



A novel heart-mobile interface for detection and classification of heart sounds



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ABSTRACT

Diagnosis of heart disease requires that a medical practitioner investigate heart auscultations for irregular sounds, followed by echocardiography and electrocardiography tests. These expensive tests also require specialized technicians to operate. We present a low-cost, patient-centered device for the initial screening of the heart sounds that can be potentially used by the users on themselves. They can later share these readings with their healthcare providers. We have created an innovative mobile-health service platform for analyzing and classifying heart sounds.

The presented system enables remote patient-monitoring by integrating advanced wireless communications with a customized low-cost stethoscope. This system also permits remote management of a patient's cardiac status while maximizing patient mobility. The smartphone application facilitates recording, processing, visualizing, listening to, and classification of heart sounds. We build our classification model using the Mel-Frequency Cepstral Coefficient and Hidden Markov Model. This application is tested in a hospital environment to collect live recordings from patients with positive results. The smartphone application correctly detected 92.68% of abnormal heart conditions in clinical trials at UT Southwestern Hospital.

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1. Introduction

The latest generation of smartphones has become an essential commodity due to its variety of sensors, powerful computing capability, high memory capacity, and open source operating systems that encourage application development. Apart from communication, smartphones also provide services and applications such as daily planners, cameras, web surfing, navigation, health applications, etc. Being palm-sized, they allow for easy mobility and portability. Hence, the mobile health (mHealth) sector is very interested in mobile applications that provide remote-monitoring

health care services. mHealth is also used for illness surveillance, patient tracking, and collecting health information.

1.1. Motivation

Interpretation of heart sounds is subjective and requires a medical expert to identify sound abnormalities. Currently, patients with abnormal cardiac sounds must visit a health professional to get diagnosed. The medical practitioner uses a stethoscope to do an initial screening that entails listening for irregular sounds from the patient's chest. Next, the practitioner employs echocardiography and electrocardiography tests for further diagnosis.

In this process, the practitioner evaluates properties of heart sounds to identify irregularities, such as the number of heart beats and gallops, intensity, frequency, and duration. Because heart sounds are generated in low frequencies, human ears tend to miss certain sounds as the high frequency sounds may mask the lower ones. To improve evaluations, traditional stethoscopes were innovated into digital stethoscopes which incorporate a small microprocessor. This microprocessor attenuates high frequency

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signals and amplifies heart sounds, enabling physicians to hear clean cardiac sounds. In addition, with digital stethoscopes, computer applications have become available to assist physicians in visualizing and identifying types of heart sounds. However, the cost of this diagnostic tool is high, so patients still need to visit a hospital or clinic to get diagnosed. Five major products are currently available in the market: CardioSleeve [1], SensiCardiac [2], Eko Core [3], HeartBuds [4], and Thinklabs [5]. At this time, only Eko Core and Thinklabs are customized electronic stethoscopes that also work with a smartphone application and desktop application software. However, the software only records, displays, and shares heart sounds. Their computer and smartphone software also does not provide analytics for or determine the type of heart sound. A physician is required to evaluate and identify the sounds. HeartBuds, a similar device, is a custom-made acoustic amplifier. CardioSleeve, a 3-lead electrocardiogram (ECG) combined with a digital stethoscope, has a smartphone application to visualize ECG and heart sounds via Bluetooth. The software calculates the systolic performance index as an indication of ejection fraction to assess heart failure and displays the value of isovolumic contraction, isovolumic relaxation, RR interval, PT interval, and QRS interval obtained from the ECG leads. SensiCardiac, a cloud-based software, analyzes heart sounds recorded from an electronic stethoscope. A user records heart sounds and sends them to the cloud to interpret if the heart sound is normal, a class I murmur, or a class III murmur. A class I murmur can be any systolic or diastolic murmur, while a class III is a flow murmur.

Apart from these products, Dr. Raj Shekhar of Children's National Health System [6], in a major research project, is building a smartphone application called StethAid that allows pediatricians to discriminate Still's murmurs from pathological murmurs in children. This allows a physician to establish a child's murmur as benign, thus eliminating the need for a cardiac referral. The application will work in conjunction with a digital stethoscope.

1.2. Objective

This paper focuses on developing an innovative mHealth service platform for analyzing and classifying heart sounds. This service enables remote patient-monitoring using advanced wireless communications by integrating a customized low-cost stethoscope with a smartphone application. It also permits remote management of patients' cardiac status while maximizing patient mobility.

