodes some input data and creates a data set with various characteristics and corresponding labels. Each label is a single value that indicates an object of the corresponding data class. Next, we used the Python Scikit Learn library to preprocess the data for our machine learning model. The purpose of data processing is to transform raw data into a form suitable for consumption using machine learning models. First, a default scaler object is created and assigned to the variable 'scaler'. A standard scaler is a data normalization technique that scales the data so that the mean and unit variance are zero. This can improve the act of some machine learning algorithms. Then they split the data and target variables into exercise and testing sets using the train_test_splitpurpose from the sklearn.model_selection module. The data and target variables are passed as 'data' and 'a'. The test_size parameter was set to 0.3. This means that 30% of the data was used for testing and 70% for training. The parameter random_state was set to 42 to ensure random data copying. The Straify parameter is set to 'a' to ensure that the target variable ratio is preserved in the working out and test sets. After the data is sliced, the appropriate methods of the Standard Scaler object are called on the training data to compute the mean and standard deviation of each feature. We then applied the Standard Scaler object transformation method to both the training and test data, standardizing the information using the mean and standard deviation calculated from the training data. Finally, the standardized training and test data are reassigned to the variables 'x_train' and 'x_test'.

4.3 Block Diagram

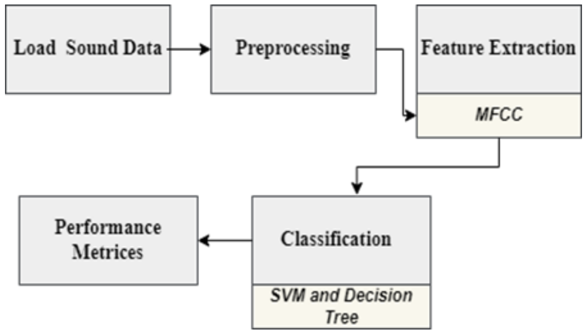

Fig. 1. Block Diagram of the existing method

The Respiratory sound dataset is loaded in the Google colab platform, the preprocessing, Feature Extraction and Classification is done, finally Performance metrics are gained is shown in the above Fig4.1

5. Dataset and Software Used

In this project, Google Colab was used as the working platform-Software and the audio files downloaded are saved in the user drive.

5.1 Dataset Used

The Respiratory Sound database was collected from the Kaggle website. This database contained 920 annotated sounds ranging from 10 to 90 seconds in duration. Samples were collected from 126 different individuals. The samples are 5.5 hours, with a total of 6,898 breathing cycles, of which 1,864 crackles, 886 whistles, and 506 both. Patients range in age from young infants to the elderly. In 2017, (ICBHI) hosted a classification competition for the research community based on random lung sound datasets [25]. The data mentioned above is used in this work.

The demographic data entered into the database are number of patients, age, sex, adult BMI (kg/m2), child weight, and child health status (cm). Patient chest regions were trachea, left anterior, right anterior, left posterior, right posterior, left lateral, right lateral. Acquisition modes include sequential/single channeland simultaneous/multichannel. Acquired lung sounds were obtained with an AKG C417L microphone, a 3M Littmann Classic II SE stethoscope, a 3M Littmann 3200 electronic stethoscope (Litt3200), and a Welch Allyn electronic stethoscope.

5.2 Software Used

Google created Google Colab to provide free access to those who need GPUs and TPUs to build AI or deep learning models. Jupyter Notebook can be compared to Google Colab's improved version. Jupyter Notebook is a program that allows you to edit and run notebook entries using an integrated development environment (IDE) or a web browser. Colab is especially useful for machine learning, data analysis, and training because it allows anyone to build and run arbitrary Python code from their browser. Technically, Colab is a hosted Jupyter engineering service that is ready to use and provides unlimited access to processing resources, including GPUs.

6. Results

6.1 Software Implementation

Lung sounds are preprocessed, subjected to a separation process, and then classified using machine learning techniques, namely SVM and decision tree classifiers. The sound database was separated into train and test sets of 70 and 30 respectively. The categories to be classified are "none, crackle, wheeze, both".

6.2 Classification Report

It provides a summary of precision, recall and f1 scores. It reports the precision, recall and f1 score for each class. The support category in the last column shows the number of samples in each category. Performance measures are identified through the evaluation report of this evaluation process.

6.2.1 Accuracy

Accuracy is a performance metric commonly used in classification tasks to measure the rate of right calculations of a model. It is calculated by separating the number of accurate estimates by the total number of predictions made by the model.

