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Cardiovascular Disease Detection using SVM

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Abstract: *Cardiovascular Diseases are commonly identified using a stethoscope. Currently there are so many device like digital stethoscope and mobile device can be used for this purpose. Without medical knowldge it will be difficult to identify the Heart irregularities. The paper introduce a new method to classifying heartbeat. It is on the basis of classifying audio heart recordings to five most commonly occuring classes that are artifact, extra heart sound, extrasystole, murmur and normal heart beat. this method is also check the precision accuracy of SVM method. This paper is also outlines practicality and next step to improve classification of heart sound.*

Keywords: Heartbeat Sounds, Heartbeat Feature Extraction, Classification of Heartbeats

I. INTRODUCTION

In Human heart is the most important organ in the body that provides blood to all parts of the body using a pumb like reaction.During the pumping reaction, electrical and mechanical activities are carried out resulting in the flow of blood. Healthy heart is very important for the normal day to day working of human body as blood carries important nutrients to the organs. Cardiovascular disease are responsible for a major proportion of death all around the world. According to survey conducted by the WHO 33% of all deaths are the results of CVDs. Different modalities are known to exist to monitor the health of heart.[6]

Stethoscope detection currently provides one of the first warning signs of heart disease. During this procedure which usually occures in ones annual physical examination, physicians manually listen for and identify variations in heart sounds that indicate a need for further investigation. Early detaction and intervention in heart disease greatly improves the lifespan and the effectiveness of treatment option. For this reason, the benefit of placing the first detection capability in the hands of the individual are immense. This study aims to use machine learning methods to identify and classify heart sound from audio collected from stethoscope and mobile devices available to the average consumer. From the audio heart sounds, 18 features, various machine larning methods are used to identify different catagories.[6]

This paper analyse the accuracy and performance of the support vector machine (SVM) method.Also it helps to identifying different features of heart sounds and classifying heartsound based on five classess.In different heart sounds, resulting from mechanical cardiac events and heared from stethoscope examination can be indicators for various heart health concerns. Typically heartbeat creates two sounds lub-dub, that can be heared through a tethoscope.

S1 and S2 are the first and second hearts sounds in a beat.the first heart sount results from the closing of the mitral and tricuspid valves. Result of this process is generation of sounds. The first heart sound by the closure of mitral valve tremed as M1, and second sound produced by closure of tricuspid valve is termed as T1. M1is much louder than T1, due to higher pressure in the left side of the heart.M1 radiates to cardiac listening posts and T1 is only heared at the left lower sternal border. Hence this makes M1is the main component od S1.S2 is a heart sound produced by the closure of the aortic and pulmonic valves. The sound produced by the aortic valve closure is termed as A2 and sound produced by the pulmonic valve closure is termed as P2.A2 sound is much louder than P2 because of high pressure created in the left side of the heart. Here A2 radiates to all cardiac listening post so it is the main components of S2. The P2 is only heared athe left upper sternal border.

Any abnormality in heart structure are often reflected in heartbeat sound. A few most common abnormal sounds occur in heart physiology is classified and identified are murmurs, extrasystole, extra heart sounds, artifact. Murmur is a sound that occur when there is a turbulence in blood flow it causes extra vibration in heart sounds. Extra systole is due to premature contraction of heart causes an extra sound before S1 and palpitations. This is because the abnormal electricalcircuitry within the heart. Extra heart sound occurs after diastole, S2 due to sudden deceleration of bloodand caused by abnormalities in cardiac muscle physiology that affect contraction characterstics. Artifact were also included this sounds to evaluate how robust the machine elearning models were in recognition of whether or not an audio sample. There are a few studies that have also done work in classifying various heartbeat sounds using machine learning methods. However, the majority has focused on data obtained from phonocardiography (PCG), which is graphical of heart sounds that are obtained via high-fidelity sensors during medical diagnosis, a technology that is not widely available to the average consumer Using PCG datasets from PhysioNet, toper form classification using various models. The classification of heart sound signals based on AR models was studied by He, achieving an overall accuracy score of 74%. Ryu used convolutional neural networks to determine normality ,and does not offer specificity into the type of abnormality if observed. Singhal so uses PCG data to study effectiveness of features and various classifiers in distinguishing between normal and murmur heart sounds. This study is based on Peter J Bentleys dataset, containing audio data, for his Heart Sound Challenge, wherehe has done preliminary analysis that resulted in 77% precision in identifying normal heart sounds. The main difference between this dataset and data obtained from PCG is that PCG conducted in a professional controlled environment, using sophisticated technology,that is able to produce clean and relevant signals. The data used for this study is derived from consumer, app-based retrieval of heartbeat audio for the purpose of exploring capabilities of machine intelligence in identifying heart abnormalities through technology available to the hands of the public.[6]