Many developing and under-developed regions lack access to medical facilities with echocardiograms and specialized doctors such as cardiologists, but these regions do have access to mobile platforms such as smartphones. So, the presented mechanism of diagnosing heart sounds provides immense value to such populations [76]. The smartphone application provides capabilities such as recording, processing, visualizing, listening to, and identifying cardiac sounds. The recorded sounds are identified as abnormal rhythms such as split sounds, aortic stenosis, pulmonary stenosis, atrial septal defect, ventricular septal defect, mitral valve prolapse, mitral regurgitation, tricuspid regurgitation, aortic regurgitation, pulmonary regurgitation, tricuspid stenosis, mitral stenosis, flow murmur, and patent ductus arteriosus.

This work focuses on mobility and remote monitoring, and centers on the patient or user. This work's significance lies in presenting a convenient, independent, and portable device that aid physicians to monitor a patient's heart while the patient is remote. Since this work is deployed on a smartphone, it makes a novel contribution to mHealth, mobile, and pervasive computing domain specifically in the following methods:

1) We use discrete wavelet transform (DWT) and continuous wavelet transform (CWT) to process heart sounds. DWT helps

to down-sample data and to remove redundant information. CWT helps to identify valve movement in the heart sound by calculating the energy level in the signal.

- 2) We can filter and amplify signals without using a digital stethoscope by using a modified traditional-stethoscope to collect heart sounds. This low-cost device is easily available in any pharmacy. We study time and frequency resolution of all murmurs using fast Fourier transform and short-time Fourier transform. Using these digital processing techniques, we have calculated a cutoff range to filter the signal, which we then normalize.
- 3) We design a classification model using Mel-Frequency Cepstral Coefficient (MFCC) and Hidden Markov Model (HMM) to detect normal heart sound and 13 types of heart murmurs. The model also works with split detection technique to determine the split intervals. Our classification model is built based on frequency features extracted using MFCC. The model has 4 systolic HMMs and 4 diastolic HMMs. We also use the auscultation area to identify certain murmurs.
- 4) We have designed a heart-sound application using a smartphone, and here we show our software and the graphical user interface's overall architecture. This software records and analyzes cardiac sounds and generates graphs, audio, and electronic medical records. As this application generates electronic medical records, we use an elliptic-curve integrated scheme to secure data while sharing information with a physician. The details of the mechanism for securing the data has been presented in a different paper [78].

The rest of this paper is organized as follows. We provide a brief description of the heart and its sounds in Section II, explaining the origin of normal and abnormal heart sounds with the heart valve's movement. The pattern of each murmur and its corresponding auscultation are also discussed here. We focus on preprocessing the recorded heart sounds in Section III for accurate split calculation and classification in later sections. In Section IV, we provide our methodology of identifying and measuring split intervals in the heart sounds. In Section V, we present the classification model used to determine split intervals and to detect normal heart sound and 13 types of heart murmurs. We outline the software design of the heart sound application using a smartphone in Section VI. Finally, Section VII concludes the paper.

2. The heart

2.1. Heart sounds and murmurs

Heart valves' movements create audible sounds, usually described as "lub-dub." The "lub" sound, also known as the first heart sound (S1), is heard when the mitral (M1) and tricuspid (T1) valves close. The M1 closure precedes T1 closure by 20–30 ms. As the left ventricle contracts first, the M1 component occurs earlier than the T1 component. An S1 split (the delay between M1 and T1) has a typical duration of 100–200 ms [9]. Its frequency components lie in the range of 40–200 Hz [9,10]. An S1 split is considered pathological if the delay time is above 30 ms [7–9].

"Dub", the second heart sound (S2), occurs when the aortic (A2) and pulmonary (P2) valves shut. S2 has a shorter duration and higher frequency (range of 50–250 Hz) than S1 [7,10]. Aortic pressure is superior to pulmonary pressure causing the A2 component to appear before P2. Analysis of the split and the relative intensities of A2 and P2 can identify the presence of cardiac abnormalities such as pulmonary stenosis and atrial septal defect. During deep inspiration, the interval between A2 and P2 prolongs, resulting in wide splitting. On expiration, the delay is less than 30 ms [7–9].

Similar to S1 split, if the interval is above 30 ms, it is considered as a pathological case.

