Identification of continues adventitious respiratory sound for Asthma detection using classification models

Research in Computing Proposal
MSc in Data Analytics

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Abstract

Wheeze is high pitched continuous Respiratory Sounds that made as a result of the obstruction of the airways. Due to continues rise in the number of cases, humans are lacking in handling all these cases within time. Hence to reduce the load Computer-based asthma detection system can help doctors to detect asthma. Till now many researchers developed a system to classify the Wheeze sound for asthma detection, with the help of machine learning algorithms and features extraction techniques and achieved good accuracy with the use of Support Vector Machine, Gaussian Mixture Model, and Random Forest. With the use of an audio database which contained a total of 5.5 hours of recording collected from 128 subjects includes crackles and wheezes. This study intends to use Decision Tree Algorithm which has never been used before on this dataset for the Wheeze Sound Classification for Asthma Detection, and further to evaluate the performance of model Confusion matrix, k-Fold Cross-validation and Root mean squared Error will use as performance evaluation.

Keywords Wheeze Analysis, Machine Learning, Mel-frequency cepstral coefficients (MFCCs), Decision Tree

Contents

1 Introduction

In the Healthcare domain, Asthma is one of the oldest diseases mentioned in it. In the beginning asthma, symptoms are composed by a Greek physician called Aretaeus, after that in 1892 Sir William Osler set out the definition for asthma Holgate (2010). The main reason for asthma is air pollution which includes traffic pollution and smoking habit, also allergens and exposure of indoor, as well as an outdoor volatile compound, can trigger asthma. As per Wikipedia in 2015, 358 million peoples globally affected by asthma which is a huge increase as compared to 180 million in 1990. But asthma death count around the world is 397,100 in 2005. There is a total of 6 types of asthma in which Adult-onset Asthma, Allergic Asthma, Asthma-COPD Overlap, Exercise-Induced Bronchoconstriction (EIB), nonallergic Asthma and Occupational Asthma are included. Day by day asthma patients count is increasing rapidly due to various factors, and to detect asthma we need well experienced and well-trained doctors, so they can detect asthma and provide proper meditation to asthma patients, so asthma wont get trigger in future. But increasing patients counts may increase the workload on doctors and this may lead to the late detection of asthma that might cause an unwanted situation. To Avoid this situation, we need a computerized solution which is trained under doctors observation with factor like wheeze sound so the computer can detect asthma. with this solution, we may reduce the doctors workload and reduce unwanted situations.

In previous studies conducted by researchers performed the classification of wheeze sound, that process contained different steps includes like Data Gathering, Data Cleaning, feature extraction, processing the model and evaluation. In most of the Studies Researcher used Audio file format as a dataset Gurung et al. (2011). In the phase of data gathering, audio files were collected from different subjects which are wither affected with asthma or not. Due to this sounds are collected from different location of lungs, other organs sounds are included in that files, in these case data Cleaning comes in place, which helps to reduce the other noises. All the files are in WAV format, hence researcher used different techniques to find out the different patterns from sound files. In this techniques, Wavelet Packet Transform, Duration, Frequency, Peak Amplitude are commonly used techniques, with the help of this u can clearly extract the most important parts from sounds hence this technique called feature extraction. All these features are processed using a machine learning algorithm to classify the wheeze sound, in Section 2 We can clearly see that Support Vector Machine (SVM), Random Forest, Artificial Neural Network, and Convolutional neural network are most widely used an algorithm for classification. To evaluate the result metrics like Specificity, Recall, Accuracy is used.

With the reference of all studies mentioned in Section 2 can use different algorithms to improve classification techniques. in the Section 3 we intend to use a different algorithm which not been used yet on this database. This study intends to improve the wheeze sound classification from the lung sound from a dataset collected from a single website. This whole research can perform by using the decision tree Algorithm with some feature extraction techniques like Mel-frequency cepstral coefficients (MFCCs), Entropy of energy can improve the performance. All this performance can be evaluated by confusion matrix, Recall, Root Mean Squared Error evaluation techniques.

1.1 Motivation

Due to a long history of asthma disease its one of the non-curable disease but it can be managed by proper treatment. According to the Centres for Disease Control and Prevention (CDC), 1 in 13 people have asthma. Identifying asthma with wheeze sound with the computer-based solution might help to identify asthma in an earlier state, which can help the patients to take manage asthma triggering situations.

The Motivation for this project is to help doctors and patients with a computer-based solution for asthma detection based on wheeze sound. With the immense range of frequencies from various infected peoples helps to increase the quality of asthma detection as compared to what physician can auscultate using a stethoscope. Asthma detection is not even easy for well-trained doctors, the main techniques are to detect asthma is getting abnormal breathing sound, but airways abnormalities can cause breathing sound to be abnormal. Only expert can detect abnormalities in breathing sound, however accurate detection of this sound is totally depending on the presence of expert and their practices Shaharum et al. (2012).

Stethoscope use in research studies has been limited due to inter-observer variability and expertise in the interpretation of lung sound, hence for this previously researcher used wheeze sound which is collected by the electronic device. To detect infected sound Computerized respiratory sound analysis (CORSA) developed a guideline to get a quality of wheeze sound, in which duration of the has sound should be more than 100ms and their dominant frequency should be greater than 100 Hz. To get sound with these standards most of the researcher used electronic devices to collect respiratory sound.

1.2 Research question

Does Wheeze Sound Classification using Entropy of energy and Time Wrapping feature extraction techniques as part of a Decision Tree model surpass the Gaussian Mixture Model prediction that involves only the Time Wrapping?

1.2.1 Research Objective

The primary focus for this study is to create a Classification model which will help to detect the Asthma from the wheeze sound. Along with this, this research also tries to address below objective.

- To find out at what minimum frequency we can detect asthma from wheeze sound.
- To find out on which factors we can identify the asthma.

1.3 Plan of Paper

In this paper, we are going to brighten some insight into various techniques and their result. every section in this paper will help to get more information about each section. In section 2 we will find the different papers and researches done on this paper. With this section, we will get some insight into different techniques. Section 3 will introduce the methodology that we proposed in this paper.Also, it will help us to find out the different stages of implementation, with subsection we will divide all implementation stages. Section 4 summarizes an overview of the work we will do in this paper.