II. LITERATURE REVIEW

In a cardiac cycle, the electrical activity is firstly generated by the cardiac pacemaker, which then triggers atrial and ventricular contractions. This in turn pumps blood flowing between the chambers of the heart and around the body. The opening and closing behaviours of the heart valves are associated with acceleration and deceleration of blood, giving rise to vibrations of the entire cardiac structure and thus producing the heart sounds and murmurs. These vibrations are audible at the chest wall, and the heart sounds can reflect the health condition of the heart. The phonocardiogram (PCG) is the graphical representation of a heart sound recording. Fundamental heart sounds (FHSs) usually consist of two components: the first (S1) and second (S2) heartsounds. Although the FHSs are the most recognizable sounds in the heart cycle, the mechanical activity of the heart may also cause other audible sounds, such as the third heart sound (S3), the fourth heart sound (S4), systolic ejection click (EC), mid-systolic click (MC), diastolic sound or opening snap (OS), as well as heart murmurs caused by the turbulent, high-velocity flow of blood. The segmentation of the FHSs is the first step in the automatic analysis of heart sounds. Previously several segmentation methods have been developed in the literatures. The automated classification of pathology based on heart sound recordings has been performed for over 50 years. However, massive challenges still remain now. Gerbarg et al. were the first group to attempt the automatic classification of pathology in PCGs using a threshold-based method, motivated by the need to identify children with rheumatic heart disease (RHD). Artificial neural networks (ANNs) have been the most widely used machine learning-based approach for heart sound classification. Typical relevant studies used different signal features as the input to the ANN classifier, including wavelet features, time, frequency and complexity-based features, and time-frequency features. A number of researchers have also applied support vector machines (SVM) for heart sound classification in recent years. The studies can also be divided into different groups according to the feature extraction methods, including wavelet, time, frequency and time-frequency feature-based classifiers. Hidden Markov models (HMM) have also been employed for pathology classification in PCG recordings. Clustering-based classifiers, typically the k –nearest neighbours (KNN) algorithm, have also been employed to classify pathology in PGCs. In addition, many other techniques have been applied, including threshold-based methods, decision trees and discriminant function analysis.[1]

The aim of this study is to develop a method for classification of heart sounds into normal and abnormal sounds so that state of heart could be periodically checked at home and everybody doesn’t have to wait for symptoms of disease to appear and then approach a cardiologist. The PCG signals can be an early indicator to heart problems so before worsening of the problem, a proper diagnosis can be done. Then, the other techniques like Echocardiography could be implemented to get a better view of problem. So, the proposed method is not a replacement of other techniques but an early indicator to the problem in order to prevent worsening of the situation. In this study the PCG signals were analyzed for normal and murmur heart sounds and established that between the fundamental heart sounds S1 and S2, the amplitude of the murmur signal is higher than normal signal Then the segments between S1 and S2 of same cardiac cycle, S2 of one cardiac cycle and S1 of next cardiac cycle were selected for further analysis. The features were extracted in order to differentiate between normal and murmur signal[2]

Feature extraction is a process of dimensionality reduction by which an initial set of raw data is reduced to more manageable groups for processing. A characteristic of these large data sets is a large number of variables that require a lot of computing resources to process. Feature extraction is the name for methods that select and /or combine variables into features, effectively reducing the amount of data that must be processed, while still accurately and completely describing the original data set. The process of feature extraction is useful when you need to reduce the number of resources needed for processing without losing important or relevant information. Feature extraction can also reduce the amount of redundant data for a given analysis. Also, the reduction of the data and the machine's efforts in building variable combinations (features) facilitate the speed of learning and generalization steps in the machine learning process.[4]

