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ORIGINAL CONTRIBUTION

Heart Sound Classification and Feature Selection Using Support Vector Machine (SVM)

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ABSTRACT

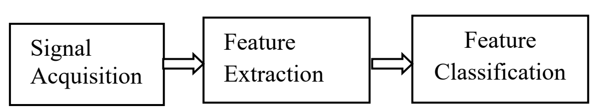
Due to rapid advancement in technology and big data science, recently a significant amount of work has been carried out in the field of feature extraction and classification techniques of heart Sound using machine learning. Usually, physicians use an acoustic stethoscope to detect abnormalities in the heart sound and predict abnormal conditions of the human heart. As the frequency range and intensity of heart sound is very low, doctors are facing problems while detecting the cardiac sound and its abnormalities. Thus feature extraction and classification techniques of heart Sound provides a better way of study of Phonocardiography (PCG) Signal Analysis which eventually reduces the cost, makes the system compact and at the same time can work with big data. Feature extraction and classification techniques are getting wide spread acceptance in a variety of fields. This paper provides a review in the field of feature Extraction, Selection and Classification technique of heart Sound using the concepts of machine learning. Different aspects of feature selection and classification techniques of heart sound have been addressed in this paper. This paper can serve as a basic reading material for students and researchers pursuing research on PCG Signal Analysis using machine learning.

Index Terms—Machine Learning, Feature Extraction, Classification ,Acoustic Stethoscope, PCG Signal.

1. INTRODUCTION

HUMAN being heart makes sounds. The sounds come from the bicuspid/mitral valves, the tricuspid valves, and the aortic valves. As these valves contract and relax, allowing blood flow to and from the heart, they produce the heartbeat sound.

Feature Extraction [1, 27] and Classification proves to be very effective when it comes to Phonocardiography (PCG) signal analysis. Although many advances have been made towards automated heart sound segmentation and heart pathology detection and classification, an efficient method for noise handling would come as a major aid for further development in this field, especially when it comes to working with PCGs collected in realistic environments such as hospitals and clinics. The feature extraction has been gone through different levels on PCG recorded signals using transformation techniques. Analyzing PCG signals with calculating parameters such as Energy, Average Power, Root Mean Square Error (RMSE), THD (Total Harmonic Distortion), Zero Crossing Rate (ZCR), Standard deviation, Variance, Kurtosis and skewness values of human heart signal which we re-extracted from Phonocardiogram were calculated and then a classification made based on different Machine Learning algorithms as explained in Figure 1.



Figurer 1: Various steps Involved in Phonocardiography (PCG) Signal Analysis [2]

II. LITERATURE REVIEW

The entire work is focused on the detection, diagnosis of cardiac sound and its analysis using different feature extraction techniques and classification methods using Machine Learning algorithms with the help of MATLAB and PYTHON software. A healthy heart beats in a continual rhythm. There are varieties of abnormal heart sounds, some of which are harmless, while others can indicate serious heart problems.

Heart sounds [3, 21] are the noises generated by the beating heart and the resultant flow of blood through it. Specifically, the sounds reflect the turbulence created when the heart valves snap shut. In cardiac auscultation, an examiner may use a stethoscope to listen for these unique and distinct sounds that provide important auditory data regarding the condition of the heart. To start with, we should discuss a few words about the physiology of heart sounds, which includes the cause of generation, characteristics, etc. The Relationship of heart sound with the cardiovascular system is given below in Figureure 2 and in Figureure 3 different types of Murmurs associated with Cardiovascular System have been shown.

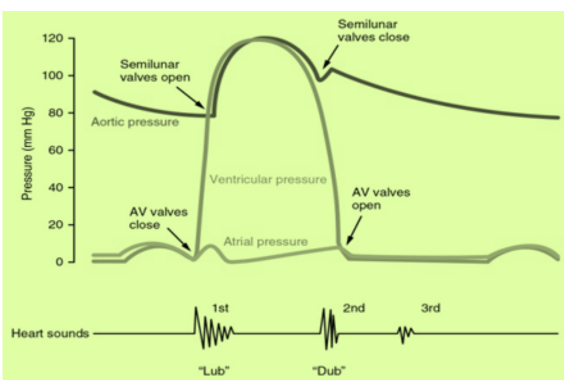


Figure 2: Relationship of heart sound with cardiovascular system

1000 samples of heart sounds have been collected in wav format using MAT LAB and then after the application of AI Modeling, the classified waveforms of different diseases have been diagnosed. For our analysis, mainly 5 different kind of heart sounds have been considered. They are Normal Sound, Aortic Stenosis, Aortic Regurgitation Mitral Stenosis and Mitral Regurgitation as given in Figure 3.

