Hybrid Algorithm To Classify The Lung Abnormalities Using The Stethoscope Recordings

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Abstract

The pandemic of 2020 brought a lot of changes to the health and medical industry where a lot of smart devices started flowing in to compensate the lack of hospitals for the less severe cases. This work primarily focuses on the lung abnormalities as the lungs were one of the first organs to break down when the virus affected the body. The lung abnormalities whilst not becoming severe but will act as a catalyst to spread the virus's effect through the lung thus concluding in complete pulmonary breakdown or irreversible lung damage. This work focuses on hybridisation of Fast Independent Component Analysis (FAST-ICA) algorithm coupled with Mel-frequency cepstral coefficients (MFCC) for independent component analysis and is fed as a input to the classification algorithm of Keras library which is the sequential algorithm. The pre-processing of the data in FAST-ICA is mainly based on three components of sound which are frequency, amplitude and wavelength.

Keywords: Mel-frequency cepstral coefficients (MFCC), auscultation, (Fast Independent Component Analysis) FAST-ICA, classification, smart stethoscope

Introduction:

The world of electronics and medical industry in unison have produced a lot of marvels which could only be fathomed by humans and in some cases not even perceived that the nano technology will take us into an era where a small device could be embedded in the human body and could monitor all the vital functions. With the era of smart technology, the health is expected to be at the fingertips and devices like glucometer, blood pressure monitor, oxygen level sensor, thermometer etc., have been miniaturising the medical diagnosis. This in turn helped in the smart stethoscope which has several inner components or different levels of identification, classification and diagnosis. The prevalence of lung disorders has dramatically increased around the world as a result of rising pollution, the impact of burning biomass, and human behaviours like smoking. Asthma and Chronic Obstructive Pulmonary Disease (COPD), both of which are characterised by the narrowing of the airways, are examples of obstructive airway diseases (OAD). According to WHO statistics, COPD caused over 3 million fatalities, and 235 million people worldwide today have asthma. Shortness of breath is one of the symptoms of both COPD and asthma, which block airflow. Bronchodilators can be used to treat asthma, but COPD is a progressive illness that, if left untreated, frequently results in death. In this paper we have 4 main lung disorders which are Rales, Rhonchi, Stridor, Wheezing. Here the sounds of actual patients with these abnormalities are used as reference where each incoming sound from stethoscope is compared with the reference sound. This ensures the unique. The FastICA algorithm and pre-processing are the two main components of the method employed in this study. The centring and whitening processes make up the pre-processing procedure. Subtracting the observed data's mean completes the centring process. As a result, the outcome of this phase yields data with zero means. To get rid of the correlation here between observed data, perform the whitening step. Since many years ago, advances in computer science have improved our capacity to automatically evaluate media material in real time. Indeed, the diagnosis-assistance technologies must have the ability to interpret auditory and/or visual data. By offering more rapid and accurate diagnostic tools, computer technology might assist medical professionals or nursing personnel. The patient might receive adaptable instruments for medical monitoring from it. Though less researched, there are certain works that analyse respiratory noises. According to a study that was recently published, earlier studies have made it possible to recognise signs like crackles and wheezes. Since previously stated, investigations on lung sound analysis now take use of this development as sound classification and detection abilities have significantly improved with the advent of machine learning and deep learning.

Doctors frequently employ auscultation to look at how the heart works. A senior doctor frequently has a lot of experience. Additionally, auscultation is more crucial in telemedicine, and it is challenging to instruct patients or users on how to position the stethoscope correctly.