III. SYSTEM STUDY

Any abnormality in the heart sound may indicate some problem in the heart. In this paper, the phonocardiogram (PCG) signal i.e. the digital recording of the heart sounds has been studied and classified into three classes namely normal signal, systolic murmur signal and diastolic murmur signal. Total number of samples used for this study are 144 out of which 60 are normal signals, 45 are diastolic murmur signals and 39 are systolic murmur signals. Various features have been extracted for the classification. A total of 28 features have been extracted and then reduced to 7 most significant features using feature reduction technique.

The system provides dead reckoning by Inertial Navigation System which uses IMU sensors that has accelerometer and gyroscopes. Acceleration will give linear acceleration of vehicle which can be used to calculate velocity and thereby distance travelled. Gyroscopes will give angular velocity of vehicle which can be used to calculate directional changes of vehicle. With this information, microcontroller using the positioning algorithm [7] calculates the position and will be displayed (Fig. 1).

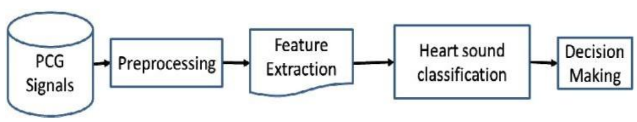

Fig.1. 1 Block diagram of the heart abnormality classification system

3.1 PCG Signal

Phonocardiogram (PCG) signal represents recording of sounds and murmurs resulting from heart auscultation. Analysis of these PCG signals is critical in diagnosis of different heart diseases. Over the years, a variety of methods have been proposed for automatic analysis of PCG signals in time, frequency, and time-frequency domains. PCG are highly correlated signals. PCG, however, enjoys a distinct advantage over ECG and PPG signals as it records the acoustic properties of the signal. These properties are better suited for murmur detection which represents abnormal heart sound . Furthermore, PCG signal also has an excellent starting trigger in the form of S1 wave. The mechanical activity of the heart can be heard using a traditional or an electronic stethoscope. Auscultation or listening to heart is an old but very effective method of diagnosis for a number cardiovascular diseases. The recording of these sounds (PCG signal) has the same spectrum as that of audio signals. The recording process, however, also picks noisy sound signals from the environment which distort the periodicity of the PCG signal making its analysis a challenging task.[6]

3.2 Data Sets

Two different datasets are used to verify the performance of the machine learning models. Dataset A has four classes with 120 total samples. The four classes are artifact, extra heart sound, murmur and normal heartbeat. This data was collected from the general public using an iPhone application, iStethoscope Pro, which collects 44100 samples of heart sounds per second. Dataset B has fewer classes and more samples, which were collected from a clinical trial in hospitals using a digital stethoscope, sampling heart sounds at 4000 samples per second. This dataset consists of three classes and a total of 461 samples, 149 of which are noisy. The three classes are extrasystole, murmur and normal heartbeat. These two different datasets are used to verify the generalizability of the machine learning models, as well as to compare both dataset results with the current state of the art [bentley].[6]

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3.3 Preprocessing

It is prior that in feature extraction, the audio signals were preprocessed. The preprocessing includes removing audio files that are less than 2 seconds, downsampling, removing high frequency noise and normalizing the data. Files less than 2 seconds are removed because those files do not capture a full heartbeat cycle, making it impossible to extrapolate whether or not those samples contain heartsound irregularities. For dataset A, a total of 120 samples are used and for dataset B, a total of 407 samples are used. The data for dataset A is first down sampled by a factor of 5 and then downsampled by a factor of 2 using wavelet decomposition. Due to the high sampling frequency of 44100 Hz for dataset A, downsampling reduces the size of the data while preserving all relevant information. The final sampling frequency of 4410 Hz is still higher than double 600 Hz, which is frequency of murmurs, the highest heart sound frequency forthese datasets. It is required that the sampling frequency is greater than twice the frequency of murmurs due to the Nyquist sampling rate. For dataset B, there is no initial downsampling, however, after the wavelet decomposition, the data is downsampled by 2. The final sampling frequency of 2000 Hz is also higher than the highest heart sound frequency of 600 Hz. Wavelet decomposition with a fourth-level order six Daubechies filter is used to denoise the signal, which proved beneficial from the results of previous papers . After the wavelet decomposition, the audio files are normalized to the same length as the shortest file length, which is 14272 for dataset A and 4011 for dataset B. The audio files capture 3 seconds and 2 seconds of heart sounds for dataset A and B respectively. These lengths are sufficient for capturing heart data for feature extraction. Since the heart sound files were recorded manually, the amplitudes for each file are different. Thus, the audio files are normalized to a maximum amplitude of 1 so that the strengths of the recorded signals will not impact the model performance.[6]