Other than “lub-dub”, there are other heart sounds such as murmurs. Murmurs, both normal and pathological, are a series of vibrations generated due to the turbulence of blood flow in the heart. Normal murmurs, also called “innocent” or flow murmurs, occur commonly in infants, children, women during pregnancy, and adults after exercise [11,12]. This murmur occurs during the first heart sound. Abnormal murmurs indicate a heart valve defect such as stenosis (constricted heart valves) and regurgitation (leaking heart valves) [7,13,14]. Murmurs, which often do not carry symptoms, are mostly discovered through a stethoscope exam, phonocardiography, or echocardiography. However, a chronic cough, chest pain, and shortness of breath may indicate a heart problem.

Murmurs are categorized as systolic, diastolic, and continuous. Systolic murmurs are heard during systole when the ventricles contract. The systolic murmur appears between first and second heart sounds. A physician can evaluate them as either ejection murmurs (aortic stenosis, pulmonary stenosis, or atrial septal defect) or regurgitant murmurs (mitral regurgitation, tricuspid regurgitation, mitral valve prolapse, or ventricular septal defect) [7,14–16].

Diastolic murmurs are heard during diastole (following systole), when the ventricles relax. These murmurs, which appear between the second and first heart sound, can be diagnosed as either early diastolic (aortic regurgitation or pulmonary regurgitation) or mid-diastolic (mitral stenosis or tricuspid stenosis) [7,14–16].

Patent ductus arteriosus is a continuous murmur the physician hears throughout systole and diastole. Often, the second heart sound is difficult to detect. The patent ductus arteriosus murmur is a heart defect wherein the blood vessel connecting the pulmonary artery and aorta does not close a couple days after birth, leading to abnormal blood flow in two major blood vessels.

2.2. Heart sounds diagnosis tests

Cardiac auscultation, the act of listening to heart sounds, usually through a stethoscope, provides the primary tool for first-stage cardiovascular evaluation used by medical practitioners and emergency responders. However, this method does not provide a medical record. Besides, the interpretation of heart sounds is subjective and depends on the skills of the health professional.

3. Signal preprocessing

In this section, we describe how heart signals are amplified and denoised for accurate split detection. Electronic stethoscopes resemble traditional stethoscopes, but have a microprocessor, a battery, and signal-processing capability. Currently available electronic stethoscopes in the market are the WELCH-Allyn Elite stethoscope [34], Jabes electronic stethoscope [35], 3 M Littmann electronic stethoscope [36], Thinklabs One digital stethoscope [5], and Eko Core digital stethoscope [3]. The latter three come with software that enables the user to record, view, share, and save heart sounds. Eko Core and Thinklabs are the only digital stethoscopes to work with a smartphone application. Although electronic stethoscopes can work with computers and smartphones, the current technology does not analyze and determine the type of heart sound. Electronic stethoscopes still require a medical doctor to diagnose the sound. Many low-resource regions lack qualified physicians and the costs of a physician visit may be beyond their patient’s capabilities. Furthermore, these electronic stethoscopes are costly, ranging from \$199–\$499, a cost that might be prohibitive in a region with few resources. We present here a low-cost smartphone application

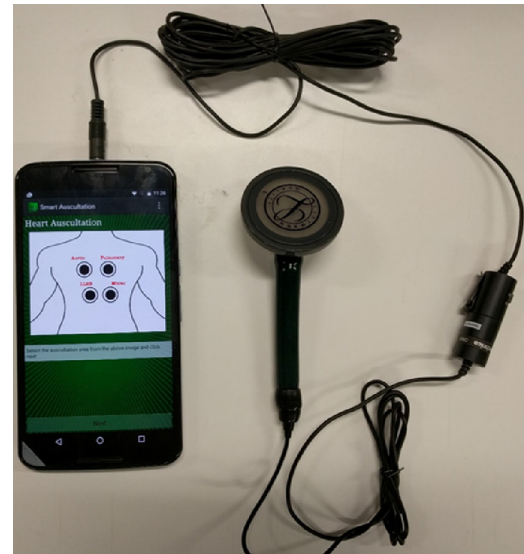


Fig. 1. Smartphone setup with a customized external microphone.

that is able to preprocess heart sounds locally without the help of an external resource and transmit them to a specialist remotely.