Related Work:

The work done in [26] Time-Frequency Distribution (TFD) study and Mel Frequency Cepstrum Coefficient-based heart sound analysis (MFCC). While the MFCC creates a signal in terms of frequency coefficient according to the Mel filter scale, the TFD displays the heart sound in terms of time and frequency concurrently. There are 100 data with no disease and 100 data with disease. From the hospital, which includes a variety of issues includes ventricular septal defect, mitral regurgitation and restriction, tricuspid regurgitation and stenosis, and other structurally related diseases. The B-Distribution is chosen among many time-frequency analysis techniques because it can most effectively represent the signal in terms of noise and cross-term reduction. The benefit of MFCC is that it is effective at reducing errors and can provide a robust feature even when the signal is being influenced by noise. The B-Distribution representation is utilised to extract the key features using the SVD/PCA approach. The subsequent classification Artificial Neural Network uses the coefficient from SVD-PCA and MFCC. The outcomes demonstrate the system's capability to create the up to 90% accuracy with the TFD and 80% accuracy with the MFCC.

In [27] the authors say that It is difficult to extract employing the standard filtering techniques, their characteristics. In signal processing, component analysis (ICA) has the capacity to obtaining separate source signals after linear transformation a media that has been blended. In this piece, we first go through the ICA model and the theory of signal feature extraction ICA. In light of the centre limit theory and the

information theory expertise and a quick ICA method based on the negentropy criteria and its application. in light of the unavailability of the independent probability density. An empirical equation is used to estimate the source signal's negentropy. This is included in the report as well.

In [31] work, we see the actual implementation of the FAST-ICA algorithm which is done on heart lung sound separation using two stethoscopes. The application is done mainly for neonatal uses. We discover that signal saturation caused the linear relationship between the received signals to be disrupted. The precision of the data has been decreased by the noise that internal sources in the patient's body or the acquisition method adds to the signal. Additionally, our system has two microphones, but the older person finds it difficult to utilise them. The patient's chest must, however, be closely touched in order to measure this system. The heartbeats of the mother and the unborn child may be distinguished in a pregnant woman using an analogous use of the ICA method. A baby's heart function may be monitored quite well with such an application.

Methodology:

From several data sources, a lung sound dataset with more than 100 lung sounds evenly divided across the normal and pathological classifications was produced. The aberrant lung sounds were sourced from a) Kaggle and b) the RALE Lung Sound Repository. Medical professionals have classified the lung sounds in both of these data sets as either normal or unhealthy in some way. Wheezes and crackles of various types, as well as squawks, stridors, grunting, squeaks, and pleural rub, are among the irregularities. This dataset is recorded through the regular stethoscope and converted to digital mp4 form. This makes the sound as raw as possible. This gives the problem of pre-processing which is solved by getting independent components from FAST-ICA and using the MFCC spectrum to check the amplitude and then increase the amplitude of peak points so that we reduce the noise and then compare the input sound file with reference sound file.

The lung sounds are first processed for feature extraction of 3 independent components and then forwarded for classification using the sequential classification with Keras. Because of good feature extraction, we will be able to get good accuracy with the classification.

The human body is comprised of many organs which have unique sounds. When a stethoscope is placed on the chest in main points as described in the figure [1], the maximum amplitude of both lung sound and heart sound is recorded. The heart sound is nothing but the valve sound which opens and closes in one direction and has the inflow of blood. The lung sound is expansion and contraction of the small structures in the lungs while they absorb the oxygen from the air inhaled and gives out the carbon-di-oxide. But, the main problem posed here is the issue of sounds mixed from other organs or structures inside the human body. The digestive system also has a lot of sounds like the gurgling sound from the stomach, the gas sound from the intestines, the flow of sounds called 'swoosh' from the liver to the intestines etc., the diaphragm also produces a lot of sounds like expansion and contraction and there are some sounds of breathing or burping which may occur at unexplained times. A feature extraction algorithm should be capable of differentiating the sounds of respiratory from various other sounds of the body. The air between the stethoscope and body also acts as noise producer and sometimes noise enhancer.