3.4 Feature Extraction

For feature extraction, the signals were analyzed in two groups. For the first group of extractions, the entire signal was analyzed in both the time and frequency domain. The second group uses significant parts of the signal as a whole to extract features. The significant parts of a signal are S1 and S2. A total of 18 different features were extracted, seven of which are based on the entire signal. The features extracted for the first set of features in the time domain are zero crossings, energy and entropy of energy. In the frequency domain, spectral spread, spectral entropy, spectral flux and Mel Frequency Cepstral Coefficients (MFCCs) were used. All features except MFCCs, were extracted using pyAudio Analysis, a python library for audio signal analysis. For MFCCs, another python library, python speech features, was used. Zero crossings is the rate of sign changes of the signal during the duration of a particular frame. This captures frequency and intensity information, which was successfully used for speech recognition tasks.

Figure III and Figure III illustrates results for dataset A and dataset B zero crossing respectively. The zero crossing for murmurs in dataset A, shown in purple, is the most distinct class. From Figure III, there are no distinct differences between the classes. Energy is the sum of squares of the signal values, which are normalized by the respective frame length. There is no apparent distinction between classes using this feature, however, the average value of the murmurs are slightly higher than the other classes. The average value of the normal heartbeats classes are slightly higher than extra heartsoundsand extrasystole classes. The entropy of energy is the entropy of the signals' normalized energies and can be interpreted as a measure of abrupt changes. Although the data is clustered together, the data points from Figure III and III are distributed among the center of each class. Spectral spread is the second central moment of the spectrum. This shows how the frequency is spread in a given class. From the results, it shows that spectral spread captures features of artifacts, extra heart sounds and murmurs well for dataset A.

For dataset B, extrasystoles are clustered within a small range, as shown in Figure III, however, due to the large spread of murmurs and normal heartbeats, some of the data points are in the same range as extrasystoles. Spectral entropy is the entropy of the normalized spectral energies for the frequency spectrum of a signal.The results for dataset A show that artifacts on average have a larger entropy and murmurs have a lower entropy. For dataset B, extrasystole and normal heartbeats have similar entropy ranges, while murmurs and the noisy signals have higher entropy values. Spectral flux is the squared difference between the normalized magnitudes of the spectra of two successive frames. To get two successive frames, each sample was split in half, with the first half as the first frame and second half as the second frame. The clusters of classes are more evident in dataset A, where each class has a different range of values compared to dataset B. MFCCs represent where the frequency bands are nonlinear but distributed according to Mel-scale . MFCCs are typically used for speech recognition tasks dueto its generation of coefficients being unique for each user.

For the feature extraction of heartbeat signals, the top three principal components for the MFCCs are used. Each component also contains one feature vector. The mean and standard deviation is taken of the feature vector as features, which results in a total of six MFCCs features representing each sample. Figure III and III show the standard deviation of the first principal component for dataset A and B. For dataset A, the MFCCs show a distinction between artifacts and heartbeats. For dataset B, the MFCCs are all within a certain range and does not give a clear distinction between classes except that murmurs tend to have more deviations in coefficients. The second group of features is characterized by the sequence of S1 and S2 in each audio recording. These spikes were found by modifying the existing Python function: find peaks cwt() to identify spikes above 15% of the signals normalized amplitude. To distinguish between S1 and S2 peaks, a similar strategy to Bentley and Deng was adapted.