2 Literature Review

In this section, we will see how different studies or researches helped to enhance the detection system of asthma from wheeze sound. Initially, need to understand what respiratory sound is? basically respiratory sound is sound which is generated by the respiratory systems. This sounds can usually be heard by performing auscultation. Auscultation involves listening to the cardiac and respiratory sound, which can carry out to check the physical health. Based on respiratory sound can categorize in Normal and Abnormal respiratory sound. Normal respiratory sound can be categories based on where they generated also different type of respiratory sound have different factors like duration, pitch, and sound. Abnormal respiratory sound includes the absence or reduced intensity sound while breathing this sound can be differentiated based on different condition and hence be very useful for diagnosis.

With the help of this study which is conducted by Pooja (2018) where various techniques like Random Forest, K-NN, Support Vector Machine (SVM), Logistic Regression were used and Random forest techniques resulted in an accuracy of 0.882 i.e. 88% with text formatted dataset. In the work of Shaharum et al. (2012) researchers carried out work in the time-frequency domain. For detecting wheeze sound researchers used a statistical method such as Fisher Discriminant Analysis (FDA), kurtosis and linear regression analysis while fast Fourier transform method commonly used in machine learning.

In this paper, researcher Pramono et al. (2017) developed an algorithm to detect the adventitious sounds in two steps. Initially, the researcher extracted the relevant features which will be used for detection variables and then in second steps the same variables used to for classification. In this paper, he used Empirical Methods And support vector machine. In Empirical rule-based method used crackle sounds for crackle classification, this classification accomplished based on mathematical morphology of a crackle event in the spectrogram. In this classification result, 86% sensitivity and 92% specificity achieved. In another method used Support Vector Machine classifier to perform wheeze detection, in which for classifier a spectral-based feature used. All recordings were divided into the segment and needful features extracted from each frame. Using this method researcher archived 71.4% sensitivity and 88.9% specificity.

With the same technology In this paper Researcher, Finkelstein and Jeong (2017) does the area in the prediction of asthma exacerbations using Machine learning approach. In this Researcher used 7001 records which are collected from asthma patients to predict Asthma Exacerbations. The technique researcher used provided a good accuracy rate which can also help to detect asthma at the beginning stage. In this study with the help of telemonitoring data to develop a machine-learning algorithm to predict the exacerbation of asthma before occurring. In this study nave Bayesian Classifier, adaptive Bayesian network and support vector machine to perform prediction. The nave Bayesian classifier is highly efficient with linear scalabilities, classifier assume that the attributes are independent. Despite this assumption, classifier predicted with a high accuracy rate. After study completed with nave Bayesian classifier researcher got 80% sensitivity and 77% specificity. And for Adaptive Bayesian Network and Support vector machine were able to predict specificity 100%, 80% and sensitivity 100% and 80% respectively.

In this paper researcher Santra and Christy (2012) developed an algorithm to detect the adventitious sounds in two steps. Initially, the researcher extracted the relevant features which will be used for detection variables and then in second steps the same variables used to for classification. In this paper, he used Empirical Methods And support vector machine. In Empirical rule-based method used crackle sounds for crackle classification, this classification accomplished based on mathematical morphology of a crackle event in the spectrogram. In this classification result, 86% sensitivity and 92% specificity achieved. In another method used Support Vector machine classifier to perform wheeze detection, in which for classifier a spectral-based feature used. All recordings were divided into the segment and needful features extracted from each frame. Using this method researcher archived 71.4% sensitivity and 88.9% specificity.

Nowadays with the help of genetic algorithm, support vector machine (SVM) methods can use to find more reliable and fast solution on the proposed system. In a recent research Nabi et al. (2019) used Respiratory sound data at 8000 Hz sampling data which contained total 55 sample includes total 34 males and 21 females with single channel wireless digital stethoscope. Nabi et al. (2019) used the Butterworth filter with 2500 Hz frequency to remove aliasing. The researcher used Fast Fourier Transform Approach (FFT) for analysing Wheeze sound. An overall research found Positive predictive rate (PPR) 92% for (SVN) and 94% for (ENS).

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Another study conducted by Khasha et al. (2019), the researcher created feature subset using wrap per approach called Boruta. In this method he divided the feature in 3 categories which are confirmed, tentative and rejected. Also, in this study Khasha et al. (2019) used Multinomial logistic regression (MLR), K- nearest neighbors (KNN), Gaussian Nave Bayesian (GNB) as base learners. Initially the researcher created cross validation individually and performed 20 runs of 5 cross folds to reduce the biases.

Even though with nave Bayesian Classifier, adaptive Bayesian network and support vector machine and Empirical Rule-Based Methods used in a previous paper by researchers and with the more than 85% sensitivity archived by using this technique, there is some more researcher who used totally different approaches to get proper and finest result for the same study.Researcher Oweis et al. (2014) used different algorithms and application to get a better result in this study, this work roll around dealing auto-correlation in the feature extraction stages, the researcher used MATLAB in all these processes and for classification process done by using Artificial Neural network and Adaptive neuro-fuzzy inference systems. In this study researcher used feature extraction on an auto-correlation function, Fast Fourier transform technique used on non-stationary data with auto-correlation function. But still, there is some complexity raising with the dataset, to avoid this complexity researcher use auto-correlation function as an alternative option on window size when using wavelet transformation. To achieve maximum result used several stages like normalization, filtration, feature extraction and classification using both ANN and ANFS and compared them. While doing filtration used frequency between 100HZ to 2000Hz, which helps to reduce unwanted organs sound. On the basis of the training phase, the test phase is used as the second phase in which the best matching model selected. As per the researcher, the ANN model was the best approach over ANFS for pattern recognition. As per the study, ANN resulted 98.6% accuracy with 100% specificity and 97.8% sensitivity and with ANFS model got 66.4%, 70.4%, and 56.9% of Accuracy, specificity, sensitivity respectively.

In most of the paper till now we saw researcher used ANN, SVM and Bayesian models to detect crackles from the wheeze or respiratory sounds that leads to researchers to predict the maximum results but might be still we can explore the new techniques which would be easy to use and complete all the processes or we can get the different type of output which can help to get proper and more accurate result into detect asthma earlier. Few researchers do this by using very different models might be we can use Gaussian Mixture Model to lead this study with a different result. In below research author used Gaussian Mixture Model to separate the crackles and to classify from respiratory sounds.