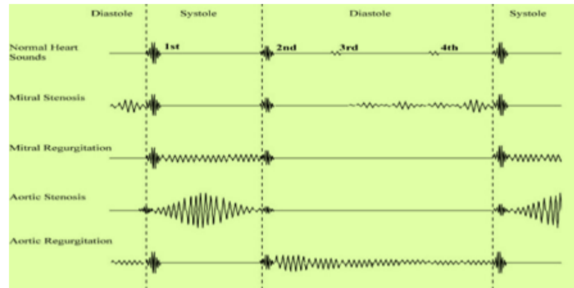


Figure 3: Different types of Heart Sounds

In healthy adults, there is two normal heart sounds often described as:

1. *Lub*2. *Dub*(or *dup*)

[4, 44] LUB and DUB occur in sequence with each heartbeat. These are the **first heart sound** (S1) and **second heart sound** (S2), produced by the closing of the AV valves and semi lunar valves, respectively. In addition to these normal sounds, a variety of other sounds may be present in the abnormal heart which is:

Cardiac murmurs: Heart murmurs [5, 22, 30] are generated by the turbulent flow of blood, which may occur inside or outside the heart. Murmurs may be physiological (benign) or pathological (abnormal). Abnormal murmurs can be caused by stenos is restricting the opening of a heart valve, resulting in turbulence as blood flows through it. Abnormal murmurs may also occur with valvicular insufficiency (regurgitation), which allows backflow of blood when the incompetent valve closes with only partial effectiveness. Different murmurs [6, 8] are audible in different parts of the cardiac cycle, depending on the cause of the murmur. **A Third Heart Sound (S3**) is sometimes heard, especially in young adults. This sound, which occurs from 0.1 to 0.2 sec, after the second heart sound, is attributed to the rush of blood from the atria into the ventricles, which causes turbulence and some vibrations of the ventricular walls.

The fourth heart sound (S4) is a late diastolic sound [7, 9, 32] that corresponds to late ventricular filling through an active atrial contraction. It is a low-intensity sound heard best with the bell of the stethoscope.

S1 30 to 45 hertz S2 has a frequency range of 50 to 70 hertz third heart sound is an extremely weak vibration ranges below 30 Hz as shown in Figure 4.

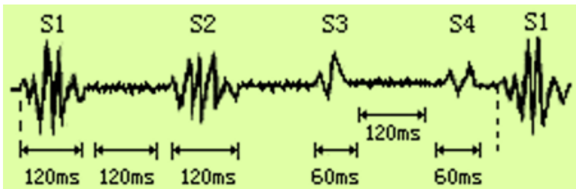


Figure.4: Different segments of heart sound

III.FEATURE EXTRACTION

Some Important Features are given below:

1. Root Mean Square(RMS)

The RMS [8, 20] can be computed in the time domain as given below

$$\textbf{RMS}\ \{\mathbf{x}\ (\mathbf{n})\} = \left(1/N \quad \sum |x(n)|^{2}\right)^{1/2} \text{------------(i)}$$

The RMS can be computed in the frequency domain, using Parsevals Theorem.

$$\sum x^2(n) = 1/N \sum |x(m)|^{2} \text{------------(ii)}$$

Where, x (m) =FFT{x(n)}

$$\textbf{RMS}\ \{\mathbf{x}\ (\mathbf{n})\} = \left(\mathbf{1}/\mathbf{N} \quad \sum |x(n)|^{2}\right)^{1/2}$$

$$= \left(\sum |\mathbf{x}(\mathbf{m})/\mathbf{N}|^{2}\right)^{1/2}$$

Average Power of a signal $x(n)$ can be expressed in terms of RMS value as

$$\text{Average-Power} = (\textbf{RMS}\{\mathbf{x}(\mathbf{n})\})^{2} \text{------------(iii)}$$

