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Speculative Analysis with Breath sound for Pulmonary disease

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Abstract—Respiratory sounds are one of the important signs of lung health and respiratory disorders. These respiratory sounds can acquire using digital stethoscopes and other recording devices. This advanced information opens up the chance of utilizing artificial intelligence (AI) to naturally analyze respiratory scatters like asthma, pneumonia and bronchiolitis. A very high number of people lose their lives to different respiratory diseases every day. Respiratory Sound Analysis has been a key tool to accurately detect these types of diseases. Earlier manual detection of respiratory sounds was used but it is not feasible to detect various lung diseases due to various reasons like audio quality and perceptions of different doctors. Modern computer aided analysis helps to give much better results in identifying the diseases from the sound i.e. identification of wheezes and crackles and thus better treatment can be given to patients. These respiratory sound diseases include Asthma, Bronchitis, Pneumonia, COPD and URTI. The prediction with decision trees gives an accuracy rate of 90 percent. This research will be very helpful for the healthcare professionals such as doctors for the easy and accurate diagnosis of respiratory diseases. This study will be a major contribution in the area of the respiratory disease classification by using lungs sounds. In this project, a web application is created with ease of access for the user as well as hospital purpose. The user will login to this application and gives patient's data as input. The machine-learning model will predict the disease patient suffering from. If the patient does not have disease, it will display as healthy.

Index Terms—Deep Learning, Lung Diseases, Machine Learning, Respiratory sounds, URTI, COPD

1. Introduction

The classification and identification of breathing diseases is a tedious task. The sound that is produced when a person breathes is directly associated with the movement of air, variations in the lung tissue inside the lung. A wheezing sound is an example for a person with obstructive disease like asthma or chronic obstructive pulmonary disease (COPD). One of the major causes of mortality and morbidity worldwide is respiratory diseases. COPD will be one of the leading causes of death worldwide. Asthma is also related to COPD, this disease also results in social and economic burden that is both substantial and increasing. The nature of crackle sound is sudden bursts and explosive. Less than 20 ms is the duration of crackle sounds and has 2002000 Hz spectrum of frequency range. These are produced during the closing in the expiration or during the opening of abnormally closed airway at the time of inspiration. The important treatment outcomes of COPD are symptoms, acute exacerbations and limitations of airflow. Interestingly, the Sounds from the lungs conveys significant information associated with respiratory diseases and it helps to assess the patients with pulmonary or respiratory disorders. For instance, wheezing sound is a common indication that that patients have diseases like obstructive airway disease (asthma and chronic obstructive pulmonary disease). The healthcare professionals use traditional auscultation methods to detect the disorders of lungs, but this method has many limitations for instance there are chances of misdiagnosis if the physician is not trained well. The most important detection errors were identified from these research like intensity of crackles, different types of crackles, different wavelengths and so on. From these analysis, we could conclude that traditional auscultation should not be considered as individual reference for validating respiratory sounds. Estimation of crackles and rhonchi is vital in lung diagnosis. However, the auscultation depends greatly on the medical skills and diagnostic experience of the physician, which are difficult to acquire. With the development of computer-based respiratory sounds, automatic lung sound recognition based on machine learning has an important clinical significance for the diagnosis of lung abnormalities. In addition, lungs are non stationary, this leads to difficulty in recognition, analysis and distinction. Because of these reasons lots of research are going on for early diagnosis and intervention of respiratory disease. In this perspective, characteristics of lung sounds provide valuable indications for the diagnosis and detection of respiratory abnormalities and infections. However, there are many limitations in the application of stethoscope in research studies because of the variability in inter-observer and subjectivity in lung sounds interpretation. An acoustic device used to detect the breath sounds of a patient is the stethoscope, a diaphragm in stethoscope can detect normal breath sounds and abnormal breath sounds without increasing lower frequency masking sounds. Diagnosis of the diseases from lung sounds needs professional training and experts. In this context a technique that can automatically and accurately classify the sounds of lungs into many groups is very meaningful. It helps to detect potential threats at a very early stage. A digital stethoscope tries to better on some of the functionalities of the traditional acoustic stethoscope. The sounds are converted into digital analogue by using ADC converter to convert the analog signal to digital signal. The digital signal is in waveform so we can predict the disease using different ranges. Each disease has different ranges based on their gender and age as a major parameter. If the signal is above the range, it will predict as a respiratory disease. Ideally, this technique will improve detection of sounds and categorization of accuracy and robustness when encountered with different modes of Sound and additional components while gaining the lung vibration wave. If the patients has high nervousness while entering the hospital their breathing sounds will be at high intensity then we cannot predict the disease. So we consult a counselling session for the patients .It will helps to reduce their nervousness and feel free about their health then we can easily analyze the breath sounds. It will be very helpful for the healthcare professionals such as doctors for the easy and accurate diagnosis of respiratory diseases. It will be a major contribution in the area of the respiratory disease classification by using lungs sounds. It serves as a stepping- stone for future research in classification of lung sounds using convolution neural networks. In addition, it helps the policy makers and researchers to make and amend the decisions in lung diseases. We can classify the respiratory disease using different types of machine learning algorithm for more accuracy about the pulmonary disease.