In this study researcher Maruf et al. (2016) used Gaussian Mixture Model to identify and classify the crackles from wheeze sound as we saw in previous paper Oweis et al. (2014) used ANN and ANFS model with 98.6% and 66.4% accuracy, and author concluded that ANN model is best for crackles identification over ANFS model, but with the help of Gaussian Mixture Model author Maruf et al. (2016) shows new possibilities. In the Same study Maruf et al. (2016) use same steps to study initially Pre-processing then Feature extraction after that feature selection and lastly classification. In pre-processing author mainly concentrated on two objectives like reducing other noises and enhancing the quality of recorded sound. With these two objective authors able to reduce lots of extra works. In feature extraction process author used processed data and extracted total 12 feature like Pitch, Spectrogram, Energy, Shannon Entropy, Mean, Range, IQR, MAD, Moment, Skewness, Kurtosis and PSD to analyze data. Selecting proper features for feature selection is a crucial task, selecting unwanted features may lead the study to unwanted result. Hence the researcher has done analysis on features. In this study Maruf et al. (2016) used Wilcoxon Rank-Sum and Ansari-Bradly test. Wilcoxon test is a nonparametric test and Ansari Bradly test compare two independent samples which comes from the same distribution, also Gaussian Mixture Model is in a category of the probabilistic model which helps to improvise result. With this study author achieved 100% specificity, 92.85% sensitivity and accuracy of 97.56% which is enhancing result with other recently published methods.

There are new few approaches still discovered by different researchers Chatterjee et al. (2019) used a total of 63 sample files for testing purpose, which is divided into 4 class normal, crackle, pneumonia, and asthma. All 63 samples are collected from R.A.L.E. lung sound repository under a special agreement. Initially, audio files passed to an audio processing module, then depending on the value of the sampling frequency, the downsampling factors selected. The author set the downsampling factor to 10, if the sampling factor is greater than 10 kHz, otherwise, it is set to 100. To reduce the noise from the audio files Chatterjee et al. (2019) used Butterworth low pass Filter for statistical analysis. After sound processing is done, the peak value of the amplitude is computed and the largest peak is determined. Based on the peak amplitude values got from the statistical analysis module. All these signals are classified into 3 different categories namely mild, soft, hard. In this classification mild stands for normal lung situation, soft stands for pneumonia and crackles and hard is for acute Asthma. in all this process total 12 samples of hard breath and 12 samples of soft breath identified based on peak values. In this classification result author used 19 samples for normal breath out of that 17 were predicted correctly with 89.4% accuracy. For Asthma 15 out of 16 sound detected correctly with 93.75% rest of the samples are used for Pneumonia, crackle, and wheeze respectively. In the above study author used statistical analysis module for asthma detection. In this classification techniques, the time complexity is one of the important factors from others. We need to detect Asthma as soon as quickly and more accurately in a single chance. Accuracy and recall are the most important facts that are needed to be considered while performing this study. The time complexity in the required time which complete the process of analyzing breath and then find the proper pattern which can be lead to the classification process in which we can identify whether the object has Asthma or not. All this process need to complete in minimum time with proper accuracy and precision. in the above study proposed system was suitable for real-time diagnosis with 1.7398 seconds as time complexity with overall 90% precision and 95.23% recall.

In 2013 Palaniappan et al. (2013) tried to detect asthma with different types of Repository sounds. Repository sound are divided into three categories: Normal respiratory sound, abnormal and adventitious respiratory sound. Based on this 3 categories sound analysis done to detect the asthma. further more adventitious sound are divided into continuous sound and discontinuous sound which divided to crackles and continuous sound lead to Wheeze and rhonchi. In this study visual analysis used to identify the abnormalities of repository sound from waveform. Also with the use of statistical analysis method used to classify the respiratory sound. Based on few factors like repository sound type, dominant frequency range, pitch, duration, and disorder author try to classify the asthma and different disease.

In the study we can see that dominant frequency which is in between 150 1000 Hz with no longer duration dont have any disease or disorder which can classify as normal, but if the duration goes up with more than 250 ms with more than 200 Hz dominant frequency can classify as Wheeze sound and the object can have Asthma or Pneumonia. Researcher Palaniappan et al. (2013) analyze more than 60 Research paper for various sound analyzing techniques, in which Machine Learning techniques like Artificial neural network (ANN), Gaussian mixture model (GMM), k-nearest neighbor (k-nn), and fuzzy analysis used most of the time for sound analysis. But the user saw that some researcher used different hybrid machine learning algorithm for better effectiveness. Researcher lighten up some more unique algorithm fast Fourier transform (FFT), autoregressive model (AR), fractal- dimension (FD), Form which indicates that most of the algorithm are frequency and signal-based, but very few researchers used time-frequency domain-based analysis like Wavelet analysis and frequency cepstrum coefficient (MFCC). Based on analysis of this different researches which undergo by researcher helps to clear the conclusion that is with the use of hybrid models we can improve the classification of sound analysis and this lead to improved result as compared previously used method.

in this Research Article research R.X.A. et al. (2017) describe the several different techniques which are used less often for sound analysis and classification. As per researcher in one paper Hidden Markov model used to classify different between normal and abnormal sound. To complete this study total data gathered from users in which 109 users are infected with emphysema pulmonary. Totally 1544 events recorded and segmented and out of them, 554 correspond to abnormal sound. All data which user collected is either from the condenser or piezoelectric microphone. In this research 93.2 % sensitivity and 64.8% specificity achieved. But in the domain of healthcare specificity is the most important factor for classification of any disease by machine learning technique. to improvise this specificity Researcher added some more features to improve the performance of overall research. In this feature, the particular duration distribution of noises and abnormal respiratory noise was used to decrease false alarm caused simply by noise. With this feature the performance achieved by using LOOCV was increased in this study, total sensitivity was achieved was 88.70% and specificity increased to 91.5%. as we can see from this study the result which we are getting from the different algorithm can increase with proper feature extraction techniques. with the same method and with the using of MFCC feature helps to improve the performance of Hidden Markov Model (HMM). In this feature, the correlation score with other auscultation points and segments are used. Best sensitivity and specificity were recorded by this method is 91.10% and 93.43% respectively.

