A NOVEL MACHINE LEARNING-BASED HEART MURMUR DETECTION AND CLASSIFICATION USINGSOUND FEATURE ANALYSIS

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ABSTRACT

An electrocardiogram (ECG) is a common method used for diagnosis of heart diseases. ECG is not sufficient to detect heart abnormalities early. Heart sound monitoring or phonocardiogram (PCG) is a non-invasive assessment that can be performed during routine exams. PCG can provide valuable details for both heart disorder diagnosis as well as any perioperative cardiac monitoring. Further, heart murmurs are abnormal signals generated by turbulent blood flow in the heart and are closely associated with specific heart diseases.

This paper presents a new machine learning-based heart sounds evaluation for murmurs with high accuracy. A random forest classifier is built using the statistical moments of the coefficients extracted from the heart sounds. The classifier can predict the location of the heart sounds with over 90% accuracy. The random forest classifier has a murmur detection accuracy of over 70% for test dataset and detects with over 98% accuracy for the full dataset.

KEYWORDS

Random Forest Network, Phonocardiogram, Heart Murmur, Sound Features

1. INTRODUCTION: HEART SOUND MECHANICS

Heart sounds are generated due to vibrations of the heart valves when they open and close during the cardiac cycle. There are four valves:

a) Aortic Valve (AV): second intercostal space, right sternal border
b) Pulmonic valve (PV): second intercostal space, left sternal border
c) Tricuspid valve (TV): left lower sternal border
d) Mitral valve (MV): fifth intercostal space, midclavicular line (cardiac apex)

As the heart pumps blood into arteries and back, these valves control the blood flow. During a typical cardiac cycle, the heart relaxes and contracts resulting in the valves to open and close. When the heart is in the relaxed state, blood flows forward through the open AV valves and the semilunar valves prevent the backward flow of blood from the arteries to the ventricles. This period is called the diastole. The atrial contraction causes more blood to flow into the ventricles, when the diastole ends and the ventricles closes the AV valves. This period is called the systole.

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There are two fundamental heart sounds called "S1" and "S2". These two sounds correspond to the "lub" and "dub" heard from a stethoscope. The first fundamental sound, "S1" happens when the right side AV valve and the left side AV valve close at the same time. The phonocardiogram captures "S1" as a single peak that rises and falls within 100ms. Once the AV valves are closed the heart is almost silent.

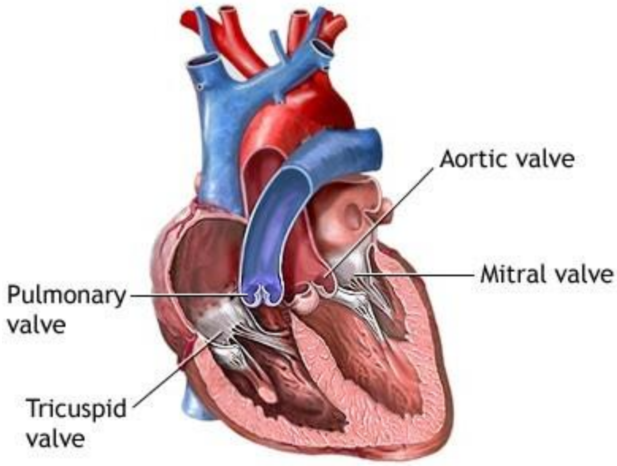


Figure 1: Heart through middle section (https://medlineplus.gov/ency/article/003266.htm)

The second fundamental sound, "S2" occurs when the heart starts to relax after the contraction or systole period. The second sound appears split during inhalation due to the pulmonic valve closing after aortic valve; whereas during exhalation both AV and PV valves close at the same time resulting in a single "S2" sound. (as seen in Figure 1)

Depending on the which part of the heart (four different valves), the sounds have different loudness. When the heart is not in these two states, then typically the heart is silent. Certain cardiac conditions may cause additional abnormal heart sounds. For example, a third sound called "S3" and a fourth sound called "S4" are associated with other acute heart failure conditions.

Phonocardiogram, PCG is a system to monitor the heart sounds in the cardiac cycle in relation to the mechanical activity of the heart (the closing and opening of the valves) and the timing of these sounds. This is different from the echocardiogram, ECG, that captures the electrical activity due to the cardiac cycle.