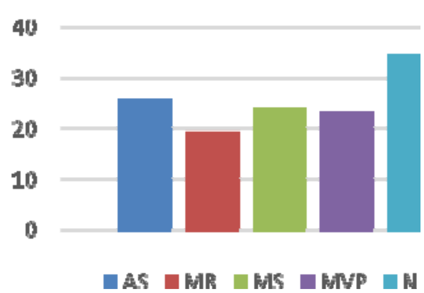


Figure 5: Comparison of RMS Value of Different Heart Sound

From the Comparative study of 1000 odd samples of different kind of heart sounds (Normal, Aortic Stenosis, Mitral Regurgitation, Mitral Stenosis and Mitral Valve Prolapse), it can be concluded that Normal heart sound can easily be identified and distinguished. As RMS Value of Normal Heart sound is the highest given in Figure 5.

2. Signal Energy and Power

Average Energy and Average Power for continuous-time signals

The terms [9, 31, 32] signal energy and signal power is used to characterize a signal. They are not actually measures of energy and power. The definition of signal energy and power refers to any signal $x\ (t)$, including signals that take on Complex values.

The signal energy in the signal $x\ (t)$ is given by

$$E = \int_{-\infty}^{+\infty} |x(t)|^{2} dt \text{------------(iv)}$$

The signal Average- Power in the signal $x\ (t)$ is given by

$$P = \lim_{T\to\infty} \ 1/2T \ \int_{-\infty}^{+\infty} |x(t)|^{2} dt \text{------------(v)}$$

If $0 < E < \infty$, then the signal $x(t)$ is called an energy signal. However, there are signals where this condition is not satisfied. For such signals we consider the power. If $0 < P < \infty$, then the signal is called a power signal. Note that the power for an energy signal is zero ($P= 0$) and that the energy for a power signal is infinite ($E= \infty$). Some signals are neither energy nor power signals.

Energy and power for discrete-time signals

The definition of signal energy and power for discrete signals parallel similar definitions for continuous signals. A discrete-time energy signal is defined as one for which $0 < E < \infty$ and a discrete-time power signal is defined as one for which $0 < P < \infty$. It is possible for a discrete-time signal to be neither an energy signal nor a power signal

The signal energy in the discrete-time signal $x\ (n)$ is

$$E = \sum |x(n)|^{2} \text{------------(vi)}$$

where ***n*** starts from $-\infty$ to $+\infty$
The Signal Average power in the signal $x(n)$ is

$$P = \lim_{N\to\infty} 1/N \quad \sum \left| x(n) \right|^2 \text{------------(vii)}$$

Where **n** starts from -**N** to +**N**

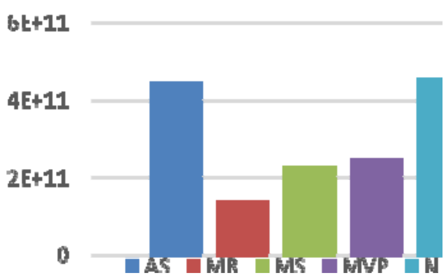


Figure 6: Comparison of Average Energy of Different Heart Sound

From the Comparative study of 1000 odd samples of different kind of heart sounds (Normal, Aortic Stenosis, Mitral Regurgitation, Mitral Stenosis and Mitral Valve Prolapse), it can be concluded that Normal heart sound can easily be identified and distinguished. As Avg Energy of Normal Heart sound is the highest given in Figure 6.

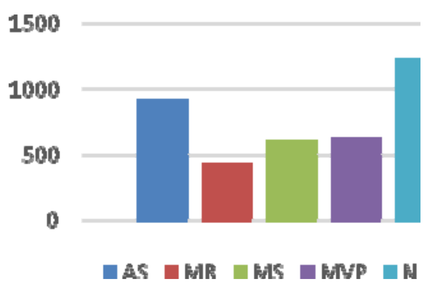


Figure 7: Comparison of Average Power of Different Heart Sound

From the Comparative study for 1000 odd samples of different kind of heart sounds (N, AS, MR, MS, MVP), it can be concluded that Normal heart sound can easily be identified and distinguished. As Avg. Power for Normal Heart sound is the highest as given in Figure 7.