In the same paper, author R.X.A. et al. (2017) described Discriminant Analysis Based Method used to crackle classification. Generally, this method is utilized in statistic, machine learning, and pattern recognition in order to find a linear mixture of feature which helps in order to separate two or even more object. In this study user collected totally 238 coarse and 153 fine crackle for the analysis. Most of the features extracted using wavelet network, the classification model which tested on this dataset able to be achieved 70% for coarse and 84% for crackles. Also, to enhance this result in the same study the data separated to 75%-25% for train and test dataset and repeated this process for 200 times, with this technique the maximum accuracy achieved was 99.75% at segment level.

researcher Riella et al. (2009) conducted the same study in which Researcher developed computer software which was created in C++. Using this software very differently predict asthma from lung sound. User collected all the samples in .wav file format, which specially use for audio recording. Using self-developed software researcher processed the wave files and generates the spectrogram in bitmap format which used in the image. Basically Riella et al. (2009) generate image file for image processing for the sound file format. Then after pattern recognition was used to recognize the asthma pattern from the generated image-based spectrogram. At the pre-processing stage, the spectrogram matrix was obtained from wave formatted audio file with using Short Time Fourier method on the single-dimensional signal to generates the images from signals. But to generate same spectrogram characteristics from a different sound recording, for this, a normalization process needs to do on sound recording. In this process, the initial sample rate is primarily detected to implement particularly the sample rate normalization. If the sample frequency rate is higher than 9 kHz down sampling techniques are used to change the value of the signal to the normalize the value of the signal. In this process, the frequency rate cut-off to the 4 kHz from 9 kHz to get the proper image, also reducing other noises is one of the main tasks performed in which other organs sound like stomach, and Heartbeat is reduced. Once all this pre-processes completed next step was performed to generate spectrogram from that sound files. Afterimage created pattern recognition comes in a picture, to detect the pattern from the images Artificial neural network used. In this process neural network containing 20 input points. Each input point having frequency and amplitude of the 10 largest edges of frequency which are generated from spectrogram and 2 neurons at the output layer. Since the frequency values containing the value from 0 to 4000 Hz, all frequency points divided BY 1000 to reduce the interval, also during the normalization magnitude of the points are divided by 100. Which helps to reduce the unwanted data from the spectrogram. At the end of the result Riella et al. (2009)

achieved the total accuracy of 84.82%, with 29% of positive and 55.36% negative prediction which is accurate. In the case of false positive and false negative 8.92% and 6.25% predicted.

Mel frequency cepstral coefficient is one of the effective techniques which is used to extract the features from sound files, this mainly uses in sound or in speech processing. in sound processing, Mel-frequency cepstrum is a representation of the short-term power spectrum of the sound base. In 2013 Palaniappan (2013) used same technique as mentioned earlier. In this study, MFCC features were extracted from the respiratory sound signals and used those features in SVM classifier for the classification process. this technique was used by other many researchers like Finkelstein and Jeong (2017) and Oweis et al. (2014) and they got pretty much positive result as compare others. In this study, the dataset which is used that is commercially available from RALE database, which containing total 70 recordings which are recorded with using EMT25C, Siemens. 68 recording were used in this research out of 70 for this study. On the basis of preprocessing, feature extraction, classification and performance evaluation conclusion were decided. Initially in pre-processing steps author filtered other organs sound which may cause a problem for crackle identification. To identify the crackling sound from other organ sound sampling rate of the respiratory is decided to 1 kHz which was originally 10kHz. Using the Mel-frequency cepstral coefficient feature on the respiratory sound analysis required outcome extracted for further processing. Within the MFCC analysis, the rate of recurrence is wrapped in compliance with the Mel range which approximates the human being auditory system's response even more closely. In this process, the Mel frequency is calculated with Fast Fourier transformation and collected in vector. This vector further passes to SVM for classification step. SVM is a kernel-based supervised based learning classification algorithm which divides data into more than two classes. Also, SVM can use for non-linear classification. In this study the vector which filled with MFCC feature use as input to SVM for further classification. SVM helps to increase the distance between the two classes for the classification process with hyper plan margin which became helpful for Respiratory classification. At the end of this study, a confusion matrix was used for performance evaluation. As per mention in a study conducted by Palaniappan (2013), the maximum classification accuracy is 91.35% and mean and minimum classification accuracy is 90.77% and 88.65% respectively. As per result concluded by researcher total 16 cases recorder as normal out of 17 which leads to the 94.11% overall accuracy. In the case of asthma 24 out of 26 cases predicted as asthma hence total accuracy 92.31% predicted. As per researcher this, all process can repeat with linear Predictive cepstral coefficient feature extraction process with this LPCC feature we might get a more accurate result in the future.

Throughout all this researcher everyone performed well with their own ideology, using a different algorithm like SVM, k-nn, Gaussian Mixture Model, etc. helped us to detect asthma in many different ways and more accurately. Getting proper accuracy, specificity or recall is one of the major tasks in all this research which is finely done by all authors. But getting a proper result is not the only important thing in research. Selecting proper dataset for research is one of the most important and primary steps in any research. What if the prediction rate is getting more than 95% but the dataset chosen is not up to the mark? In that case, the research what done in the domain is totally worthless. A dataset which we get is should be genuine and precise also what we want to achieve should be clear, Researcher needs to check their datasets credibility at the beginning of research so the study could not lead to the wrong direction. Next researcher helps to decide the proper credible dataset. Researcher Ghulam Nabi et al. (2017) analyzed different papers, journals, blogs from different electronic databases like SCOPUS, IEEEXplore, ACM, Springer to find the different techniques of wheeze sound analysis using computer-based techniques. in this paper, we will find different approaches to analyze the wheeze sound from multiple dataset sources. Dataset collection starts from collecting wheeze sound from different patients with using different acquisition techniques. as the author describes there are two major approaches when microphone are used to collect the data which is kinematic and acoustic. In the case of mechanical tools vibrations are collected from the condenser and piezoelectric sensors and converted into electronic signals. Also in some studies, air-coupled microphones are used to collect data. As we saw in previous studies Palaniappan (2013) used dataset which is already acquired by RALE and another commercial company MARS use the same techniques to collect wheeze sound data, in both data is collected from the accelerometer and air-coupled microphones. All the data which are collected by the company are standardized by CORSA in which wheeze duration standard are maintained from 100 ms to 150ms. When the dataset is selected According to these standards there will be no need to rethink about the dataset which we are going to use in the researches.

Furthermore in the next study researcher used different data acquisition method in which he collected wheeze samples from normal and infected subjects. Researcher Lozano et al. (2016) used 34 Asthamic subjects to collect the sound samples for study. To form the dataset total of 870 inspiratory cycles samples collected from different quantiles. Totally 861 normal and 633 CAS segment collected to perform this study. All these samples collected from a proper physician under CORSA guideline in which frequency was kept above 100 Hz and duration kept over 100 ms. The data which is collected in this process called as RS Respiratory sound, which needs to decompose before using as instantaneous frequency. For this used Ensemble Empirical Mode Decomposition EEMD algorithm which is an updated version of EMD (Empirical Mode Decomposition).