The stethoscope has been the primary device to listen to the heart sounds for more than two centuries. The "listening to" the heart sounds is called "auscultating". For a very long time, till recently, the key way to interpret heart sounds was using trained ear. This is the case even today in many parts of the world where advanced machines and mathematical tools are not available.

The advantages of PCG from a patient's heart sounds is valuable tool for physicians and cardiologists. A PCG can detect even softer heart sounds and capture these sounds over several cardiac cycles with high precision. The abnormal heart sounds like murmurs and gallops can be used for diagnoses of specific types of cardiac disorders. In this paper, the focus is on heart murmurs and its classification for diagnosis.

2. HEART MURMURS

Heart murmurs are sounds caused due to turbulent blood flow caused by some abnormality in one or more of these heart valves or other heart problems. Types of murmurs include:

a) Systolic murmur - occurs during a heart muscle contraction.
b) Systolic murmurs are divided into ejection murmurs (due to blood flow through a narrowed vessel or irregular valve) and regurgitant murmurs.
c) Diastolic murmur - occurs during heart muscle relaxation between beats. Diastolic murmurs are due to a narrowing (stenosis) of the mitral or tricuspid valves, or regurgitation of the aortic or pulmonary valves.
d) Continuous murmur - occurs throughout the cardiac cycle.

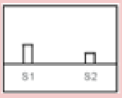
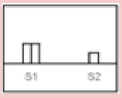
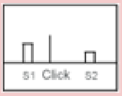
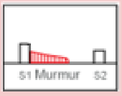
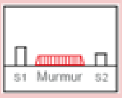
Name	Shape	Cause
Single S1 S2		Normal
Split S1		Normal
Mid-Systolic Click		Mitral Valve Prolapse
Early Systolic Murmur		Acute Mitral Regurgitation
Mid-Systolic Murmur		Mitral Regurgitation due to CAD (Coronary Artery Disease)
Late Systolic Murmur		Mitral Regurgitation due to MVP (Mitral Valve Prolapse)
Holosystolic Murmur		Classic Mitral Regurgitation - or- Ventricular Septal Defect when heard along the left sternal border

Table 1: Mitral Area Heart Sounds / Heart Murmurs

Tables 1 through 4 show tabulated murmur types from each of the four valve regions and give the mapping of all four broad classes of murmur locations. The shape of the fundamental sounds and relative positions with respect to murmurs and their characteristics are illustrated in the figures for each region. Table 1 illustrates the murmurs in the Mitral Valve (MV) region. The murmurs in this region are mostly caused due to mitral regurgitation. Table 2 illustrates the Tricuspid Valve (TV) region. Table 3 illustrates the Aortic Valve (AV) region murmurs and its mapping to the causes for such murmurs. Aortic stenosis is one the primary causes for murmurs in the AV region. Table 4 shows the Pulmonic Valve (PV) area and one of the key causes for murmurs in this region is arterial defect.

Heart murmurs help early detection and diagnosis of several heart failures and heart disorders, including, coronary artery disease, atrial or ventricular septal defect, etc. However, the challenge is sometimes these murmurs are so hidden between the fundamental sounds, in terms of amplitude or loudness of heart sounds as well as presence of any noise, that it can become difficult to even an experienced cardiologists to distinguish between no murmur/benign murmur and malignant murmurs. The identification of location of these murmurs and complex murmurs compound this challenge multi-fold. Additionally, a general physician may not have access to an ECG infrastructure, but digital PCG is portable and easily accessible but do not have the expertise to detect heart conditions from PCG.

Name	Shape	Cause
S4 Gallop		Left Ventricular Hypertrophy
S3 Gallop		Both Normal and Cardiomyopathy
Systolic Click with Late Systolic Murmur		Mitral Valve Prolapse with Mitral Regurgitation
S4 and Mid-Systolic Murmur		Ischemic Cardiomyopathy with Mitral Regurgitation
S3 and Holosystolic Murmur		Dilated Cardiomyopathy with Mitral Regurgitation
Mitral Opening Snap and Diastolic Murmur		Mitral Stenosis

Table 2: Tricuspid Area Heart Sounds / Heart Murmurs

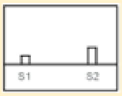
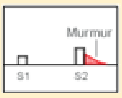
Name	Shape	Cause
Normal S1 S2		Supine Normal
Systolic Murmur with Absent S2		Severe Aortic Stenosis
Early Diastolic Murmur		Aortic Regurgitation
Systolic and Diastolic Murmurs		Combined Aortic Stenosis and Regurgitation