3. ZCR (Zero Crossing Rate)

The [10, 29] zero-crossing rate (ZCR) is the rate of sign-changes along a signal, i.e., the rate at which the signal changes from positive to negative or back. This feature has been used heavily in both speech recognition and music information retrieval, being a key feature to classify percussive sounds. In some cases only the "positive-going" or "negative-going" crossings are counted, rather than all the crossings. Since, logically, between a pair of adjacent positive zero-crossings there must be one and only one negative zero-crossing.

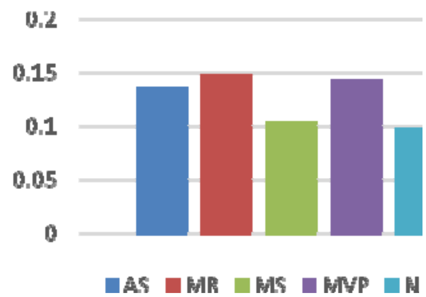


Figure 8: Comparison of ZCR of Heart Sounds

From the Comparative study for 1000 odd samples of different kind of heart sounds (N, AS, MR, MS, MVP), it can be concluded that Normal heart sound can easily be identified and distinguished. As ZCR for Mitral Stenosis is the lowest given in Figure 8.

4. Total Harmonic Distortion (THD)

The THD [11, 17] function computes the Total Harmonic Distortion (THD) of a periodic distorted signal. The signal can be a measured voltage or current.
The THD is defined as the root mean square (RMS) value of the total harmonics of the signal, divided by the RMS value of its fundamental signal. For example, for currents, the THD is defined as

Total Harmonic Distortion (THD)=I_H/I_F

$I_H = \{(I_2)^2 + (I_3)^2 + (I_4)^2 + \ldots + (I_n)^2\}^{1/2}$

I_F:

RMS value of the fundamental Harmonic

The THD has a null value for a pure sinusoidal voltage or current.

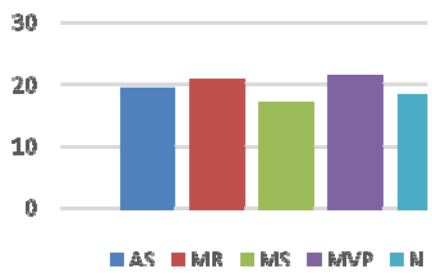


Figure 9: Comparison of THD of Different Heart Sound

From this Comparative study for 1000 odd samples of different kind of heart sounds (N, MR, MS, MVP, AS) it can be observed that different heart sounds can easily be identified and distinguished.

IV. FEATURE SELECTION USING MACHINE LEARNING

Machine Learning [12, 28] is the field of study that gives computers the capability to learn without being explicitly programmed. ML is one of the most exciting technologies that one would have ever come across. As it is evident from the name, it gives the computer that which makes it more similar to humans: *The ability to learn*. Machine learning is actively being used today, perhaps in many more places than one would expect.

Supervised Machine Learning

A supervised machine learning algorithm (as opposed to an unsupervised machine learning algorithm) is one that relies on labeled input data to learn a function that produces an appropriate output when given new unlabeled data.

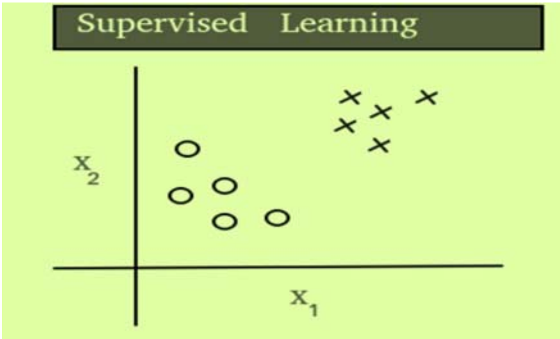


Figure 10: Supervised Learning

As you can see clearly, the data in supervised learning is labeled.

SVM Algorithm

[13, 23] Support Vector Machine (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well.

Support Vectors are simply the co-ordinates of individual observation. Support Vector Machine is a frontier which best segregates the two classes.