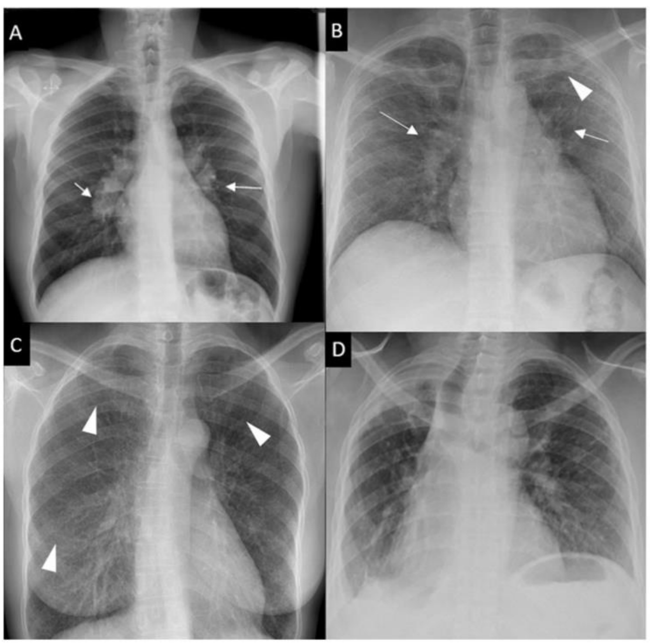

Figure 1: (A) Stage 1-bilateral (B) Stage 2-bilateral hilar lymphadenopathy (white arrows) and pulmonary infiltrates in upper lobes (white arrowhead); (C) Stage 3-pulmonary infiltrates (white arrowhead) without bilateral hilar lymphadenopathy; (D) Stage 4-pulmonary fibrosis.

a. The fast ica algorithm is as follows:

The Fast-ICA algorithm and pre-processing are the two main components of the method employed in this study. The centring and whitening processes make up the pre-processing procedure. Subtracting the observed data's mean completes the centring process. As a result, the outcome of this phase yields data with zero means. To get rid of the correlation here between observed data, perform the whitening step. The eigen-value decomposition of the mixed signal's covariance matrix is a typical technique for whitening.

1). Center the data to achieve mean zero.
2). Whiten the data to give.
3). Choose an initial (e.g., random) vector ***w*** of unit norm.
4). Calculate
$w+ = E\{x.g(wT.x)\} - E\{g'(wT.x)\}.w$
5). Let $w = w+/|w+|$
6). If not converged, go back to step 4.
The term *converge* in step 4 above refer to the condition that the value of ***w*** of the current iteration is the same as the previous ***w*** value. ***E*** denotes the expectation. The function *g(.)* should have either as:
$g_1(u) = \tanh(a_1 .u)$, where a_1 is any value that fulfills $1 \leqq a \leqq 2$ [15].