FFT was the first technique used for analysis of heart sounds [37,38]. El-Segaier et al. [39] developed a digital algorithm using STFT (Short-Time Fourier Transform) to analyze first and second heart sounds and characterize the systolic murmur. Djebbari et al. [40] analyzed phonocardiogram signals using STFT to measure cardiac cycle durations and characterize each heart sound’s spectral frequency. In [73], the authors propose a correlation-based pattern classifier, which they use to differentiate the heart sounds from the S3 split. We have briefly discussed the S3 split in Section IV.

Wavelet transform methods have also been used to study the heart sound’s behavior. This signal processing technique has been used to extract feature vectors to categorize heart sounds [41] and denoise the signals [42]. The technique has also been used to decompose and reconstruct the signal using only the most relevant frequency range [43]. These relevant studies each use complex mathematical models such that implementing the models requires processors with high computation power.

Algorithm 1 Peak selection algorithm

1. **procedure** SelectPeaks \triangleright Selects the peaks and adds it to lub-dub list
2. **for** peak in peakList **do**
 - a. Find out the difference between previous peak time and current peak time
 - b. Add the difference in differenceList
3. previousPeakTimeStamp = currentPeakTimeStamp
4. $i=0$
5. **for** item in differenceList **do**
 - a. **if** previousItem > 250 && previousItem < 350 && item > 350 && item < 800 **then**
 - set firstS1TimeStamp=peakList(i-2)
 - set firstS2TimeStamp=peakList(i-1)
 - set secondS1TimeStamp = peakList(i)
 - Add this signal to Lub-dub signal list
 - previousItem = item
6. $i++$

3.1. Setup of smartphone for recording heart sound

Collecting heart sounds data with a smartphone requires a customized external microphone connected to a smartphone. Our setup as shown in Fig. 1 [46] has been used in other

research [44,45]. The microphone's design consists of an acoustic stethoscope diaphragm, a hollow tube, a 3.5 mm mini-plug condenser microphone with frequency response 50–18,000 Hz, and a 3.5 mm microphone adapter for mobile phones. The stethoscope diaphragm and the hollow tube are attached to the microphone. The microphone is attached to the adapter, which acts as a sensor to record heart sounds. The cost of the instrument and material is \$30, considerably less expensive than other solutions commercially available for similar purpose. (A cost comparison with other available products is presented in the Appendix Table A.2.)

3.2. Detection of first and second heart sound

The stethoscope diaphragm is placed on one of the four auscultation areas to record heart sounds. The audio data is formatted to 8 kHz sample rate and pulse-code modulation (PCM) of 16 bits per sample. Next, the recorder pulls the audio data from the microphone sensor. The FFT algorithm converts the raw PCM data to its discrete Fourier transform to identify frequency domains. We identify S1 and S2 using a peak detection method. We perform the transformation to frequency domain on multiple small segments of PCM data as computations will be faster on small data amounts. In the peak detection module, since S1 and S2 are in the range of 40 Hz to 200 Hz, we can easily detect S1 and S2 peaks. Once the peaks are detected, we use the peak-selection method to select the appropriate heart sound signals for classification.

Our peak detection method may detect noisy peaks between the original heart sound signals. According to our observations, the rubbing sound of the device's diaphragm with the chest occasionally appears as noise. To eliminate such peaks and other heart sound signals where we do not have the required signals, we use peak selection. Algorithm 1 shows our implementation of this method. Observation with heart sounds from different patients has shown that the timestamp difference between S1 and S2 ranges from 250 to 350 ms and the timestamp difference between S2 and the next S1 ranges from 350 to 800 ms. Based on this observation, we select the peaks that fit within this range.

3.3. Noise reduction and signal amplification

The presence of noise in any signal makes it difficult to extract useful information from it. Therefore, it is important to remove noise artifacts from the recorded signal to retain the information about S1, S2, and murmurs. As the frequency characteristics of heart sounds need to be studied, we perform two forms of frequency analysis. Each type of heart sound falls within a certain range of frequencies.

In previous work [48], 14 heart signals (1 normal including first and second heart sounds and 13 abnormal) were analyzed using Fourier transform techniques. A discussion of the frequency spectrum of each of the 14 heart sounds is discussed in detail in [48]. Due to limited space, we have summarized the frequency range in Table 1. Most frequency ranges overlap, which provides an advantage of setting one threshold value to eliminate high-frequency, redundant data without compromising every heart sound's frequency content.