Clinical research concluded that the diastolic period between S2 and S1 is normally longer. Thus, the maximum difference between two peaks was declared the diastolic period with the first peak labeled as S2 and the following peak as S1. The starting and ending boundaries of each S1 and S2 were determined based on observation. Different bounds were determined for dataset A and dataset B due to different sampling rates and signal quality. Six statistical features in the time domain were found according to the S1 and S2 peaks. These features include the time between peaks, standard deviation of the intervals and the maximum to mean ratio of each peak. The duration of the diastolic period was chosen because it has proven to be a consistent predictor of murmurs in current models . To calculate the maximum to mean ratio of each peak, the signals were first normalized and rectified. The maximum value within each S1 and S2 along with the mean value of a peak interval was used for this calculation. Since each heartbeat exhibit different oscillations and amplitudes, the standard deviation within each interval and the deviation of the diastolic period was used to represent the different classes within each dataset.

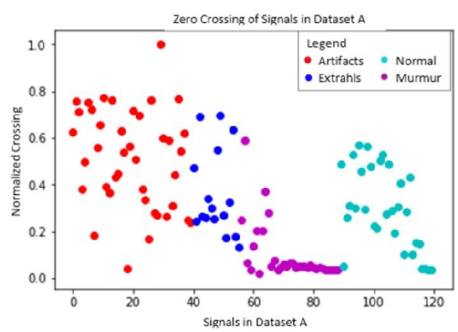

Fig 1.zero crossing result of dataset A.

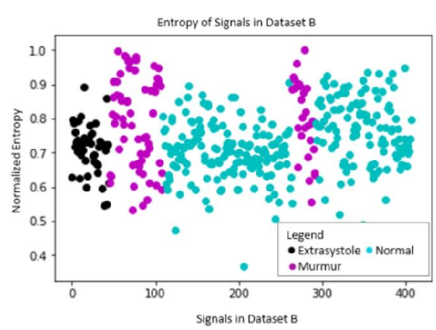

Fig 1.3 entropy of energy for dataset B

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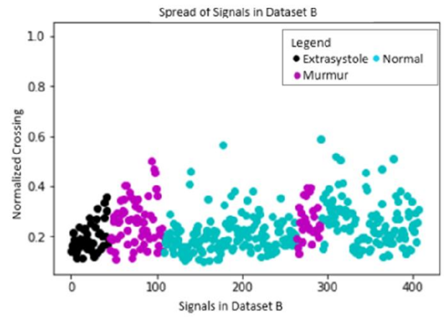

Fig 1.4 Zero crossing result of dataset B

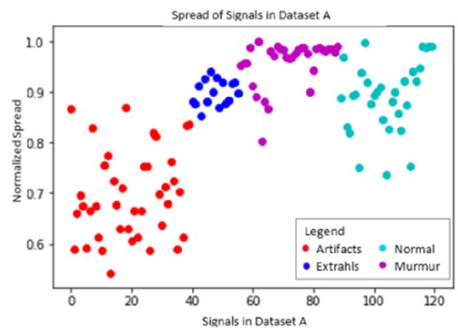

Fig 1.5. Spectral spread result of dataset A.

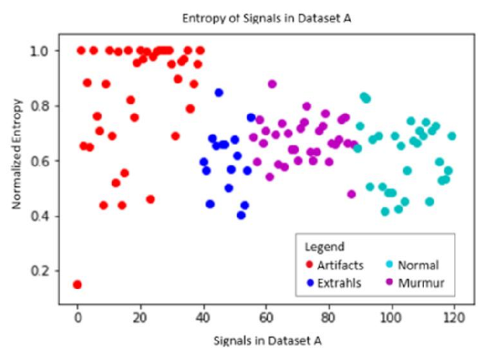

Fig. 1.6. Entropy of energy for dataset A.