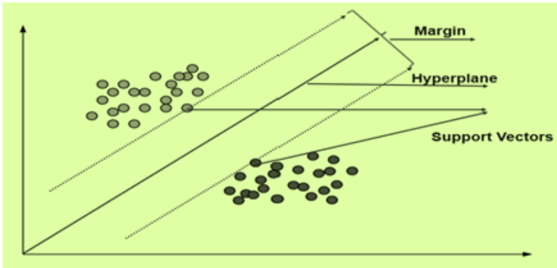
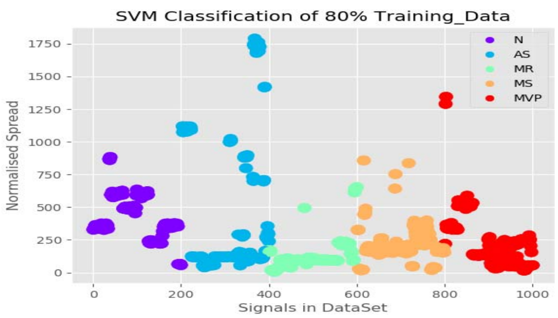


Figure 11: SVM Block Diagram

We have considered 1000 heart sounds of 5 different kinds (N, AS, MR, MS, MVP), each having 200 heart sounds. With the help of Machine learning (20% Test data and 80% Training data) , we used Classification methods like SVM and got results given below.



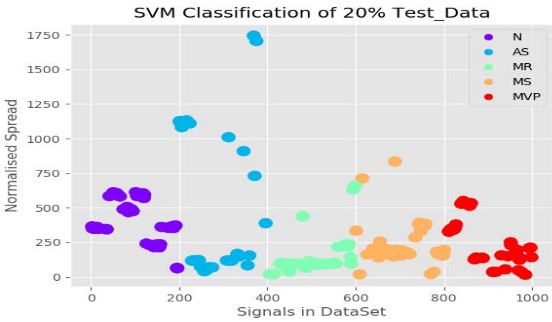


Figure 12: SVM Classification of 80% Training Data and 20% Test data

Different features [14, 25] like Avg Energy, MS, THD, ZCR and Avg Power have been considered for classification but out of all these features only RMS value and Avg Energy gives the best result. Below given Figureures explains the Normalized Spread with Dataset for every considered features.