We find filtering a simple and effective way to retain low-frequency data by suppressing unwanted high-frequency components unrelated to the heart sounds such as noise artifacts that include signal spikes and bursts. Zhang et al. [49] uses a Butterworth low-pass filter to limit the frequency of a recorded signal. The Butterworth filter is designed to have a maximum flat frequency response with no ripples in the pass-band and zero roll-off response in the stop-band [50,51]. Butterworth filters are mostly used as an anti-aliasing filter in data converter applications, audio applications, and digital filters for motion analysis.

Table 1
Frequency Range For Each Type of Cardiac Signal Obtained By Taking FFT and STFT [48] of A Normal (First and Second sound) and 13 Abnormal Cardiac Signals.

Cardiac Signal	Minimum Frequency (Hz)	Maximum Frequency (Hz)
First heart sound	100	200
Second heart sound	50	250
Aortic regurgitation	60	380
Pulmonary regurgitation	90	150
Aortic stenosis	100	450
Pulmonary stenosis	150	400
Atrial septal defect	60	200
Ventricular septal defect	50	180
Mitral regurgitation	60	400
Tricuspid Regurgitation	90	400
Mitral Stenosis	45	90
Tricuspid stenosis	90	400
Mitral valve prolapse	45	90
Patent ductus arteriosus	90	140
Flow murmur	85	300

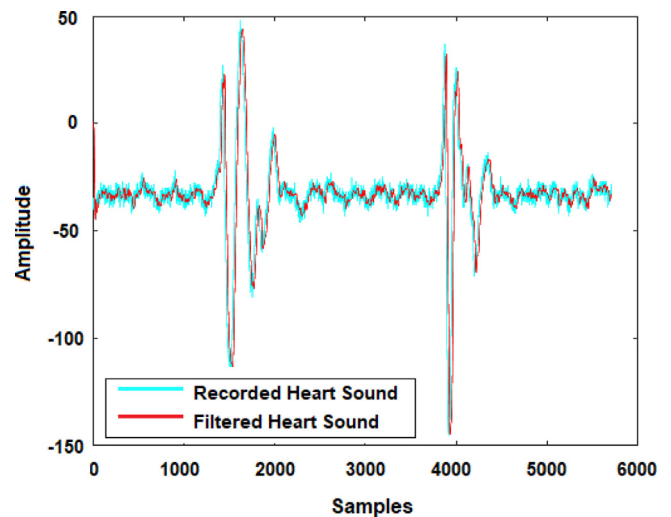


Fig. 2. Normal Heart Sound and its Corresponding Filtered Signal.

A Butterworth filter with a cutoff frequency at 450 Hz was designed to attenuate the signals with frequency higher than 450 Hz. Fig. 2 shows an example of a normal heart-sound audio signal and its filtered form. This signal is being recorded with the user being still and quiet, and breathing normally. The signal in cyan color is the heart sound recorded using the setup shown in Fig. 1. The signal in red color is the filtered signal. Fig. 3 provides an example of a recorded heart sound with the user creating small movements such as moving chest and arms. The filtered signal shows that the noise artifacts are removed and the original signal is smoothed.

Some electronic stethoscopes come with playback capabilities in which the recorded signals are preprocessed and amplified so the user can hear a clean, louder heart sound. We also implemented this feature in our smartphone application. As mentioned earlier, we digitize the audio signal data into 16 bits using PCM. Initially, each data point has an integer value. When we feed this data to a low-pass filter, the filtered data contains floating points due to a frequency response computation. Furthermore, each recorded signal has a different amplitude range. For example, in Fig. 2, the filtered signal has a range of -144.9 dB to 43.74 dB while in Fig. 3, the filtered signal has an amplitude range of -60.36 dB to -15.41 dB. Hence, we must equalize the recorded signals to the same amplitude range and generate the same quality of audio playback. To do