A. LUNG DISEASES

Tuberculosis is an infectious disease, caused in most cases by microorganisms called Mycobacterium tuberculosis. The microorganisms usually enter the body by inhalation through the lungs. One of the most serious disease in the world is lung cancer.Moreover it can be totally cure using early detection. Er et stated that Pneumonia is an inflammation or infection of the lungs most commonly caused by a bacteria or virus. Moreover Pneumonia can also be caused by inhaling vomit or other foreign substances. According to Er etal.Asthma is a chronic disease characterized by recurrent attacks of breathlessness and wheezing. During an asthma attack, the lining of the bronchial tubes swell, causing the airways to narrow and reducing the flow of air into and out of the lungs. COPD is a preventable and treatable disease state characterized by airflow limitation that is not fully reversible. Furthermore airflow limitation is usually progressive and is associated with an abnormal inflammatory response of the lungs to noxious particles or gases, primarily caused by cigarette smoking.

B. ASTHMA

Asthma is a condition in which your airways narrow and swell and may produce extra mucus. This can make breathing difficult and trigger coughing, a whistling sound (wheezing) when you breathe out and shortness of breath. For some people, asthma is a minor nuisance. For others, it can be a major problem that interferes with daily activities and may lead to a life-threatening asthma attack. Asthma can't be cured, but its symptoms can be controlled. Because asthma often changes over time, it's important that you work with your doctor to track your signs and symptoms and adjust your treatment as needed.

C. COPD

Chronic obstructive pulmonary disease (COPD) is a type of obstructive lung disease characterized by long-term breathing problems and poor airflow. The main symptoms include shortness of breath and cough with sputum production. COPD is a progressive disease, meaning it typically worsens over time. Eventually, everyday activities such as walking or dressing become difficult. Chronic bronchitis and emphysema are older terms used for different types of COPD. The term "chronic bronchitis" is still used to define a productive cough that is present for at least three months each year for two years.