Table 3: Aortic Area Heart Sounds / Heart Murmurs

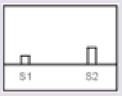
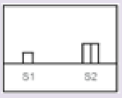
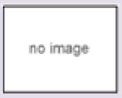
Name	Shape	Cause
Single S2		Normal in Elderly
Split S2 Persistent		Complete Right Bundle Branch Block (On ECG)
Split S2 Transient		Normal
Ejection Systolic Murmur with Transient Splitting S2		Innocent Murmur
Ejection Systolic Murmur with Persistent Split S2 and Ejection, Systolic Murmur		Arterial Septal Defect
Ejection Systolic Murmur with Single S2 and Ejection Click		Pulmonary Valve Stenosis

Table 4: Pulmonic Area Heart Sounds / Heart Murmurs

There is a need for automated tools and methods to be able to detect such conditions from PCG. Using the proposed approach, it is possible detect, classify and provide early diagnosis of heart conditions. The correct diagnosis of the heart conditions depends on identifying the peak of these murmurs, its timing and relation or position with respect to the two fundamental hearts sounds.

The basic approach proposed is to extract sound features or coefficients as described in section 3, then determine the key statistical moments of these coefficients, formulations for which are given in section 4 and finally use a Random Forest classifier that will be used for heart murmur detection and classification. The following sections are divided based on this proposed approach into: section 3 Sound Features, section 4 Statistical Moments, section 5 Results and Data Analysis, and section 6 Conclusions.

3. Sound Features

Phonocardiograms capture heart sounds in terms of sound intensity over time. Heart sounds have more frequency components in the low frequency range and fewer frequency components in the higher frequency range. The heart sound signals are basically time varying signals. These are both non-stationary and non-linear bio signals. These signals can be split into smaller, short time windows resulting in discrete sound signals. These discrete heart sound signals are split into time windows, *k*. The signal in the time-domain is transformed to the frequency representation as below using discrete Fourier transform (DFT):

$$, 0 \leq k \leq N-1, \qquad Y(k,f) = \sum_{n=0}^{N-1} x(n) e^{\frac{-j2\pi nk}{N}} \qquad\qquad f = \frac{n}{N}$$

The coefficients from above equation are used to determine the magnitude spectrum. A set of filter banks, *wb(f)*, at each sub-band within the frequency range is predefined. The sub-band energies at the k^{th} time window and b^{th} sub-band is given as:

$$SSE_y(k, b) = \sum_{f=lb}^{hb} w_b(f)|Y(k, f)|^2$$

The spectral sub-band centroids (SSCs) are the center of mass of the sub-band in terms of frequency using a weighted average technique. These features are not disturbed by the additive noise distortion and provide representation of the higher amplitude frequencies. The sub-band spectral coefficients, SSC are computed as [3]:

$$SSC(m) = \frac{\sum_{k=0}^{N-1} k \cdot [|X(k)|^2 H_m(k)]}{\sum_{k=0}^{N-1}[|X(k)|^2 H_m(k)]}$$

For each time window a set of the centroids are computed and the values normalized within the range [-1, 1].

3.1. Statistical Moments of Signal Coefficients

In statistics, moments are used to describe characteristics of a distribution. The moments are of different orders, that measure the spread of the data around a central value. They provide sufficient information to reconstruct the probability distribution function. Moments of any order can be computed using following equation:

$$M_k = \frac{\sum_{i=1}^{N} {X_i}^k}{N}$$

Where, M_k is the k^{th} order moment and X_i is the i^{th} data sample. The first four momentsare called: mean, variance, skewness and kurtosis. These four moments can be written as:

- Mean – 1st moment about the origin
  - $\overline{X} = M_1 = \frac{1}{N}\sum_{i=1}^{N} X_i$
- Variance – 2nd moment about the mean
  - $\mathrm{Var}(X) = \sigma^2 = M_2 = \frac{1}{N}\sum_{i=1}^{N}\left(X_i - \overline{X}\right)^2$
  - Standard deviation can be determined using, $s = \sqrt{M_2}$
- Skewness – 3rd moment without standardization, M_3 and standardized, a_3
  - $M_3 = \frac{1}{N}\sum_{i=1}^{N} {X_i}^3$
  - $a_3 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i}{s}\right)^3$
- Kurtosis – 4th moment without standardization, M_4 and standardized, a_4
  - $M_4 = \frac{1}{N}\sum_{i=1}^{N} {X_i}^4$
  - $a_4 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i}{s}\right)^4$

Consider the sound signal's coefficients, namely, Spectral Sub-band Energies (SSEs) andSpectral Sub-band Centroids (SSCs) as random variables across different samples ofheart sounds. In this case, each SSE and SSC is a random variable with a certain probability distribution. This distribution is not known, however there is data from the heart sound signals that are captured as SSEs and SSCs. The first four moments of SSEs and SSCs can be computed using the above equations for mean, variance, skewness and kurtosis.