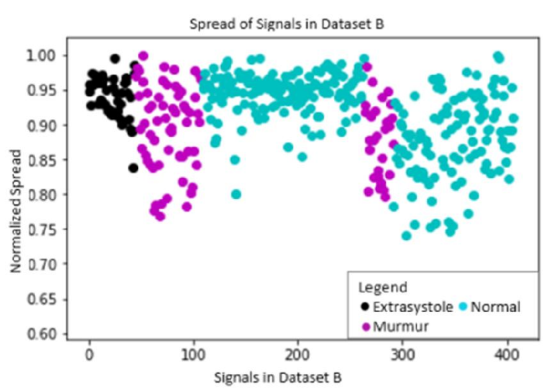

Fig. 1.7 Spectral spread result of dataset B

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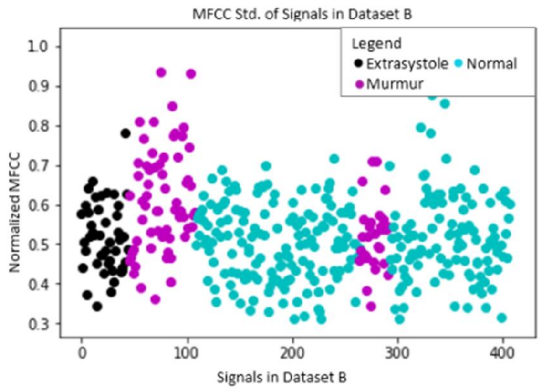

Fig 1.8 Standard deviation for dataset B

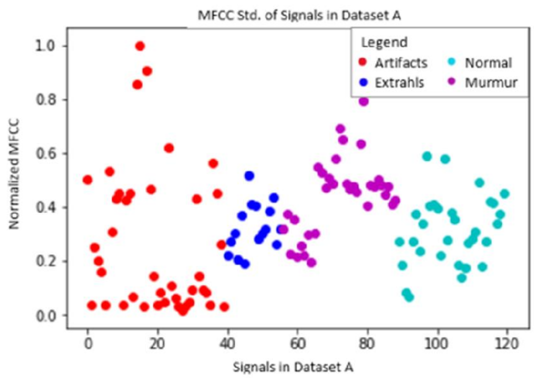

Fig 1.9 Standard deviation for dataset A

IV. METHODS

4.1 Support Vector Machines

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily,it is used for Classification problems in Machine Learning.The goal of the SVMalgorithm is to create the best line or decision boundary that can segregate n dimensional space into classes sothat we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane. SVM chooses the extremepoints/vectorsthat help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine.

SVMs is used for audio classification tasks. SVMs with MFCCs for speech recognition using a limited dataset size and achieved improvementin recognition rates. It also used SVM to classify content based audio using perceptual and cepstral features. They found that given the feature set, SVMs were able to learn optimal class boundaries between classes. Based on the results from previous works and in addition to SVMs working well with MFCC features, SVMs are also used in this paper. SVMS are a supervised machine learning method used for classification. A subset of training points, called support vectors, are used for the decision function which also makes this technique memory efficient. Similar to Bayesian Classifiers, SVMs are also versatile as there are different kernel functions that can be specified for decision functions to classify classes in higher dimensions.Here SVM with radial basis function (RBF) kernel and C support vectors are used, which was implemented by Sciki Learn .The C parameter is a penalty for the error term. SVMs with large C values will choose a smaller margin hyperplane if that hyperplane is able to have higher correct classifications. To control the RBF kernel, both gamma and the C parameter are used. Gamma defines how much influence a single training example has, where a large gamma has little influence and results in the support vectors only including themselves. For the training, C and gamma are both set to 1 for dataset A and B.

V. CONCLUSION

The process of classifying heart sounds is presented and machine learning techniques for this task are compared. Two audio heart sound datasets are used to check and verify the SVM method. Mainly four process is taken to acheive heart sound classification thats are collecting dataset,
preprocessing,feature extraction, compare these feature with exisisting result .Preprocessing was done to normalize the data. Feature extraction then uses the preprocessed data to extract features using the whole signal and significant parts of the signal, such as S1 and S2. Using the feature extracted, SVM is used to classify heartbeats. Based on the individual class precisions, the results are significantly better than the state of the art results except for the precision for extrasystole and normal heartbeats.the SVM classifier is found to be the most promising approach to classifying audio heart sounds. However, when selecting methods to use in practice, a classifier which provides explainability as well as high precision, such a gradient boosted trees, are preferred. Additionally, improvements to feature extraction techniques and handling of unbalanced datasets still need to be made to improve the result of these models.

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