It is given by,

$$Accuracy = (TP + FP)/(TP + FP + FN + TN)$$

6.2.2 Precision

It measures the accuracy of a classification model and the proportion of true positive estimates to the total number of positive forecasts made by the model. However, very accurate model detection can be low. This means that many positive cases are missing from the dataset. Therefore, to comprehensively assess the presentation of a classification model, accuracy should be considered along with other metrics such as recall and F1 score.

It is given by,

$$Precision = (True\ Positive\ /\ False\ Positive + True\ Positive$$

6.2.3 Recall

Recall is the proportion of patients who actually had the disease and were correctly diagnosed by the model. A high recognition rate means that the model suitably identifies the majority of confident cases, and a low recognition rate means that the model misses a significant number of positive cases..

It is given by,

$$Recall = (True\ Positive\ /\ False\ Positive + True\ Negative$$

6.2.4 F1 score

The F1 score is a system of measurement used to estimate the presentation of a sorting model and represents both precision and recall. It is a balanced average of accuracy and memory, yielding a single value that summarizes the balance of the two measures. A high F1 score means that the model is making accurate positive predictions while identifying the most positive cases in the dataset. The F1 score is a useful metric when together accuracy and recall are important and can be used to equivalence the performance of different sorting models. However, this may not be the best metric in all situations. Other measures such as accuracy, precision, and recall may be more appropriate for some problems.

It is given by,

$$F1\ score = 2 * (Precision * Recall)/(Precision + Recall)$$

6.3 SVM classifier

The efficiency of this classifier was high compared to the decision tree classifier. Because the accuracy of this classifier is 80% for 624 provided support variables. Hence, SVM recognizes audio data and performs well in classification based on the inputs given to it. The performance indicators obtained for the four classes are Precision, Recall, f1 score. The Roc curve was also drawn successfully. The Performance metrics obtained for the four classes are tabulated in Table.1 below.

Target Classe	*Precision*	*Recall*	*F1-Score*
None	0.81	0.91	0.86
Crackle	0.83	0.81	0.82
Wheeze	0.75	0.62	0.68
Both	0.60	0.37	0.46

Table.1 Classification report of SVM classifier

The harmonic mean of precision and recall gives the f1 score. For F1 scores, class 1 gives better results. The macros and weighted average metrics obtained from the SVM classifier are shown in the table.2 below.

Metrics	Macro Average	Weighted Averag
Precision	0.52	0.64
Recall	0.53	0.64
F1 Score	0.53	0.64

Table.2 Macro and weighted Average Metrics

6.4 Decision Tree

Compared to SVM classifier, decision tree gave low accuracy. The accuracy obtained for this classifier was 65%. The classification report of Decision tree is tabulated in Table.3 below.

Table.3 Classification report of Decision Tree classifier

Target Classes	Precision	Recall	F1-Score
None	0.74	0.77	0.75
Crackle	0.68	0.66	0.67
Wheeze	0.46	0.42	0.44
Both	0.30	0.31	0.30

In the Performance metrics, the F1 score obtained from the SVM classifier gives the better result than the Decision tree does. The Macro Average Metrics got from this classifier is tabulated in Table.4 below.

Table.4 Macro and weighted Average Metrics

Metrics	Macro Average	Weighted Averag
Precision	0.75	0.79
Recall	0.68	0.80
F1 Score	0.70	0.79

6.3 Confusion Matrix

A confusion matrix is a graphic diagram used to define the act of a classification algorithm. It illustrates and summarizes how the classification algorithm works. In this work, multi-class classification is implemented. A matrix is constructed for four target categories, namely "none, wheezes, crackle, both". Precision, recall and F1 scores are obtained using this confusion matrix. The confusion matrix helps to clearly visualize accuracy and performance metrics. The resulting confusion matrix for SVM classifier and decision tree classifier is shown below. This matrix gives metrics such as true positive, true negative, false positive, and false negative. The sum of all diagonal values gives the total number of true positive predictions, and the sum of all corresponding rows, excluding true positive predictions, gives the total number of false negative predictions. The sum of all the corresponding columns, except for true positive predictions, generally gives false. Positive Predictions The sum of all rows and columns, except for the column and row of a specific category, gives true negative predictions. These four metrics and Confusion Matrix obtained by SVM and decision tree classifier are given below in Table.5, Table.6 and Fig. 2, Fig .3 respectively.