4. DATA ANALYSIS

The CirCor Digiscope dataset for phonocardiogram is used to develop and test the method. The database includes phonocardiograms from 1568 patients and have overall 5282 recordings from pulmonary, aortic, mitral and tricuspid valve points. The dataset is classified as normal and abnormal at the first level and then, further classification in terms of heart disorders as systolic, diastolic, holosystolic, early/mid/late systolic classifications are provided for each of the recordings.

The time-varying heart sound signals from different patients are pre-processed such that the length of the signals is common across all signals. This is done by padding the signals to give equal length for all patient recordings. The heart sound signals from the recordings were divided into 5ms time windows and transformed to frequency domain. The sound feature coefficients, namely, Spectral Sub-band Energies (SSEs) and Spectral Sub-band Centroids (SSCs) were evaluated. The first four statistical moments were computed for all these coefficients. The distribution of these first four moments (mean, variance, skewness, kurtosis) are showing in the following figures.

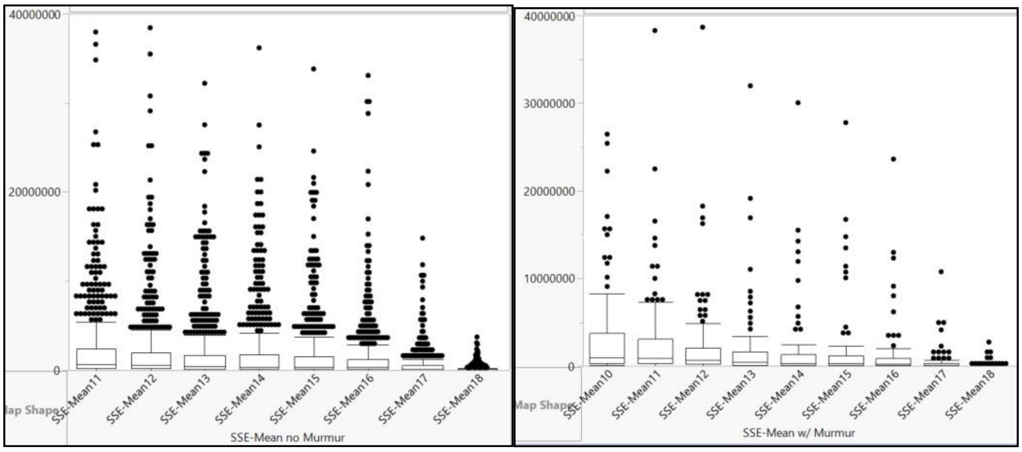


Figure 2: SSE no Murmur (left) and w/ Murmur (right) Mean Distribution

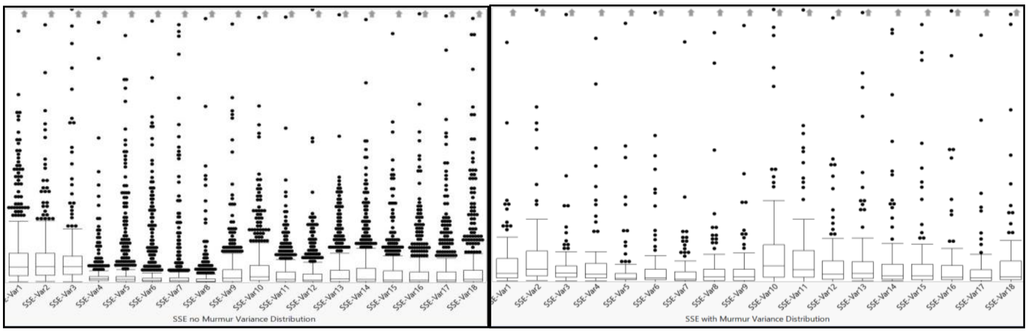


Figure 3: SSE no Murmur (left) and w/ Murmur (right) Variance Distribution

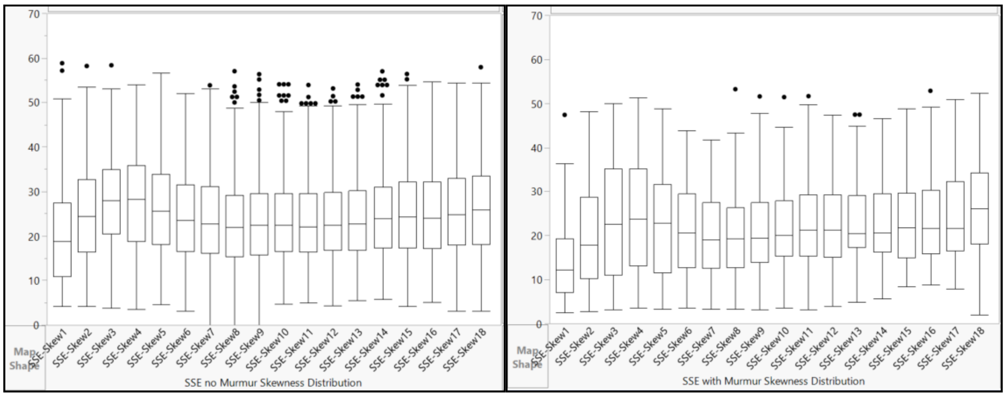


Figure 4: SSE no Murmur (left) and w/ Murmur (right) Skewness Distribution