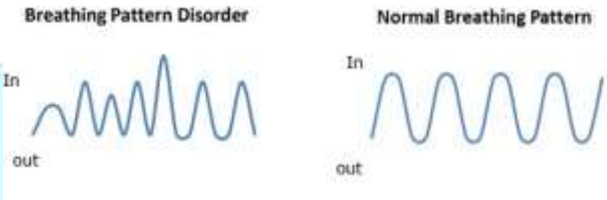


Fig. Difference between the normal breathing pattern and abnormal breath sound

II. RESPIRATORY SOUNDS

Identification of normal and abnormal respiratory sounds such as crackles, wheezes is very essential for accurate diagnosis of the diseases. These sounds include a lots of information about the pathologies and physiologies of lung structure and any obstruction in airways can be identified from the sounds. Around the beginning of the 19th century, doctors diagnosed their patients by keeping their ears to the thorax and chest to hear the noises with in and this method was called immediate auscultation. Various studies were done, and research was made to test human ears' capacity to identify crackles. The research consisted of crackles simulated to superimpose as real respiratory/breathing sound. The most important detection errors were identified from these research like intensity of crackles, different types of crackles, different wavelengths and so on. From these studies we could conclude that traditional auscultation should not be considered as individual reference for validating respiratory sounds.

1. **Lung Sounds**

Air flow of the chest causes the respiratory sounds. Pulmonary deficiencies result in the changes of the lung sounds.

2. **Breath sounds**

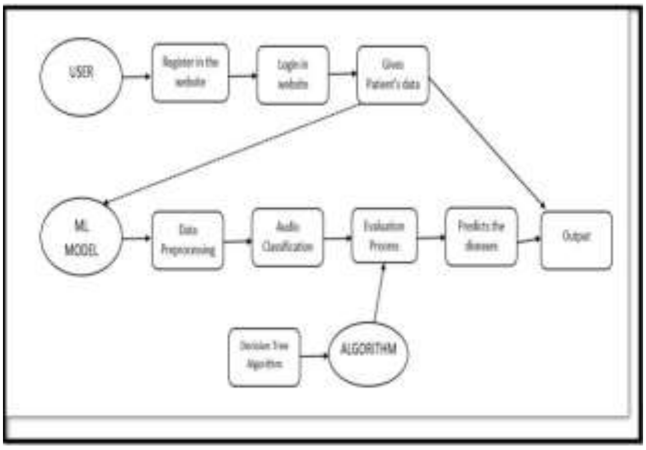
Airflow through the trachea-bronchial tree. According to Hadjileontiadis and Moussavi (2018), breath sounds are crackling, plashing, wheezing and bubbling sounds coming from the chest. Respiratory sounds are classed as normal andadventitious or abnormal sounds.

3. **Normal respiratory sounds**

The normal breath sounds are categorized as vesicular, bronchial, or Broncho vesicular. Based on anatomical features of the location where you are auscultating these sounds have different acoustic characteristics. These sounds are produced from healthy lung.

4. **Crackle**

The nature of crackle sound is sudden bursts and explosive. Less than 20 ms is the duration of crackle sounds and has 200-2000 Hz spectrum of frequency range. These are produced during the closing in the expiration or during the opening of abnormally closed airway at the time of inspiration. Each of the immediate closing or opening of an Airway represents single crackle. Forgac's theory states that a gas pressure is developed across the airway during inspiration which is then collapse during expiration.



III. Materials and Methods

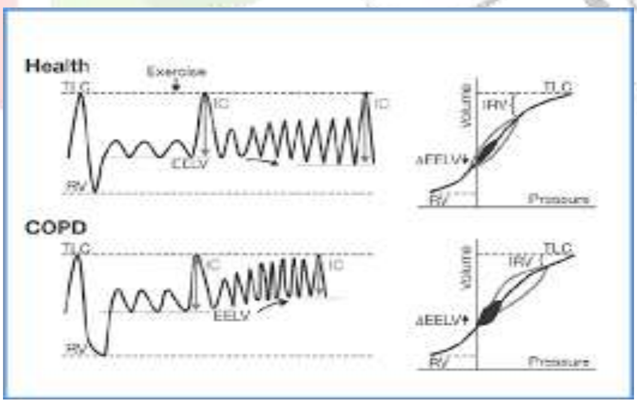
The rate, time, and sounds of respiratory are essential in diagnosing respiratory system diseases. Inspiration and expiration stages of respiratory sounds contain important information about the respiratory system.. Generally, the systems consist of two steps. Firstly, the crucial features of respiratory sounds are extracted. Secondly, these crucial features are used for detecting or classifying adventitious respiratory sounds. Commonly preferred methods for feature extraction in the literature are spectral features, Fourier. The Autoregressive MFCCs, Model, and Wavelet coefficients. For classification, algorithms such as ANN, SVM, GMM, kNN, and LR models are used.