After this process total, 870 inspiratory cycles were 559 cycles of 20 patients allocated to training purpose and 311 cycles of 10 patients allocated to the testing purpose. All this training data passed to SVM for classification in which nonlinear optimization is done with 10 fold-cross-validation used. Throughout this, all process SVM Classifier also evaluate performance at the cycle level. By comparing inspiratory cycle classification obtained with classifier. In the end, total accuracy was achieved on the training set is 95.4% and on test dataset 94%. In term of specificity and sensitivity are 94.5% and 96% for the training dataset and for testing dataset 92.8% and 94.8% respectively. The overall accuracy of 92.8% was achieved in this study.

Till now the researcher used SVM, Gaussian Mixture Model for processing data which contribute the proper result in their respective studies. Using proper classification model is one of the main aspects from the overall process like previously as we saw the selection of data for research also one of the main aspects. Selecting proper data, feature extraction, using a proper algorithm to run base model are important steps in any research study. Feature extraction is what identify the patterns from the dataset and helps to build an accurate model for precise detection. Most of the time not getting a proper result is a good example of the wrong feature selected which leads to building the wrong model. till now in the Literature review, we saw Researcher used Mel-frequency cepstral coefficient, dominant frequency range, pitch, duration features to extract information from the dataset. But researcher Liu et al. (2016) use Peak frequency component and entropy measures for feature extraction. In the whole process, short-time Fourier transformation and peak detection mask are used. In this Study researcher Liu et al. (2016) used data from National University Hospital in Singapore as well as from the different website. Totally 45 samples used to complete this study in which normal lung sound, Crackles, Wheeze, Stridor included. In this process, the waveform is converted into frames which can help to get clear plots of adventitious lung sound. After that with the using of peak detection system identify the dominant frequency also remove the smaller value from the frequency this done by masking filter.

Masking filter helps to produce N no. of dominant frequency which is denoted by $\mathcal{C}_1, \mathcal{C}_2, ..., \mathcal{C}_\mathrm{n}$. And the normalized values of are computer generated by spectral. To the normal breath sound, the particular distribution tends to become uniform across frequency in addition to time. For stridor, greater separations are observed in in order to occur between the optimum frequency components. Energy circulation of stridor also generally seems to vary more drastically over time compared to some other two adventitious lung noises. hence entropy is the basic feature extraction algorithm used. From this process, the author observed that peak value entropy value larger for stridor, then Wheeze and for normal lung sound and for crackles are much smaller.

In the last step which is a validation of the proposed method is done by The Receiver Operating Characteristics (ROC) analysis. Based on this system 99% accuracy obtained for stridor, 70% for Wheeze, 87% 99% for Crackle and Normal Lung Sound respectively. In this research dataset was used was small size, maybe we can get more accuracy for classification wheeze sound using the same techniques for larger data set and also proper recall.

As we saw the feature selection is one of the main and important steps involved in any research. In previous research, the author Liu et al. (2016) used Peak frequency component and entropy measures for feature extraction with Support Vector Machine (SVM) and got a pretty nice detection rate. But in this study, the Author Mendes et al. (2016) used multi-featured approach for detection of events from frame space which the author used more than 20 features including musical Information Retrieval, wavelet-based features, and Teager energy and entropy. For the classification Logistic Regression Classifier used for further process. In this study, data is collected from 17 patients which are showing sign of adventitious sound and 3 healthy volunteers used. Totally 31 features extracted in this study out of 27 features used for the model. For this process, the wavelet-based method was used on non-stationary part of the sound and extracted data in frames after that Katz fractal dimension feature used to set a first and second threshold which is 0.85 and 1.25 threshold set respectively. Under musical features total 31 features selected using MIR Toolbox in which includes RMS, Roughness, WS-SS, Teager Energy, entropy, etc. all these features are used as feeder to Logistic Regression classifier and run the model to get prediction in which user got overall 91% accuracy for predication and identifying between adventitious sound and normal sound.

In this paper Researcher Li et al. (2012) Aimed at characteristic morphology of crackles in time-domain, which is based on theories of fractional Hilbert Transform with various fractional values. And later correlation function use to build a detection system. The characteristic morphology of crackles based on waves because crackles have sharp and deflection in sounds. As a result of the CMC the task of the recognition generalized to get kind of immediate adjustment signal detection, in this case, Fractional Hilbert Transform shows great effectiveness. After these features like fractional Hilbert transform and correlation coefficient are processed with the threshold method and in result overall 95% accuracy achieved.

In contrast to the previous study Researcher Chen et al. (2019) used Support Vector Machine (SVM), Extreme Learning Machine (ELM) and K-Nearest Neighbor (KNN) used on the publicly available dataset. In this research pre-processing stage, Feature extraction stage and Classification stage are the main steps performed to wheeze sound detection. Under the pre-processing stage, Artefacts were removed such as heart sound, spikes, and other noises and downsampled the Respiratory sound as per CORSA Standards. Also, AMIE_SEG method used to segment the inspiratory and expiratory wheeze sound. For the feature extraction EGST method used because in EGST, S-transform offers better time-frequency resolution as compare STFT, hence ST windows were adjusted as per need which enhances the feature extraction process. once proper feature extracted the input provided to classifier for detection and the output collected is based on a segment level. Overall in this research, researcher Chen et al. (2019) got 98.02% accuracy for SVM classification and 98.29% for ELM classification after 25 iterations.

From the above literature Review of Asthma detection from Wheeze sound we can clearly see the most of the researcher used dataset which are publicly available or derived from commercial website for Research purpose, also feature selection method is also one of the important factors which need to provide as input in various Algorithm. In context of method which are previously used are SVM, ANN, Gaussian Mixture Model, Discriminant Analysis Based Method for classification, and got impressive result with this all techniques. Reviewing all these techniques will really help for further study, next section will describe the opted approach to carry out this research.