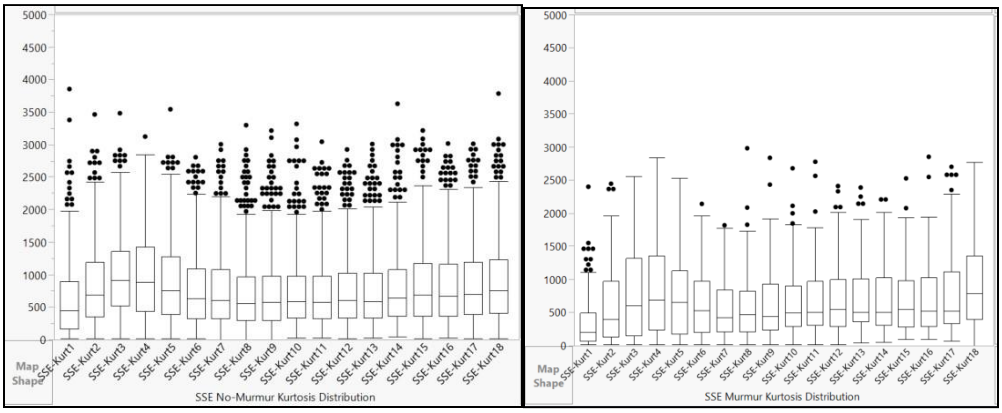


Figure 5: SSE no Murmur (left) and w/ Murmur (right) Kurtosis Distribution

From the distributions of these moments for both no-Murmur and with-Murmur case, following observations can be made:

- First moment: For with-Murmur case, the "mean" for the coefficients spreads more when compared with no-Murmur case. There is a slight shift in the average first moment as well. This is more see for the coefficients 10, 11. (See Figure 2)
- Second moment: For the with-Murmur case, the "variance" distribution shows a shift as well as spread across most coefficients when compared with the no-Murmur case. (See Figure 3)
- Both "skewness" and "kurtosis" show reduced spread. (See Figure 4 and Figure 5)

5. RANDOM-FOREST CLASSIFIER RESULTS

Random forest classifier is a tree based classification algorithm. In this algorithm, a large number of decision-trees are used to make the final predictions. Each sub-tree in the forest gives a prediction. And, finally the best solution through majority voting is selected. Additionally, random-forest classifier also provides a handle to assess the importance of different features relevant for the problem. For the heart murmur detection and classification, there are 18 SSEs and 18 SSCs coefficients used to train the model. The training is done using the statistical moments of a number of filter bank energies (SSEs) and spectral sub-band centroids (SSCs) of the heart sounds.