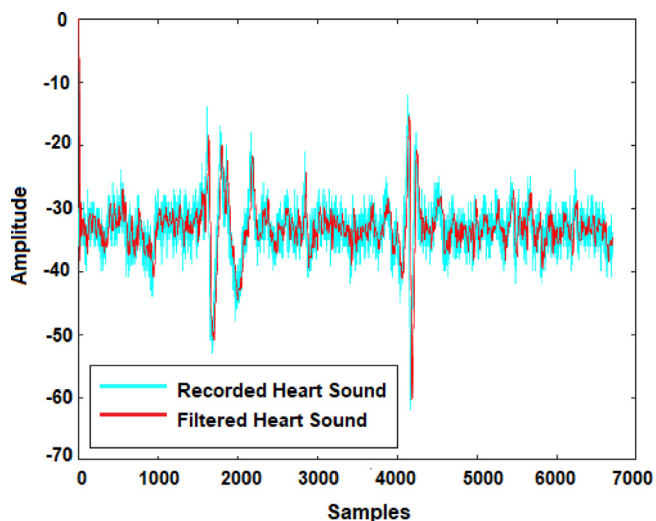


Fig. 3. Normal heart sound with the user creating noise artifacts (moving his chest and arms) and its corresponding filtered signal using Butterworth filter.



Fig. 4. Different lengths of stethoscope tubes used for testing the impact of the length on the quality of heart sounds.

this, we first amplify the filtered signal using the following equation:

$$X(t) = \frac{x(t) - \mu}{\sigma} \quad (1)$$

where $x(t)$ is the filtered signal, μ is the mean of the filtered signal, and σ is the standard deviation of the filtered signal.

Then, we normalize the amplified signal to have an amplitude range of 0–1 using the following equation:

$$s(t) = \frac{X(t) - \min(X(t))}{\max(X(t) - \min[X(t)])} \quad (2)$$

The Android media library [4] has an audio application program interface for audio playback. It allows the streaming of PCM audio buffers to the smartphone speaker. This normalized signal will be used as audio playback, visualization on the smartphone screen, and heart sound classification. If the data is formatted in floating points, the amplitude range has to be from -1.0 to 1.0 . Normalization of the filtered audio signal takes care of this issue.

It is also important to determine that the design of the device does not compromise the quality of recorded signals. In particular, we are interested in the impact the length of the stethoscope. Therefore, we perform signal recording using different length of tubes (as shown in Fig. 4). Upon testing, we witnessed no issues

with impedance mismatch, and the length of the tube did not impact the quality of the heart sounds.

4. Splits in heart sound

Normal splitting or physiological splitting occurs in normal individuals during deep inhalation. The split occurs due to delayed closure of P2. This interval narrows during expiration where only a single sound is heard. This is considered as a normal case. Persistent splitting occurs when A2 and P2 can be heard as two sounds. Splitting is audible during inhalation and expiration caused by early closure of A2 or by delayed closure of P2 with a significant variation in the time interval.

Initially, the split in heart sound is detected using auscultation methods such as subjective hearing, phonocardiograph, and electrocardiograph [17–22]. However, the signal analysis depends on a medical practitioner's interpretation. Also, the split lies in a milliseconds range. Hence, it is difficult to quantify the heart sound properties using these methods. Thus, digital signal processing tools increase our ability to reliably diagnose heart sounds. Among several signal processing methods available, wavelet transform methods have been proven to be able to extract features from the heart sounds [23–25].

Continuous monitoring and analysis of heart sounds can provide a detailed documentation of cardiac events and improve health management. Therefore, a physician's ability to monitor heart sounds remotely, outside the hospital environment, is critical to improved medical care. Attempts have been made to create portable devices to measure heart sounds. In-home monitoring of heart sounds has been proposed by Mendoza et al. [26] and Zhingwei et al. [27]. A low-cost wearable, battery-free tag for monitoring heart sounds was developed by Mandal et al. [28].

In this section, we describe a mobile phone based S1 and S2 analysis for split detection and monitoring using a low-cost, customized microphone attached to a stethoscope. The detection consists of three phases. First, the heart sounds are recorded using a customized stethoscope. Second, the audio signals are processed using wavelet transforms and the four components of the heart sounds – aortic, pulmonic, mitral, and tricuspid – are identified. In the last phase, we calculate the intervals between each component of the two heart sounds.

One other sound, S3, may exist in some patients [47]. While uncertainty exists regarding the sound's genesis, when heard with the patients over 40, physicians have long regarded its presence as a sign of ventricular dysfunction. Additionally, S3 correlates highly to decreased cardiac output, reduced ejection fraction, and to elevated end-diastolic pressures that are most common in heart failure. However, we have not considered this sound for our study though it may be added as a future work.