Figure 2: The detailed steps in FAST-ICA algorithm

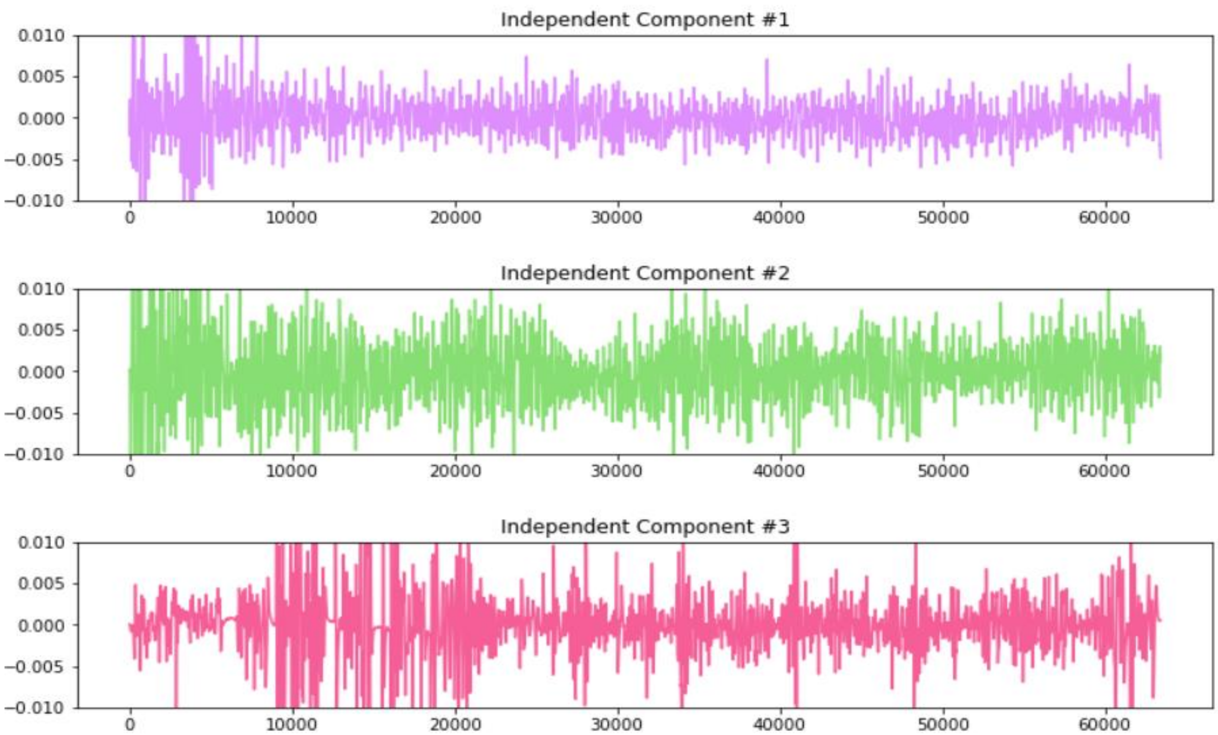

Figure 3: The 3 components from FAST-ICA which are frequnecy, amplitude and wavelength

The majority of biological signals are lower frequencies impulses that are frequently masked by louder sounds. Using the typical filtering techniques, it is difficult to extract their characteristics. After being linearly mixed by an unknown medium, distinct source signals can be recovered using independent component analysis (ICA) in signal processing. In this post, we first go over the ICA framework and the idea behind utilising ICA to extract features from signals. A quick ICA method based on the negentropy criteria and its implementation are then provided in accordance with the centre limit theorem and understanding of information theory. Due to the independent source signal's probability density function being unavailable, its negentropy is calculated using an empirical equation that is also provided in the study. In order to simplify calculation, it is important to preprocess the data by eliminating the average value and whitening the dataset before employing ICA. The flowchart also displays the whole implementation of the ICA algorithm (Figure 2).

ICA is made up of efficient algorithms and object functions (criterion). How to quantify the independence of separated components is crucial to understanding ICA theory and the separating method. The centre limit theorem states that regardless of how the statistically independent variables are distributed, if a random variable is composed of mutually exclusive independent random variables that have limit mean values and variance, the stochastic process must be near to Gaussian distribution. The random variable with a Gaussian distribution has the highest information entropy among those with the same variance. The information entropy of a variable decreases as its non-Gaussian degree increases.

As per the depicted sound waves in Figure 3, we get 3 components for analysis and then we can get the MFCC (Mel-frequency cepstral coefficients) which is a vital parameter for classification.

MFCCs are commonly derived as follows:

1. Perform a signal's Fourier transform on a windowed extract..
2. Use triangle overlapping windows or, alternately, cosine overlapping windows to map the values of the spectrum acquired in step 1 onto the mel scale..
3. Calculate the power logs for all of the mel frequencies..
4. Treat the collection of Mel log powers' discrete cosine transforms as if it were a signal..
5. The magnitude of the resultant spectrum are the MFCCs..