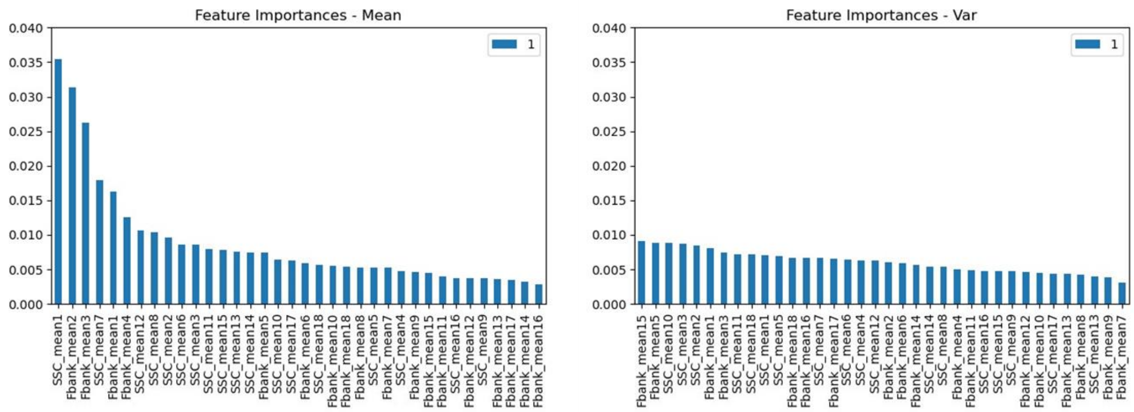


Figure 6: Mean and Variance of Filter Bank Energies and Spectral Sub-band Centroids

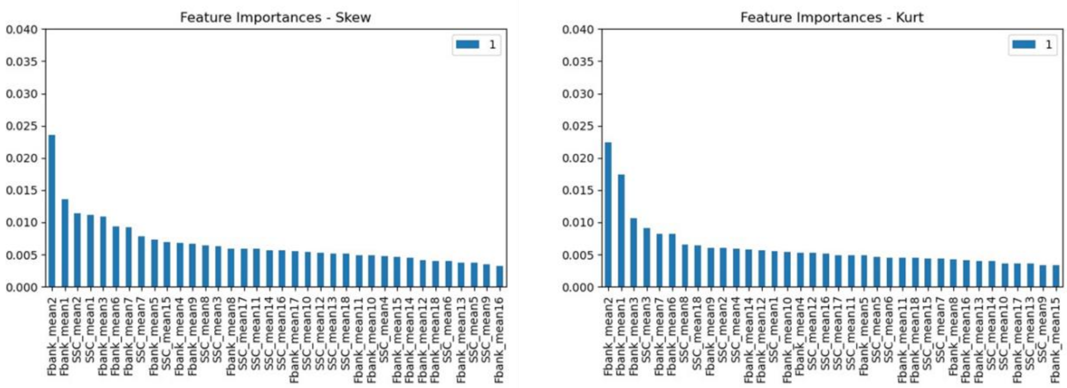


Figure 7: Skew and Kurtosis of Filter Bank Energies and Spectral Sub-band Centroids

From the above figures, it is clear that there are few features that have a clear higher importance when considering first statistical moment (namely, mean). However, the importance of different features for the second moment, namely variance, is small. For skewness and kurtosis, the feature importance exists only for a small number of features.