Reference	Feature	Method	Performance
Nabi et al. (2019)	Spectral-based Feature	Empirical Methods, Support Vector Machine.	86% Sensitivity and 92% Specificity for EMM, 71.4% Sensitivity and 88.9% Specificity for SVM
Khasha et al. (2019)	Warp per Approch	KNN, MLR	Wheeze Sound detected
Chatterjee et al. (2019)	Peak Amplitude	Statistical Signal Processing	overall 90% Precision and 95.23% Recall
Chen et al. (2019)	EGST, Time-Frequency Resolution	SVM, ELM Extream Learning Machine	98.02% accuracy for SVM Classification, 98.29% for ELM
Pooja (2018)	Chi Square	Random Forest	Overall Accuracy 88%
Ghulam Nabi et al. (2017)	Butterworth filter, Fast Fourier Transform Approach	SVM + ENS	Overall Accuracy ENS 94%, SVM Accuracy 92%
Pramono et al. (2017)	Time-Frequency Domain	CNN	Overall Accuracy 88%
Finkelstein and Jeong (2017)	Duration, Frequancy Range	Nave Bayesian, SVM	80% Sensitivity and 77% Specificity for Nave Bayesian, 80% Sensitivity and 80% Specificity for SVM
R.X.A. et al. (2017)	wavelet network	Discriminant Analysis Based Method	Overall Accuracy 99.75% at Segment Level
Ghulam Nabi et al. (2017)	Wavelet Packet Transform	ANN	98.89% Best Average Accuracy
R.X.A. et al. (2017)	Leave-one-out Cross Validation	Hidden Markov Model	Sensitivity and Specificity 91.10% and 93.43%
Maruf et al. (2016)	Pitch, Spectrogram, Energy, Shannon Entropy, Kurtosis and PSD	ANN, Wilcoxon Rank-Sum and Ansari-Bradly test	Overall 100% Specificity, 92.85% Sensitivity and Accuracy of 97.56%
Lozano et al. (2016)	Ensemble Empirical Mode Decomposition	SVM	On Training set 95.4%, Test Dataset 94%
Liu et al. (2016)	Mel-frequency Cepstral Coefficient, Dominant Frequency Range,	SVM + Gaussian Mixture Model	89% Accuracy for Stridor, 70% for Wheeze, 87% for Crackle and 99% for Normal Lung Sound
Mendes et al. (2016)	Peak Frequency Component, entropy measures	Support Vector Machine	Overall 91% accuracy
Oweis et al. (2014)	Adaptive Neuro-fuzzy Inference Systems	ANN	Overall Accuracy 98.6%
Palaniappan et al. (2013)	time-frequency domain	KNN	Wheeze Sound detected
Palaniappan (2013)	Mel Frequency Cepstral Coefficient	SVM+Non Linear Classification	Accuracy is 90.77% for SVM, 88.65% for NLC
Shaharum et al. (2012)	Time-Frequency domain	Fisher Discriminant Analysis	All Wheeze Sound detected
Li et al. (2012)	Fractional Hilbert Transform, Correlation Coefficient	threshold	Overall 95% Accuracy
Riella et al. (2009)	spectrogram signature	CNN	Overall Accuracy 84.82%

3 Research method and specification

From the above Literature review we can clearly see that the data which we are using is in audio format, also dont have any idea about any sound clip which is infected or not. In that to Achieve the Desire result, KDD Knowledge Discovery in Database technique will help to identify the different aspect of Dataset Kavakiotis et al. (2017). KDD process includes multidisciplinary activities which include Data Gathering, Cleaning, Exploration, and Data mining. One of the main steps include in KDD is choosing the mining algorithm to discover hidden pattern from the dataset and with the help of those patterns create a model for the overall process.

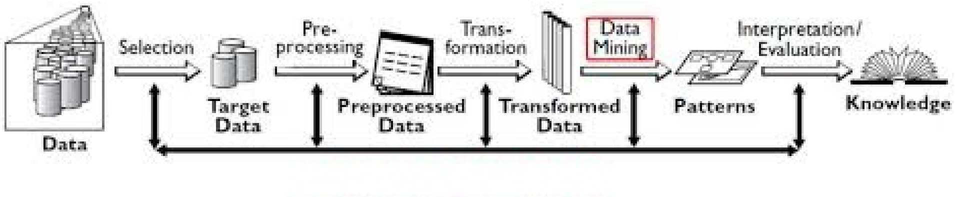

Figure 1: Knowledge of Discovery Database

3.1 Data Gathering

For this study, Data gathering is one of the important factors from others. Till now from literature review we analyzed that data is base key to initiate any study, in case of identifying wheeze sound from lung sound, data should be well maintained, and precise. Also, data should contain the combination of crackles, Wheeze Sound, and Normal breathing sound in well-balanced form. To continue this study further data which used is derived from ICBHI Challenge which is freely available. The recording collected by using heterogeneous equipment and their duration from 10s to 90s This data contains audio files, totally 5.5 hrs of recording which include 1863 crackles, 886 wheezes, and 506 contain both crackles and wheeze which is collected from 128 subjects. The cycles were annotated by simply respiratory experts as which includes crackles, wheezes, a combo of them, or not any adventitious respiratory sounds. Each file from Dataset having 5 elements which contained Patient number, recording index, chest location, Acquisition mode, and recording equipment. Also, this dataset having text files which contained Participant ID, Age, Sex, Adult BMI (kg/m2), Child Weight (kg), Child Height (cm). [1]

3.2 Data Cleaning

As data set explained in the above section having files in WAV format. And some files in text format. As discussed, the text file contained information about patients. Hence, in that case, there might be some junk values or missing values available. in that case, Data Cleaning process helps to remove this value Kaiser (2016). For the cleaning process, we will use Python programming for software for clean and check text-formatted files.

[1]DataSet Link: https://bhichallenge.med.auth.gr/

3.3 Data Mining

Typically, the digging through data to find out the connection and foresees future trend called data mining, data mining also known as Knowledge Discovery in Databases. Before building the prediction model. To need to build a model we need to organize the data in such a way in that some part of data should be unique for the prediction. There are two ways to do this thing either Hold out and Simple split or Cross-validation techniques Lee et al. (2018). Hold, out and Simple Split technique data is split into two parts randomly for training and testing purpose. training data is a data where we train data with model and on testing data, we check the trained model. Usually, 80-70% of data is allocating for training purpose and remaining keep for testing purpose. In our study, we will use cross-validation because this methodology gives the opportunity to train on multiple train-test divides and hence we will get a better guide to check how well our model performs on unseen data. Also, hold on and Simple split is good to use when we are using large dataset.