Audio signals, which include ambient sounds, noises, foley, wildlife sounds, speech sounds, and nonspeech utterances, offer a wealth of information that may be used for successful video indexing either by itself or in conjunction with visual information. These factors make audio categorization and retrieval an essential and difficult study area. The feature extraction phase of audio categorization is crucial. An effective representation should be able to capture the most important sound characteristics for the job at hand, be resilient in a variety of contexts, and be broad enough to encompass several sound classes. Environmental sounds are typically far more difficult to define than spoken and musical sounds because they include numerous noisy and textured components as well as higher order structure components like iterations and scatterings. The classification algorithm is used by Keras. It is a sequential algorithm which is not normally used but here it gives good accuracy. One of the crucial classes in the whole Keras sequential model is the Keras sequential class. This class aids in the development of clusters, which are made up of layers of data or information that flow from top to bottom while incorporating several levels. The majority of Keras' features are learned using techniques that provide the model a lot of sequence.
There are several prerequisites and processes that must be properly fulfilled in order to use this model:
First, a suitable setup is necessary. The Keras library or API, which has precisely one layer of input and one layer of output, will then be included into this configuration. Select a suitable method next, such as add() or delete(), where the characteristics will be determined by the need..

According on where they occur in the cardiovascular system, breath sounds might vary.
These are the categories that healthcare practitioners place them in:
• Normal lung or vesicular breath sound: With the use of a stethoscope, a tool for listening to a person's internal body noises, a doctor may hear this sound throughout much of the chest. When breathing, air enters and exits the lungs in vesicular breath noises. The sound has a deep, rustling character and is
gentle. During inhalation, it is likewise continuous, stronger, and higher pitched than during exhale.
• Bronchial breath sound: As someone exhales, the bronchial breath sound may be heard across the trachea. It has a harsh, hollow, and high-pitched sound. However, it might be a sign of a health problem if a doctor hears bronchial breaths outside the trachea.

Rales, another name for crackles, are sporadic noises that are often noticeable during inhalation. They may have a bursting, popping, or clicking sound to them.

• Fine: These are soft and loud pitched, and they occur in the narrow airways. Only occurring during inhalation, fine crackles may be more frequent than coarse crackles during a breath.

• Medium: These are the consequence of the tiny bronchi, two tubes that transfer air from the throat to the lungs, bubbling through mucus. The bronchi split off into progressively smaller passages, leading to air sacs known as alveoli..

• Coarse: Larger bronchi tubes are where coarse crackles are more common; they are louder, lower-pitched, and continue lengthier than fine crackles. They can also occur during exhale, albeit they often happen during inhalation.

High-level, mid-level, and low-level aspects of musical signals are classified as levels of abstraction. Temporal Scope: Instantaneous, segment-level, and global time-domain properties. Musical Aspect: Beat, rhythm, timbre (sound color), pitch, harmony, melody, and other acoustic qualities.Signal Domain: Features in the time, frequency, or both domains.

In the figure 4 we demostrate the methodology of FAST-ICA in which we extract the features and then these features are fed to the classifier. In the classifier we take the input and reference where we compare the extracted features with the unique features of each abnormality and then get to the best conclusion.

ICA is considered to be the best methodology for non-Gaussiann data, which is typical in processes systems because it is a linearly operated non-Gaussiann multivariate statistical approach. The use of Higher-Degree Statisticss(HOS), such as kurtosis and negative energy entropy ICA vectors are not orthogonal like PCA vectors, and each component is equally crucial. There are three approaches to get ICA: use the HOS directly, work with the HOS after doing PCA, or mix second-order and higher-order statistics.

Testing and Analysis:

Here we see the count of CSV file. How the different abnormalities of the lungs are distributed. The crackles are mostly common due to many factors contributing to the lung disease.