Table.5 Performance Metrics from SVM

Target Classes	True Positive	False Negative	True Negative	False Positive
None	281	28	250	65
Crackle	151	36	405	32
Wheeze	49	30	356	16
Both	18	31	560	12

Table.6 Performance Metrics from Decision Tree

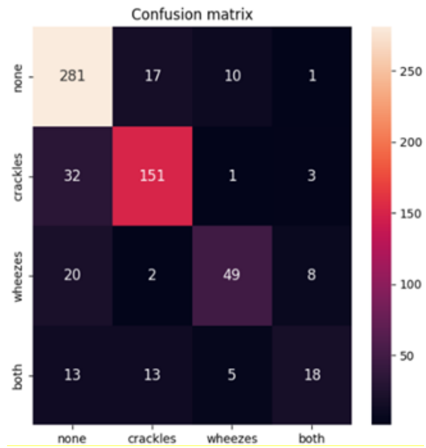

Fig .2. Confusion matrix of SVM classifier

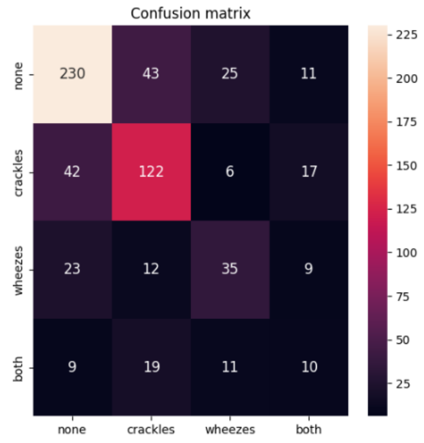

Fig .3. Confusion matrix of Decision tree classifier

6.4 ROC Curve

A graphical representation, named the Receiver Operating Characteristic (ROC) or simply the ROC curve, shows how a binary classifier behaves when the discernment edge is changed. It is produced by plotting the proportion of true positives among positives (TPR = true positive rate) and the proportion of false positives among negatives (FPR = false positive rate) at several threshold settings. TPR stands for sensitivity and FPR corresponds to minus points for specificity, often called the true negative rate.

6.4.1 Using SVM

The ROC curve of classes none, wheeze, crackle, both are illustrated below in Fig. 4, Fig .5, Fig .6, Fig .7 respectively.

Target Classes	True Positive	False Negative	True Negative	False Positive
None	230	79	241	74
Crackle	122	65	405	74
Wheeze	35	44	514	42
Both	10	39	538	37

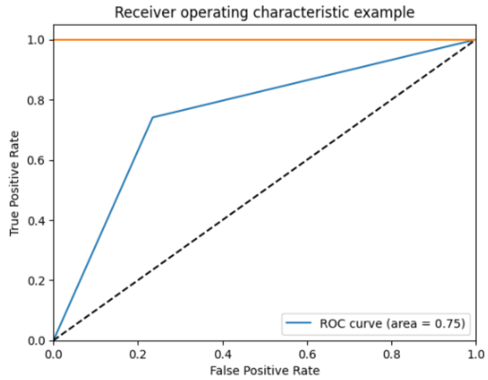

Fig .4 ROC curve of class "none"

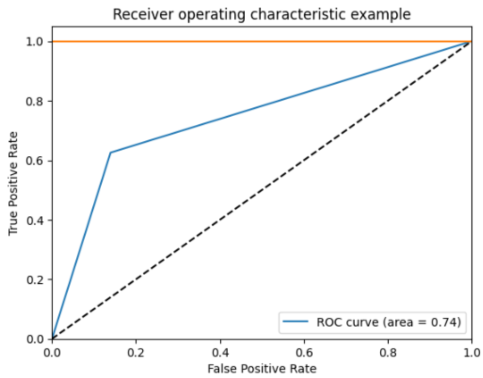

Fig .5 ROC curve of class "Crackle"

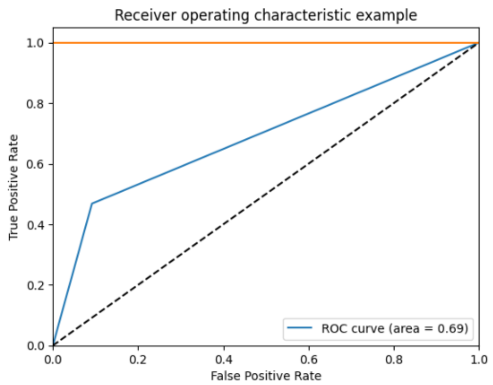

Fig .6 ROC curve of class "Wheeze"

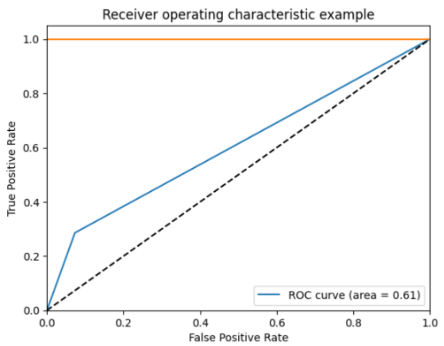

Fig .7 ROC curve of class "Both"

6.4.2 Using Decision Tree

The ROC Curve of classes none, wheeze, crackle, both are illustrated below in Fig .8, Fig .9, Fig .10, Fig .11 respectively.