D. Respiratory sound acquisition

During the inspiration and expiration stage of respiration, vibrations occur as a result of rapid changes in gas pressure in the airways. Respiratory sounds occur when the vibrations pass through the lung tissue and reach the chest wall. Changes in vibration create sounds with a certain amplitude and frequency. Respiratory sounds are divided into normal and adventitious (abnormal). Normal respiratory sounds are those are heard when there is no pathological airflow in the airways. Adventitious respiratory sounds are caused by pathological effects in the lungs or respiratory tract. A data set consisting of wheeze and rhonchi adventitious sounds and normal sounds was used in this study. The normal lung sounds are both louder and larger amplitude sounds during the inspiration stage than during the expiration stage. The signal frequency band of the sounds is between 150-1000 Hz. Wheeze and rhonchus sounds are determined airway obstruction pathology. They are common signs of obstructive lung diseases like asthma or COPD. Wheeze respiratory sounds are musical, continuous, and coarse sounds commonly heard during the expiration stage as a result of high-speed airflow through narrowed airways. Some parts of the respiratory tree must be narrowed or obstructed for the wheezing adventitious sound to occur. Rhonchus respiratory sounds are low- pitched and continuous sounds that result from obstruction or secretions in larger airways heard during the inspiration and expiration stage. According to the American Thoracic Society (ATS), wheezes have a dominant frequency of 400 Hz or more, while rhonchus has a dominant frequency of about 200 Hz or less, and the event is longer than 250 ms. In this study, the Respiratory Sounds (RS) were recorded by specialist physicians in the Hafsa Sultan Hospital, Manisa Celal Bayar University. All records were obtained using Littman 3200 Electronic stethoscope from 25 healthy and 25 patient volunteers treated in the clinic of respiratory medicine of the hospital. The study population was picked among the patients who have different demographic attributes and lack previous comorbidities of the study population. Normal respiratory sounds were recorded by selecting 7 female and 18 male volunteers among volunteers who had never smoked or used tobacco products. Wheeze respiratory sounds were recorded from 12 volunteers, 4 females and 8 males, with asthma or COPD. Rhonchus breath sounds were recorded from 13 volunteers, 7 females and 6 males, with Pneumonia and Chronic bronchitis. Each volunteer was asked to breathe in and out of the mouth four times, and the recording was made to include four full breaths. Thus, 100 normal, 52 rhonchus, and 48 wheeze RS were obtained. All sounds sampled at a frequency of 11025 Hz were recorded by the auscultation protocol determined by specialist physicians. According to this protocol, sounds were recorded in a calm environment, with the patient sitting and loosening his/her posture muscles. The records are obtained from the most appropriate places for the maximum collection of data about patients' pathologies, as determined by the CORSA standard. 100 abnormal and 100 normal respiratory sounds were used.