The testing is done with 100+ sound recordings available in the open database, which are a mixture of patients who have normal lungs and also with lung disorders. Here, the concentration of Crackles is more in the dataset we have taken as crackles is the most easily acquired lung abnormality. The lung function as a filter of air and when there is too many dust particles at an alarming rate, the dust settles off in the tiny structures of the lungs which are mainly responsible for filtering. Here, due to evaporation of moisture from the dust settled on the structures, the dust hardens which blocks a part of the structure and hence that part is hard and cannot expand or contract. This gives rise to sound like crackles which gives off the audio like when the paper which is hard is crushed and then uncrumpled. This is mainly affected when the patients are living in the dust polluted areas. Now, Rales is a condition which normally affcets the people with pnemonia. Pnemonia is a condition where the moisture in the air is not effectively filtered out and is retained in the lungs. The alveoli are the tiny structures that are responsible for filteration and also for taking out the moisture. For patients with pnemonia, especially people living in humid climate, the moisture is retained in the structures. This gives rise to more volume of lungs as water is dense than air and the patient starts to feel heavy. Here, the water starts weighing down in the lungs, it settles down due to its weight and poses a risk to the patient. Deep wheezing breathes are seen as more air is needed for the body. The water retention in the lungs also cause damage and puts pressure on the rest of the unaffected lungs to filter more to balance the oxygen needed by the body. Now, when these structures, the alveoli start to function more than indented, they begin to burn out where the Rales situation settles in.The affected alveoli collapse giving rise to the bubbles being popped sound in the lungs.

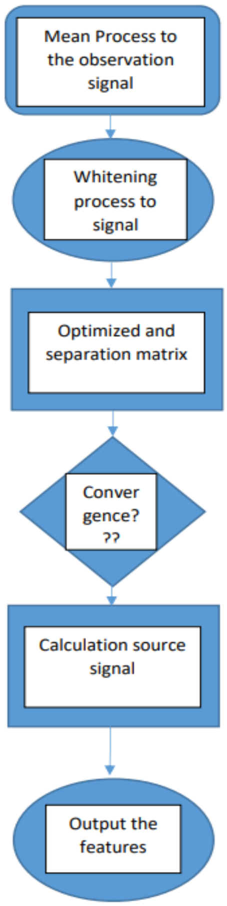

Figure 4: The Methodology of FAST-ICA

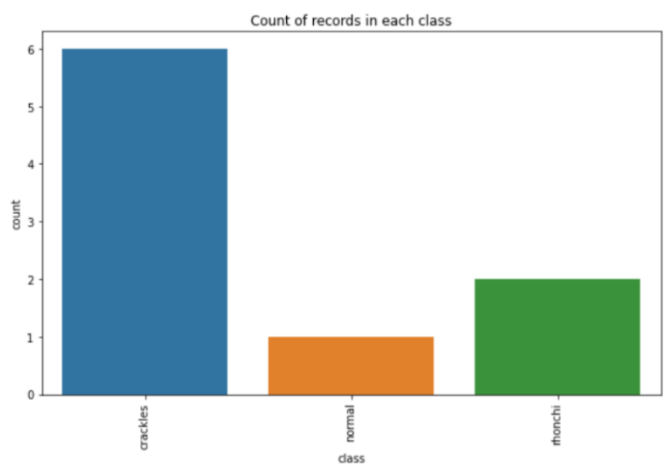

Figure 6: The distribution of CSV file

Rhonchi is the condition of the airway and not of lungs. But due to the airway directly being connected to the lungs, the sound emits from the lungs even though it is not directly connected to the tiny structures.
The block in the airway is caused mainly by dust or tiny structures growing inside and hence creates a gargling sound inside. This is also a unique sound for the lung abnormality detection. This also coincides with wheezing.

While testing, first we use the already referenced sound to train the model in the sequential algorithm of Keras. For this, we have 3 layers in Keras:
Input layer: The training observations are fed and the number of predictor variables are mentioned, where we have the 3 major features.
The hidden layers: The layers where the actual work is done where the output of one intermediate layer is the input to next intermediate layer.
Output layer: The final output layer which is where the classification is shown.