	Precision	Recall
AV	0.927	0.870
PV	0.884	0.877
TV	0.909	0.924
MV	0.866	0.903

Figure 8: Precision-Recall for Murmur Classification in each heart region

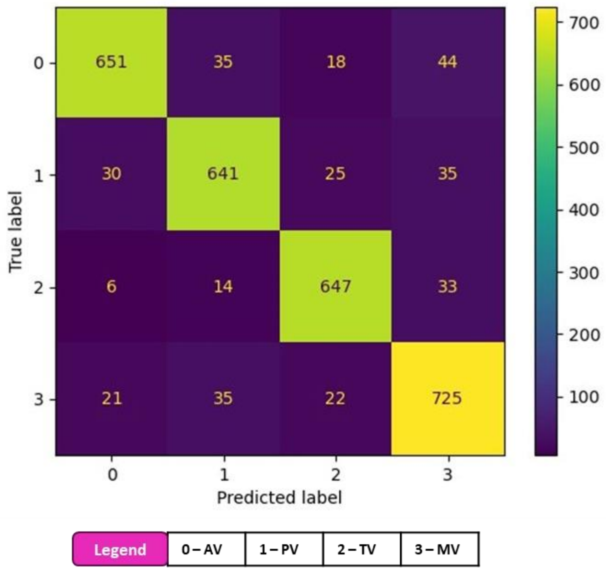


Figure 9: Random Forest Classifier performance: true label vs. predicted label

Each murmur classification results in a set of coefficients that show distinct characteristics when compared with a normal (no murmur) heart sounds. The analysis of the statistical moments for all the AV, PV, TV, MV show that there is unique characteristics that can help classification and model building. The first four statistical moments for all the 36 coefficients were used for to build a Random Forest classifier. The ROC (receiver operating curve) for all the four murmur locations (AV, MV, PV, TV) are illustrated in following figures. The ROC curves for both full dataset and the test dataset are shown. It can be seen that for full dataset the ROC curves show an accuracy of over 90%. The AUC (area under the ROC curve) is over 98% when considering full dataset and for test dataset, the AUC is over 70% for AV, PV, and TV dataset. MV test dataset shows slightly lower AUC. This is primarily due to o a restricted number of murmur recordings from MV class.