E. Wavelet Transform

WT is a signal processing method used as an alternative to Fourier Transform (FT) [33]. FT is an analysis method used to analyze stationary signals defined in the time domain, providing frequency information by examining the signal in the frequency domain. However, only frequency analysis is not sufficient for dynamic and non-periodic signals. WT is a commonly used method for non-stationary, nonlinear, and non-periodic signal analysis, such as lung sounds. With WT, the signal is defined in both the time domain and frequency domain, thus providing information on how the signal's frequency components vary with time. WT uses short window size when high-frequency information is essential, while long window size uses when low-frequency information is important. Coefficients are used for the classification process in many signal processing applications. In the analysis of signals using DWT, the selection of the appropriate main wavelet function and the determination of the appropriate decomposition level are very important. The main wavelet function, which is one of the most important parameters of the wavelet transform, takes on the task of the window function in the Fourier transform. There are many main wavelet functions with different properties and uses. In previous studies on the application of DWT in respiratory sound analysis, Daubechies 8 (db8) main wavelet function was used and found to give good results. Therefore, db8 is also preferred. Another important parameter is the number of decomposition levels, determined according to the dominant frequency components of the signal. In the study, the number of decomposition levels is chosen to be 7. Thus, respiratory sounds are decomposed into detail coefficients D1-D7 and approximation coefficient A7. Since the frequency range of D3-D7 sub-bands carries important information, these subbands are preferred.



F. Classification

The classification stage comes after the feature extraction stage. For classification, are used k-NN, SVM, and ANN. SVM and ANN classifiers have two stages training and testing. During the training stage, data from each RS class is introduced to the system as training data, and the system makes a distinction by class. Unknown sounds are analyzed during the test stage, and the most appropriate class is selected. In the KNN classifier, which is instance-based learning, no training phase is required. Samples divide into training and test samples. Training samples are multidimensional vectors, each with a class label. In the classification phase, unlabeled test vectors are labeled by taking into account the closest k training examples. In classifier algorithms, the effects of model parameters on performance and the effects of these parameters on classifier capacity and complexity were observed, and the most suitable model parameters were determined. The parameters selected for each method are given in the relevant section. The classification performance of a classifier in medical tests depends on the ability to detect patients and healthy people. Standard parameters such as sensitivity, specificity, and accuracy were used for performance evaluation. Sensitivity is the ratio of the number of correctly classified patients to the total number of patients, while specificity is the ratio of correctly classified healthy people to the total number of healthy people. Accuracy is the ratio of the number of sick and healthy people correctly classified to the total number of people.

G. Methodology

1. Support Vector Machines

Support vector machines are a type of machine learning algorithm used for classification and regression analysis. In the context of sound classification , SVM can be trained on features extracted from audio recordings to accurately distinguish between different sounds. Here are the steps to classify the sounds using SVM :

1. Data classification and pre-processing: Collect a audio recordings of the different types of breath sounds and pre- process them to remove any noise or unwanted frequencies.
2. Feature extraction: Extract relevant features from the pre- processed audio files. This can include time-domain features as well as more completed features like Mel-frequency cepstral coefficients.
3. Data preparation: Split the dataset into training and testing sets. The training sets will be used to train the SVM classifier, while the testing set will be used to evaluate its accuracy.
4. SVM model training Train an SVM model using the training dataset and the extracted features.
5. SVM model evaluation: Evaluate the accuracy of the SVM model using the testing dataset.This can be done by comparing the predicted labels to the true labels of the testing data.
6. Optimization: Adjust the hyperparameters of the SVM model to improve its performance such as kernel type,regularization parameter and kernel bandwidth.
7. Prediction: Once the SVM model is trained and optimized

,it can be used to classify new audio recordings by extracting their features and feeding them into the trained model.

2. K- Nearest Neighbours Algorithm

KNN is a supervised and nonparametric classification method that classifies data based on the proximity of training samples in the data set. This classification method finds the k nearest neighbors of unknown data between the dataset according to a distance equation. Then, it uses the majority vote approach to estimate the data label. Distance equations such as Manhattan, Hamming, Euclidean, and Minkowski are used for distance calculation. In this study, the Euclidean distance equation was used to locate the nearest neighbor. The basic steps to be applied for classification with the k-NN algorithm are as follows:

1. The number k is determined.
2. The new data is evaluated individually with all the data in the training data set, and the distances between them are calculated by distance functions.
3. The k data closest to the new data is selected.
4. The class to which most of the selected data belongs is determined, and the new data is assigned to this class. In this study, the results were obtained for k=1 and k=3.