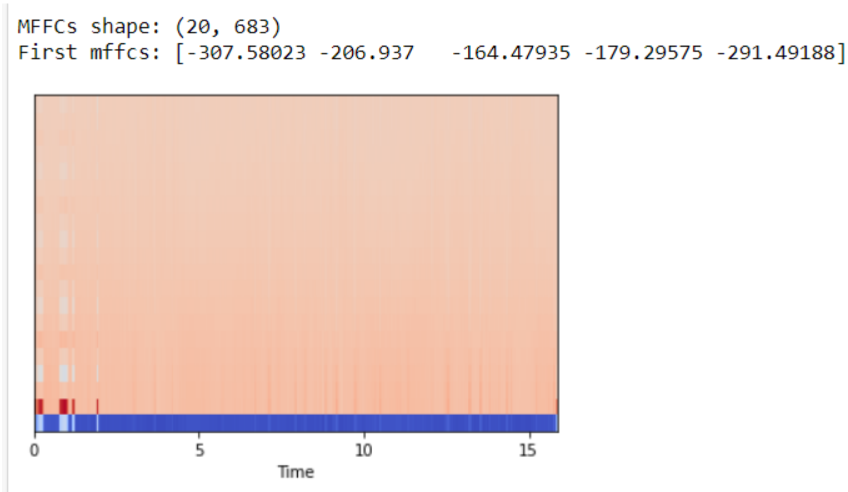

Figure 7: MFCC for the analysis

Singular value decomposition (SVD) is now a crucial technique for signal processing and statistical data analysis. It took the Italian mathematician Beltrami about 20 years after Cayley's notion of a matrix as a multiple quantity before he proved the existence of SVD. To lessen the impact of noise from TFD when dealing with singular matrices or matrices that are extremely near to being singular, an SVD-based approach is developed. They are an eigen decomposition extension made to fit non-square matrices.
Any matrix may be broken down into a group of distinctive eigenvector pairs known as the component factors and the corresponding eigenvalues known as the singular values. Using MFCC, the segmented ecg signals sample is converted. With an initial parameter of 16 coefficients, this experiment is run with 250 samples for each panel and an overlap of 80 samples between each frame. The transformation scale for MFCC is linear for frequencies below 1 kHz and expands logarithmically for frequencies beyond 1 kHz. Due to its compatibility with the human auditory spectral region, this characteristic works well for speech processing. The greater filter bank scale won't have much of an impact on the heart sound analysis, though, as the majority of the heart sound components lie below 1 kHz.
The accuracy formula is as follows:
Accuracy = Number of correct predictions / total number of predictions.
We have taken around 136 samples to test and out of which 117 samples were predicted correctly. We get 86% accuracy for the current algorithm.

Results and Conclusion:

Categories	Convolution Kernel shape	Accuracy rate (%)	F-score
MFCC Deep Feature	**1 X 13**	**85.54**	**86.23**

		95.68	**96.30**
MFCC Deep Feature	**1 X 26**	**90.23** **98.22**	**91.01** **97.33**
MFCC Deep Feature	**1 X 39**	**91.44** **96.33**	**89.22** **78.22**
MFCC Deep Feature	**1 X 65**	**93.45** **98.33**	**94.01** **97.33**

Table 1: Comparison of features from current work and previous works

We get around 86% accuracy for the samples in this work, with not much removal of noise and not much refinement of the sounds from stethoscope.

In this paper we present a way to classify the abnormalities of the lung abnormalities using an unusual classification algorithm which is the sequential classification algorithm from Keras Library. We can conclude with the results that there is 86% accuracy in classification. The decrease in the accuracy can be attributed to noise in the sound captured through the stethoscope. If the small increase or decrease in the sounds of the air is reduced with some medium, like the ultrasound gel, then the medium tension or friction is greatly reduced. The conclusion is that, the algorithm while serves the purpose of classification, the reference sounds need to be proper for the algorithm to be able to compare. A future enhancement would be to extract more independent components from the raw sound file as this is aimed to a pipeline in the smart stethoscope.

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