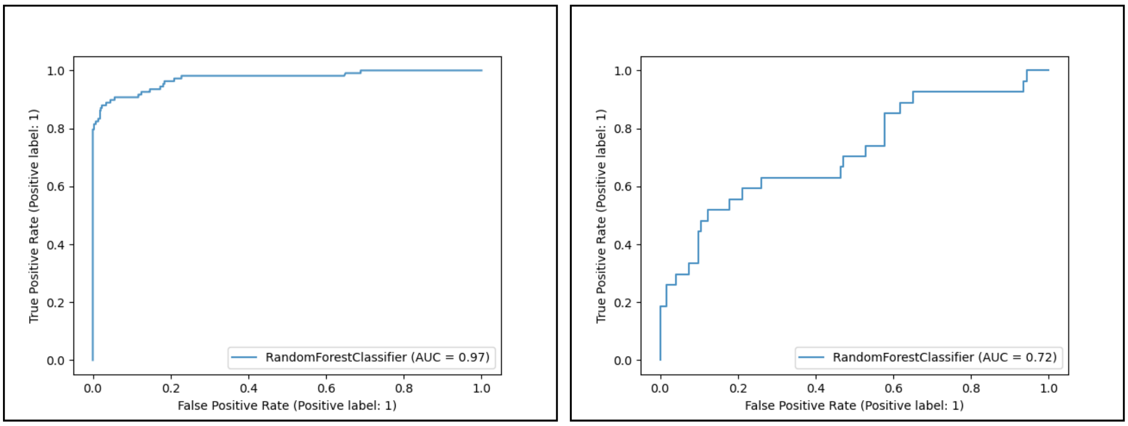


*Figure 10: **AV** Full Dataset (left) and Test Dataset (right) ROC Curve*

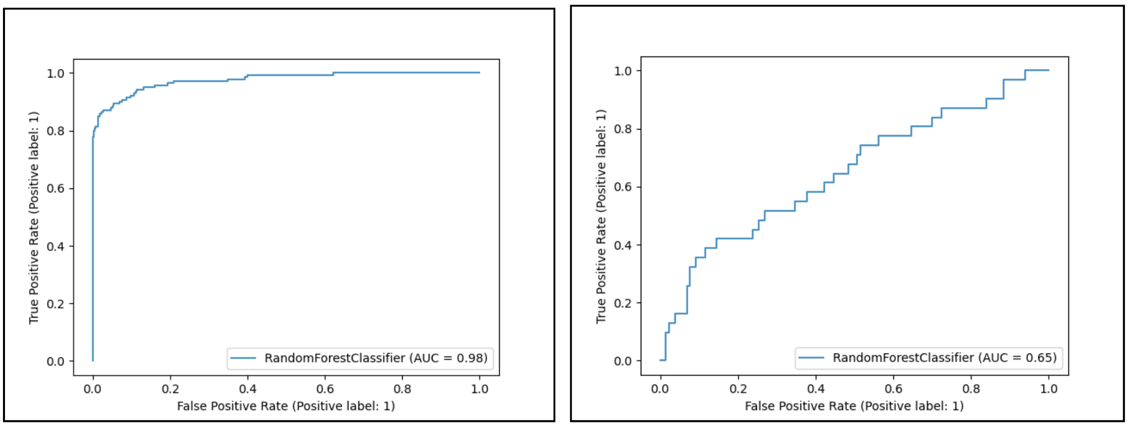


*Figure 11: **MV** Full Dataset (left) and Test Dataset (right) ROC Curve*

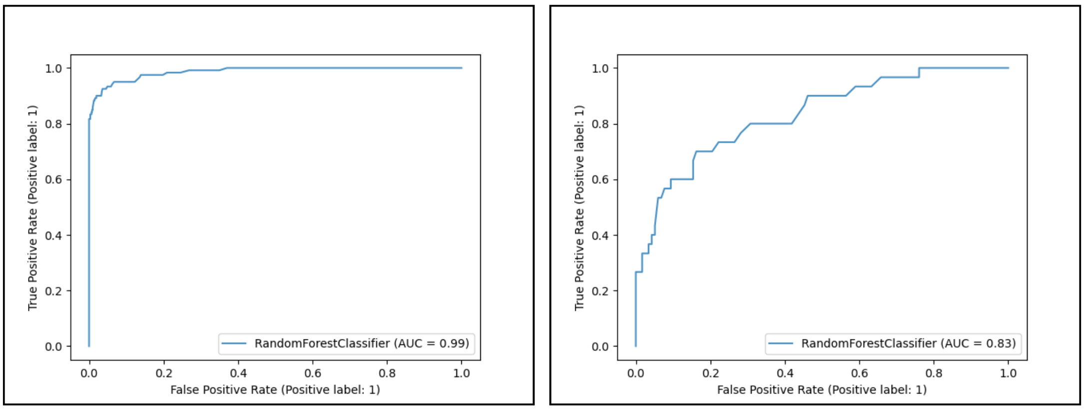


*Figure 12: **PV** Full Dataset (left) and Test Dataset (right) ROC Curve*

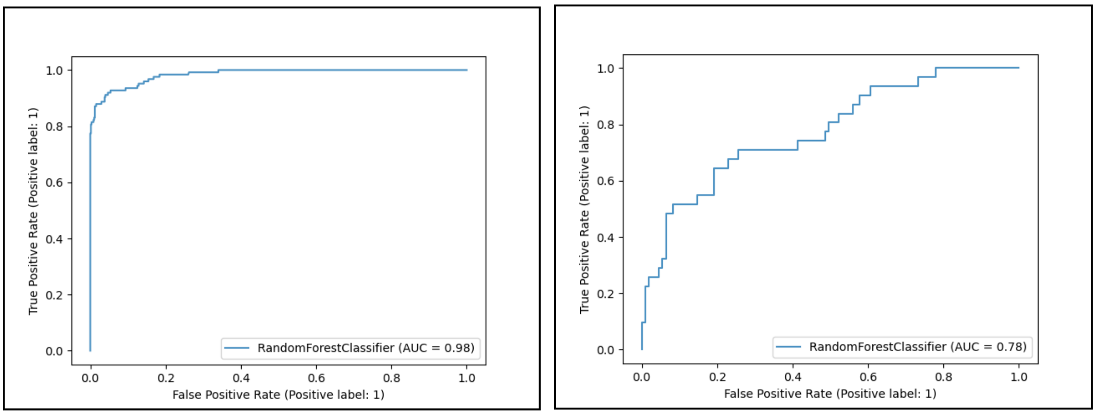


*Figure 13: **TV** Full Dataset (left) and Test Dataset (right) ROC Curve*

CONCLUSIONS

This project successfully implemented software tool to evaluate the heart sounds using the Mel-frequency cepstral coefficients extracted from the heart sounds. The software can take in raw phonocardiogram signals and process them into data that can be used for training and model building. Furthermore, sound features-based Random Forest (machine learning) classifier was developed using the first four statistical moments of the Spectral Sub-band Energies (SSEs) and Spectral Sub-band Centroids (SSCs). The classifier allows to classify phonocardiogram signals into different types of murmurs (AV, PV, MV, TV) with an accuracy of over 90% across the dataset. The AUC (area under the ROC curve) is over 98% when considering full dataset and for test dataset, the AUC is over 70% for AV, PV, and TV dataset. MV test dataset shows slightly lower AUC. The sound feature based machine learning model provides an early diagnosis tool for physicians and cardiologists in real-time. This tool is simple to use and can aid doctors in interpreting PCGs for possible heart abnormalities. In specific, classify heart sounds for murmur and create a model to help physicians and cardiologists in real-time for early detection and classification of heart murmurs. This can provide valuable feedback to the patients and early diagnosis of heart disorders.

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