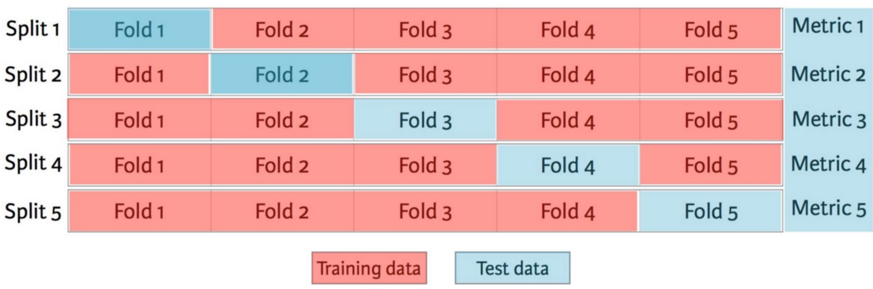

Figure 2: Cross Validation

Once data is prepared to build the training model, we are ready to perform some classification method on the dataset Hämäläinen and Webb (2019). As we see while reviewing literature, classification and regression model are performed best till now, so we will use these techniques to get the more proper and accurate outcome. But still, in some case, the result which is getting in the literature review is contradicting some other techniques, hence, to overcome this drawback we will use multiple techniques to increase the prediction rate and to get proper and handy output. Also, with the help of these, we can able to find out which model is become handy and shown more suitable for sound classification. subsequently, below 3.4 are the models which we will train on a dataset in order to evaluate the result and to answer our research question.

3.4 Classification Models

3.4.1 Support vector Machine

In this research, we are going to embrace the Support Vector Machine. As we see most of the researcher Chen et al. (2019), Finkelstein and Jeong (2017) used support vector machine model to classify the wheezing sound and they got a pretty good result. We will try to enhance the result which bothers research acquired in this study. SVR With the use of associated kernels is a powerful supervised technique which offers the capability to handle both linear and nonlinear parameters VAVREK et al. (2010). SVM set a boundary at the certain distance from the hyperplane and the information points which can be nearest in order to the plane and are also within the boundary region will be selected as the almost all suitable predictors.

Hyperplane can be written mathematically as below.

$$\beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dot{..}. + \beta_n * x_n = 0$$

In this research, SVM can end up being turned out to become a great choice associated with the regression model because it considered a single of the most efficient amongst the regression model.

3.4.2 Decision Tree

In this Research the technique we are going to adopt is Decision Tree which will become as a novel technique. as from the literature review, we can clearly see the Decision tree algorithm is not yet used. The reason to use this algorithm is firstly it's highly accurate and robust and secondly it's simple and efficient for real-time efficient. We can achieve excellent results with the combination of proper feature selection and the decision tree. this algorithm uses the various time-domain parameters like audio signals, zero-crossing rate and frequency domain paraments like spectral energy and Mel frequency cepstral coefficient (MFCC). As per this research done by Chen et al. (2019) decision tree algorithm consist of two-phase, in 1st phase, can collect data from wheeze sound separately and set the threshold to analyze the feature separately. And in 2nd phase input signals can divide into short time segment and feature extraction and all features can compare with their corresponding threshold. also, various post-decision techniques can use to improve the classification.

3.5 Feature extraction:

3.5.1 Mel-frequency cepstral coefficients (MFCCs)

Mel frequency cepstral coefficients is a representation of the short term power spectrum of sound in sound processing. MFCCs is based on the linear cosine transform on a log power spectrum. Most of the time MFCCs is commonly using as a feature in speech recognition and sound analysis. In this process, we need to process the signal in small segments, that process called segmentation. Initially segmentation help to improve the accuracies in our study. In this study researcher, Rubin et al. (2017) did segmentation with sounds, then using Mel-frequency cepstral coefficients we can use capture the features from the segments. Researcher initially create segments of each audio files, then using Fourier transformation technique extracted features from each segment and then that features used as input for the model. Researcher Chapaneri (2012) shows another approach of Weighted MFCC which is updated version MFCC. In research, the researcher uses Weighted MFCC for feature extraction. The advantages of this approach are mainly for compress the signal into a feature and, secondly use that feature for the recognition process. with the use of a few steps author extracted features. Initially, using Pre-emphasis filter author reduced the negative frequencies to improve the efficiency of spectral analysis. After that, signals are converted in small frames and cepstral and spectral analysis performed on those frames. After the framing process windowing process done in which all frames divided in small moving windows, so after that, it became possible to select a small amount of data to efficiency purpose. Furthermore Spectral coefficient of each frame estimated using fast Fourier transform method. And finally, Mel filtering used to extract the features. The same procedure will help us in this study to identifies the wheezing sound for asthma detection. The formula will be used to calculate Mel Frequency will be :

$$f_{mel} = 2595 * log_{10}(1 + \frac{f}{700})$$

3.5.2 Dynamic Time Wrapping

In time series analysis, to compare the similarity between two temporal sequences, Dynamic time wrapping is used. This technique can be used for speaker recognition and signature recognition. Researcher Tan et al. (2015) and H.Mansour et al. (2015) uses Dynamic Time Wrapping technique to calculate the distance between two-time series that vary in time. DTW looks for the similarity between two signal. this technique will help in our study to capture the high and low frequency. Also, we can shrink and stretch the signals to compare the two frequency which will help to identify and enhance the pattern in a proper way which also enhances the input that providing to our model.

3.5.3 Entropy of Energy

Basically, Entropy is used to measure the energy of dispersal. In which we can quantitatively relate the energy distribution based on temperature Yoo et al. (2019). As in Sound analysis, we can use this technique to extract the information from a single frame. Sound analysis is totally depending on the frequency of high and low nodes. High node frequency can be measured and visually seen with the use of Entropy of energy. In 2017 author Djebbar and Ayad (2017) use Entropy of energy technique to calculate that how much energy of amount a signal carries. In the same research, the author used the same techniques to identify the energy and after detecting minimum energy which needs for further process, using visualization of Energy Entropy removed unwanted data, these steps increase the efficiency of the model . In our study, we can use these techniques to reduce the unwanted noise which is generated by other organs and that captures in our audio dataset. Visualization of this energy can helps to identify the high and low pitch signals, which we can use that as input. The basic formula to calculate the signal Entropy

$$H(x) = -\sum_{i} p(x_i) \cdot \ln(p(x_i))$$

Where :

$P(x_i)$ is the probability of signal

3.6 Proposed Evaluation Metrics to Measure Performance of The Models

Every model has its own errors and these errors are mostly called as bias; these errors are reducing the performance of Machine Learning model. So to tackle these drawback we need to find out how much these model performed well. For this, we need evaluation techniques which can help to find out the performance of model **?**.