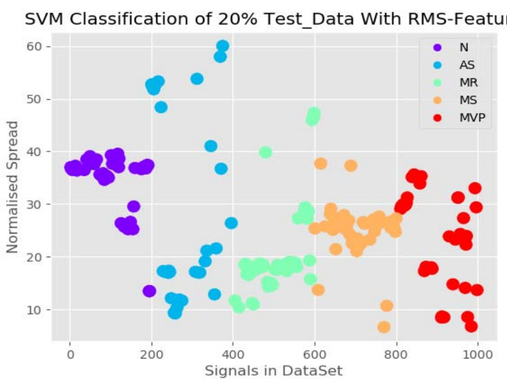


Figure 13: SVM Classification of Test data with RMS

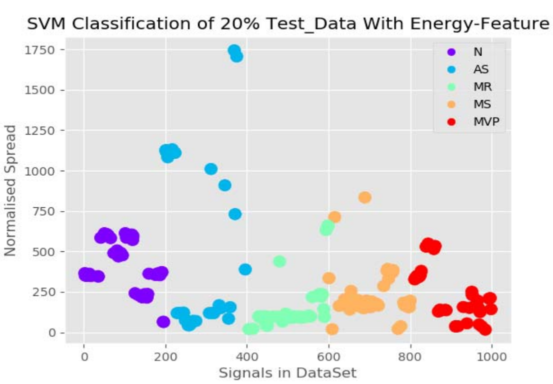


Figure 14: SVM Classification of Test data with Avg Energy

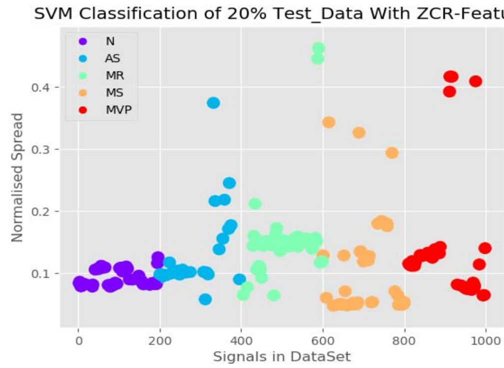


Figure 15: SVM Classification of Test data with ZCR

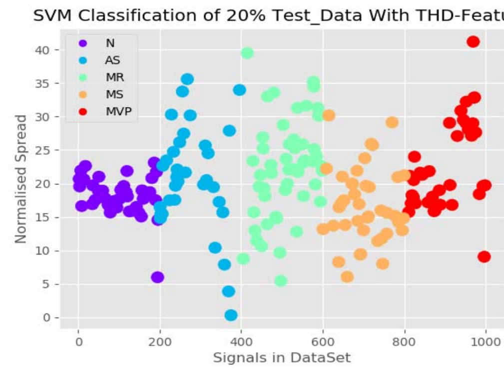


Figure 16: SVM Classification of Test data with THD

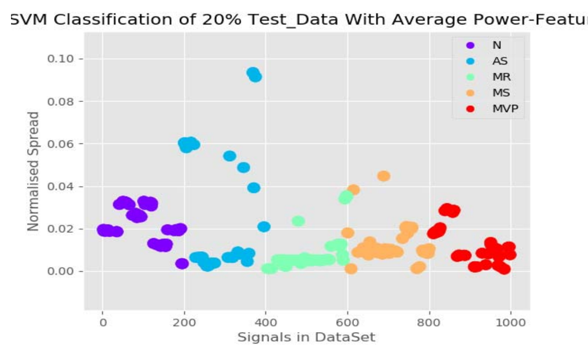


Figure 17: SVM Classification of Test data with Avg Power

V.RESULTS AND DISCUSSIONS

Metrics Used for evaluating different Machine Learning Algorithms

Accuracy - Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. One may think that, if we have high accuracy then our model is best. Yes, accuracy is a great measure but only when you have symmetric datasets where values of false positive and false negatives are almost same. Therefore, you have to look at other parameters to evaluate the performance of your model. For our model, we have got 0.99 which means our model is approx. 99 % accurate.

Accuracy = TP+TN/TP+FP+FN+TN

Precision - Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The question that this metric answer is of all passengers that labeled as survived, how many actually survived? High precision relates to the low false positive rate. We have got 0.99 precision which is pretty good.

Precision = TP/TP+FP

Recall (Sensitivity) - Recall is the ratio of correctly predicted positive observations to the all observations in actual class - yes. The question recall answers is: Of all the passengers that truly survived, how many did we label? We have got recall of 0.99 which is good for this model as it's above 0.9.

Recall = TP/TP+FN

F1 score - F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall. In our case, F1 score is 0.99.

F1 Score = 2*(Recall * Precision) / (Recall + Precision)

Features	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Energy	1.00	1.00	1.00	1.00
THD	0.98	0.98	0.98	0.98
RMS	1.00	1.00	1.00	1.00
ZCR	0.995	1.00	0.99	0.99
Power	0.995	1.00	0.99	0.99

Table 1: Comparison of Different Features

In our experiment we classified different heart sounds (N, AS, MS, MR and MVP) using different features. It is observed that RMS Value and Avg. Energy gives the best Feature Selection result obtained in terms of Accuracy and precision.

Classifiers	**Accuracy**	**Precision**	**Recall**	**F1-Score**
SVM	0.99	0.99	0.99	0.99

Table 2: Comparison of Different parameters in SVM

Normally in our research work, 1000 heart sounds of different types have been taken for classification purpose. Out of which 80 percent of samples (800) have been used for training the algorithm and 20 percent of them (200) have been used for testing the algorithm.

VI. CONCLUSION

Recently PCG signal analysis has been an emerging research area where researchers are trying to design different techniques of PCG signal analysis using machine learning, which can provide more accurate measurements to the user and at the same time, can help in the diagnosis of a diseased heart.

From this Comparative study of PCG Signal Analysis for 1000 odd samples of different kind of heart sounds (N,AS,MR,MS,MVP), it can be concluded that different heart sounds can easily be identified and distinguished. The Feature

Extraction and Selection can be used to detect normal heart sounds and abnormal heart sounds. Thus it can also be used to diagnose between a normal and abnormal heart sound properly. The preliminary idea about PCG Signal analysis has been provided, and along with basic idea of various algorithms of signal processing, Machine Learning used in PCG Signal analysis have been discussed. The prototype developed with a concept of direct data acquisition using legacy input of the sound card of a Laptop PC and use of Mat lab and Python computational power. The initial approach is successful and the research will continue for further development of the hardware and software based on the outcome of the project.

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