3. XGBoost algorithm

XGBoost (eXtreme Gradient Boosting) is a popular supervised-learning algorithm used for regression and classification on large datasets. It uses sequentially-built shallow decision trees to provide accurate results and a highly-scalable training method that avoids over fitting. Here are the steps to classify the sounds:

1. Read the dataset.
2. Identifies the independent variables and the dependent variables.

Splits the data into the training & testing using 70-80 ratio.

3. Define the XG Boost algorithm without any specific parameter tuning; i.e, leaving everything as default.
4. Train the algorithm on the testing dataset.
5. Obtain the accuracy for this project.

H. Implementation

The various machine learning, methodology can be applied to get a accurate disease prediction. A respiratory sound can be collected using a noise cancelling stethoscope which can record the breath sounds without the background noise. These sounds were save as sound database to find out the disease. Wavelet coefficient and advanced signal processing techniques are used to analyse the sound waves. The machine is trained by the various methodology like support vector machine, k-nearest neighbour algorithm which is used to predict the disease quickly and we use the new algorithm XGBoost algorithm to speed up the detection and classification of disease. XGBoost and SVM algorithm show comparable prediction accuracy. XGBoost models are more stable and efficient then SVM algorithm. When we upload the sound recordings into the system it will predict the disease by using the various methodologies. This algorithm will read datasets which we used in our project then identifies the independent variables and dependent variables. It can splits the data into training and testing datasets using different ratio. Define the XGBoost model without any specific parameter tuning. Train the algorithm on the training dataset and apply the trained model to the testing dataset and then we get the accuracy of prediction for respiratory disease.

IV. Results and Discussion

Classifying with the ANN method, 80% of the data was used for training and 20% for testing. While using SVM and kNN methods for classification, training and test groups were determined by applying 10 cross-validations to the data. Besides, we have iterated the whole classification method 10 times, and average performance values have been calculated.The potential future direction suggested could further improve the efficiency and increase the number of deep learning aided disease detection applications.

- We use the digital stethoscope for recording the breath sounds when wearing the layers of clothes.
- Modern computer aided analysis helps to give much better results in identifying the disease.
- Noise cancelling stethoscope is used to reduce the background noise. It helps to focusing in specific sounds during auscultation withstethoscope.
- Advanced signal processing techniques can be used to extract more features from the breath sounds, which can improve the accuracy of classification.
- The usage of Support Vector Machine and XGBoost algorithm gives an accuracy of 90 percent.

V. Conclusion

The identification of the respiratory disease with the help of the datasets that consists of the people with breathing problems. It identifies and tells us the exact respiratory problem that occurs for the individuals. The prediction is exact and all the algorithms used are highly efficient in finding the problem with the help of the spectrograph frequencies. This helps in knowing the problem prior to the last stage. As a result, collected data usually needs to be put through data profiling to identify issues and data cleansing to fix them. Finding relevant data. With a wide range of systems to navigate, gathering data to analyze can be a complicated task for data scientists and other users in an organization. The use of data acuration techniques helps make it easier to find and access data. For example, that might include creating a data catalog and searchable indexes. Deciding what data to collect. But leaving out useful data can limit a data set's business value and affect analytics results. Dealing with big data. Big data environments typically include a combination of structured, unstructured and semi structured data, in large volumes. That makes the initial data collection and processing stages more complex. In addition, data scientists often need to filter sets of raw data stored in a data lake for specific analytics applications. Low response and other research issues.

This project is used to detect the respiratory diseases based on breathing sound parameter by using machine learning. Taking consideration of recent work and future work we are here collect sound data of different respiratory disease i.e., URTI, LRTI, Bronchiectasis, Bronchiolitis and COPD and also have healthy patient's sound records. We are using advanced signal processing concept for sound feature extraction. For future, finding the respiratory disease is helpful to reduce the mortality in the world and need to improve the technology in the stethoscopes.

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