3.6.1 Confusion Metrix

A confusion matrix is mostly known as the contingency table in which a matrix form based on a number of variables available. CM is one of the most famous and common evaluation models to calculate the performance of any model. There are total 4 important terms are in confusion matrix, which is True Positive, True Negative, False Positive and False-negative Santra and Christy (2012). In our Research Confusion matrix will help to evaluate the model which classify the asthma detectionConfusion matrix1. The advantage of a Confusion matrix is that the number of correct and incorrect predication summarize in a matrix with values in each class, hence it became easy to understand any layman.

Accuracy of the matrix is calculated on the below equation.

$$Accuracy = \frac{\text{True Postive} + \text{False Negative}}{\text{Total number of Sample}}$$

3.6.2 k-Fold Cross-Validation

K -fold cross-validation is techniques divide total dataset split into K sets. And, each set of Dataset selects only once. And then one by one all set used as validation set until all possible combination has been evaluated Wong (2015). This technique is one of the common techniques which are used in Cross-validation techniques.

3.6.3 Root Mean Squared Error (RMSE)

RMSE is used to calculate the error rate of regression model which means we can calculate the difference between the predicted values and actual responses. Studies like used same to evaluate the measure. It is calculated as below

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (p_i - a_i)^2}{n}}$$

Where:

$$a = \text{Actual Target}, \; p = \text{Predicted Target}$$

3.7 Project Plan

Below Gantt chart shown an overview of plan where the project will can be carried out over the coming semester.

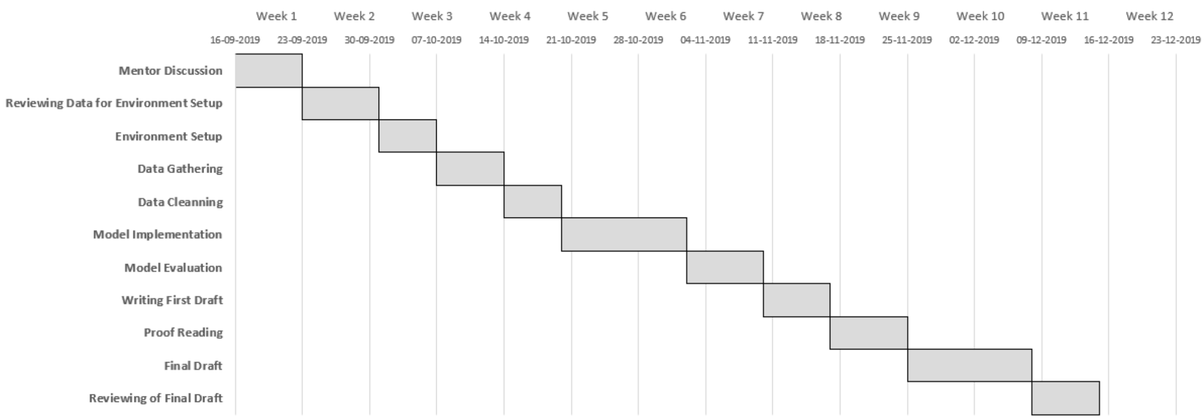

Figure 3: Gantt Chart

All Methodology is Explained in below Chart [2] :

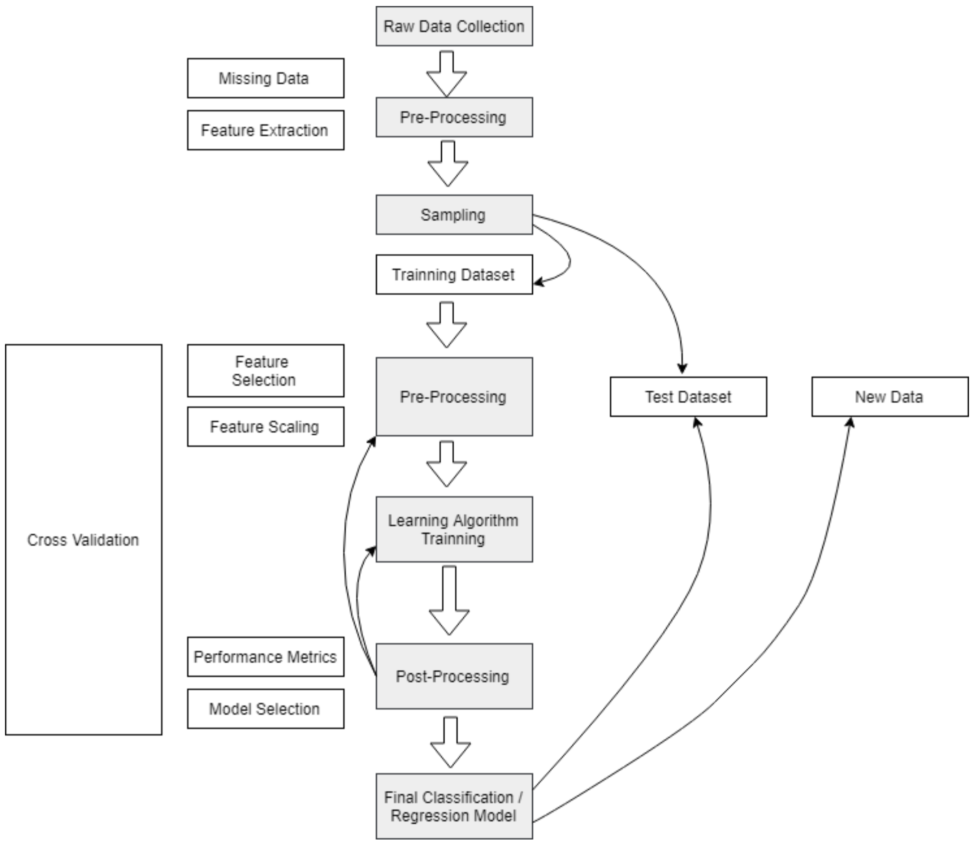

Figure 4: Proposed Process

4 Summary

After reviewing all papers from literature review we can clearly say that even though some of the machine learning models are used to perform the classification of wheeze sound and with the respect of that most researcher got proper outcome, but still some aspect of the machine learning model unfolded yet, so with the use of different model we can try to get the better performance which can help to classify the asthma. In this methodology different models like Support Vector Machine and Decision Tree are planning to use with MFCC, Dynamic Time Wrapping, Entropy of Energy features, that will use as input for the model. This techniques and features will lead us to classify the wheezing sound for Asthma detection with more precision and accuracy. At the end of the report detailed project plan showing the various steps and process involved in this study which will help to get the expected result in the limited time stamp.

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[2]https://www.draw.io/

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