We have used Discrete Wavelet Transform (DWT) using the Daubechies 2 (db2) wavelet to decompose the heart signal into approximation and detailed coefficients. The approximation coefficients are iteratively filtered to increase frequency resolution. Once a desired level of resolution is achieved, the approximation coefficients are reconstructed to the original scale by up-sampling. This signal will now contain low frequency information with all of the high frequency data, such as noise artifacts, removed.

An automated program of measuring the split in heart sounds was developed using Java to run on the Android platform. The flowchart of the automation is show in Fig. 5.

A cardiac cycle shown in Fig. 6 contains a pair of heart sounds – S1 and S2. Once identified, these two signals are fed into the algorithm separately to analyze the split interval. First, the S1 is processed, followed by the S2.

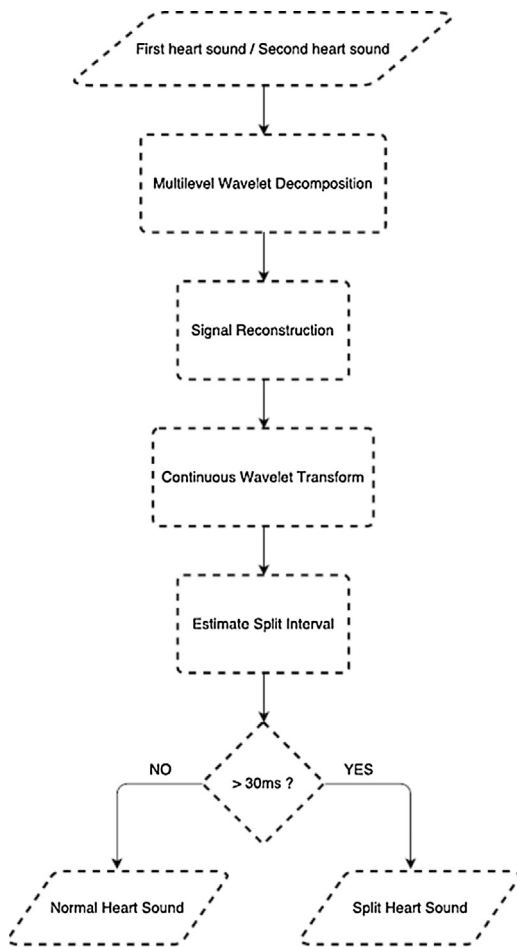


Fig. 5. Flow chart of identification and automatic measure of the split in first and second heart sounds.

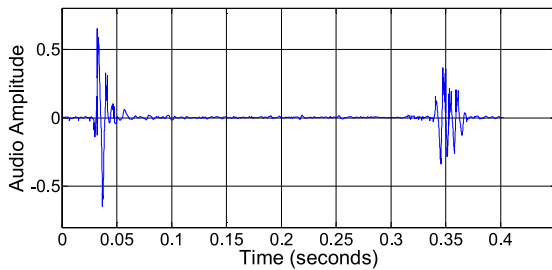


Fig. 6. A normal cardiac cycle containing first (S1) and second (S2) heart sounds.

4.1. Localization of components

The signals are sampled at 8 kHz. A 5-level wavelet decomposition is applied on the signals. The final approximation coefficients obtained from the final level of decomposition will be in the range of 0 Hz to 250 Hz.

In Fig. 7, an example of a cardiac signal with S2 split is shown. This cardiac signal is separated into S1 with length of 1889 samples and S2 with length of 4155 samples. Five levels of successive wavelet transform is performed on the S1 and S2 signals of Fig. 7. The approximation coefficients obtained are respectively shown in Figs. 8 and 9.

These approximation coefficients are then up-sampled to 8 kHz to obtain the original length of the signal, as shown in Fig. 10.

A Continuous Wavelet Transform (CWT) is applied to the reconstructed signal with a scale parameter of 1–500. The scalogram of

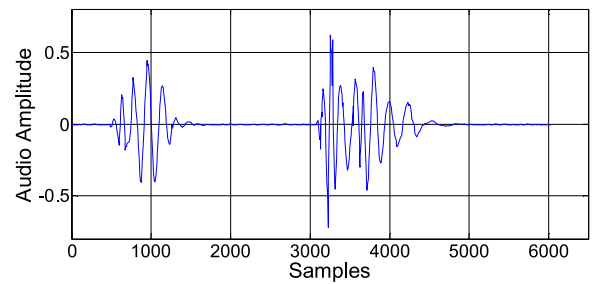


Fig. 7. An example of an abnormal cardiac cycle containing normal first heart sound (S1) and split second heart sound (S2).