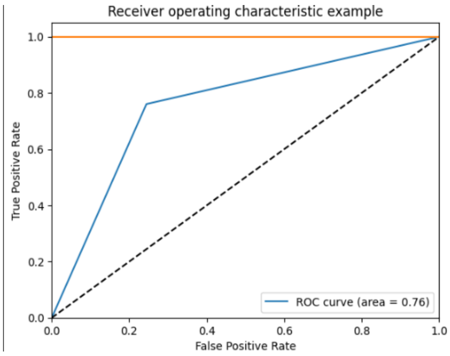

Fig .8 ROC curve of class "none"

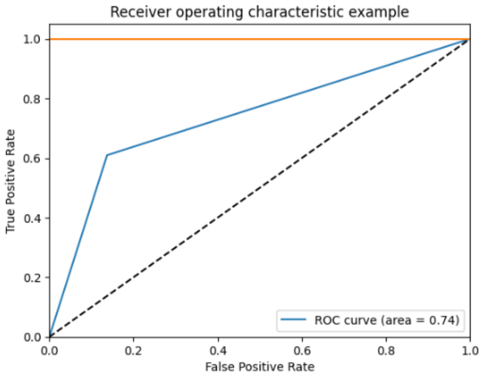

Fig .9 ROC curve of class "Crackle"

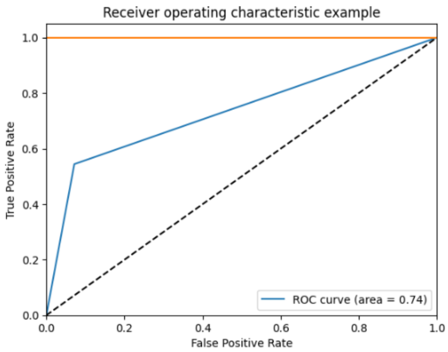

Fig .10 ROC curve of class "Wheeze"

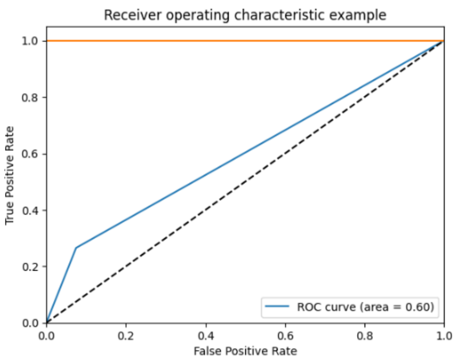

Fig .11 ROC curve of class "Both"

7. Discussion

Lung sounds are classified and identified according to the methods and conditions used in the literature review. Recent work on lung sound classification is listed in the literature review. Automatic lung sound classification uses machine learning and deep learning techniques such as CNN, SVM, decision tree, LFT and EBT classifiers. A large number of images were taken as input to the pre-processing, feature extraction and classification process. To improve treatment and measurement of lung health, this classification greatly improves patient potential. At the same time, lung sounds are classified by SVM and decision tree classifiers based on these literatures in this work.

8. Conclusion

Lung sound classification is a complex task that requires expertise in medicine, signal processing, and machine learning. In summary, both SVM and decision tree algorithms have been used to classify lung sounds with promising results. SVMs have been shown to perform well with high-dimensional data, and decision trees have been successfully used in medical diagnosis. Lung sound classification used SVM to classify lung sounds based on features extracted from the sound signal. SVMs are shown to achieve high classification accuracy within 80° in this work. However, the act of an SVM classifier may depend on the specific structures used in the classification. On the other hand, decision trees were also classified based on these features, the accuracy of which is 65% here. Decision trees are particularly useful in medical diagnosis because they provide a transparent and interpretable model for identifying the most important features of a classification. In general, both SVM and decision tree algorithms can be effective in lung sound classification. The choice of algorithm can depend on the characteristics used in the classification, the magnitude of the dataset and the desired level of interpretability.

9. Future Scope

Lung sound classification models can be improved by adding additional features such as patient demographics, medical history, and other physiological information. In the future, researchers can focus on developing models that can extract relevant information from multiple sources to improve classification accuracy. This classification model can be functional in various clinical environments such as telemedicine, mobile health and home maintenance. In the future, researchers can focus on exploring new applications of lung sound classification models to improve patient outcomes.

Conflicts of interest

The authors declare no conflicts of interest.

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