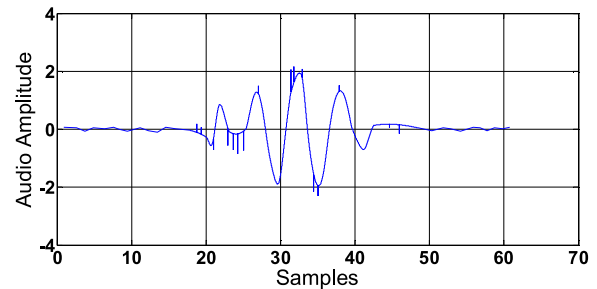


Fig. 8. Approximation coefficients after five levels of multilevel wavelet decomposition of S1 from Fig. 7.

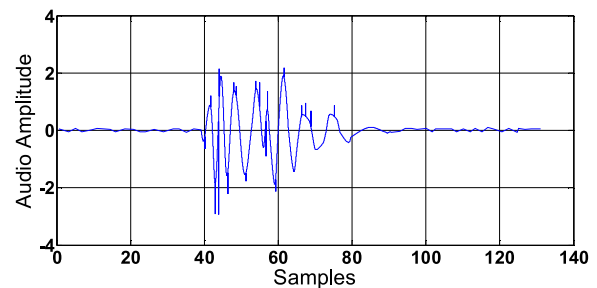


Fig. 9. Approximation signal after five levels of multilevel wavelet decomposition of S2 from Fig. 7.

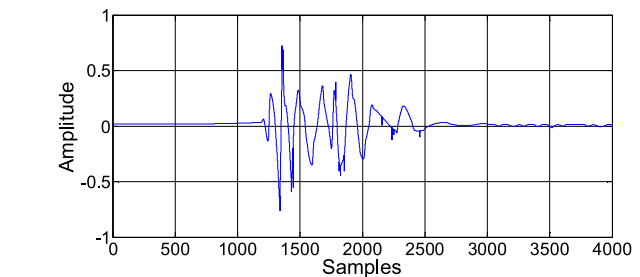
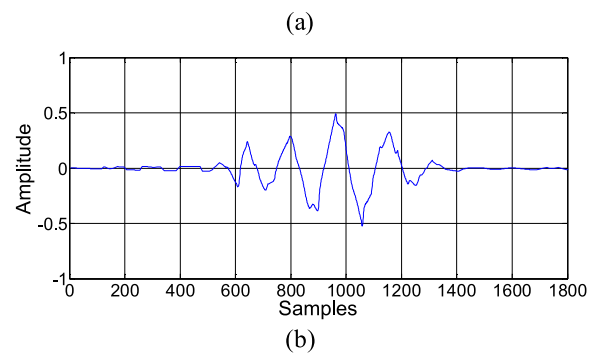


Fig. 10. Reconstruction of approximation coefficients to the original sample length by up-sampling low frequency approximation coefficients of (a) S1 from Fig. 8 and (b) S2 from Fig. 9.

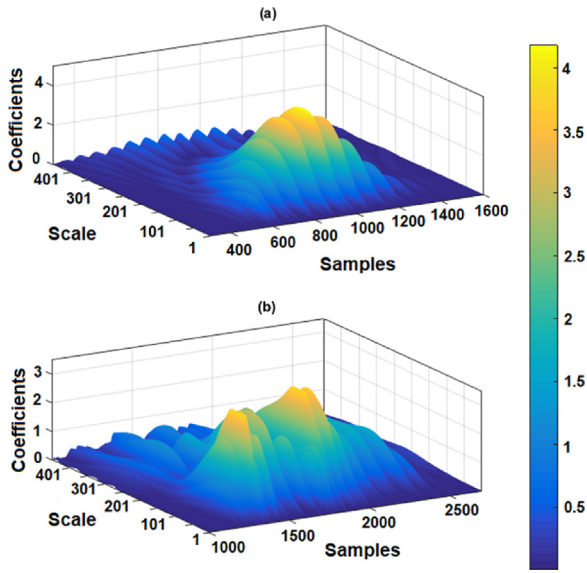


Fig. 11. Three-dimensional plot of the continuous wavelet transform coefficients obtained from Fig. 9, the color bar indicates the percentage of energy for each wavelet coefficient (a) For S1 (b) For S2.

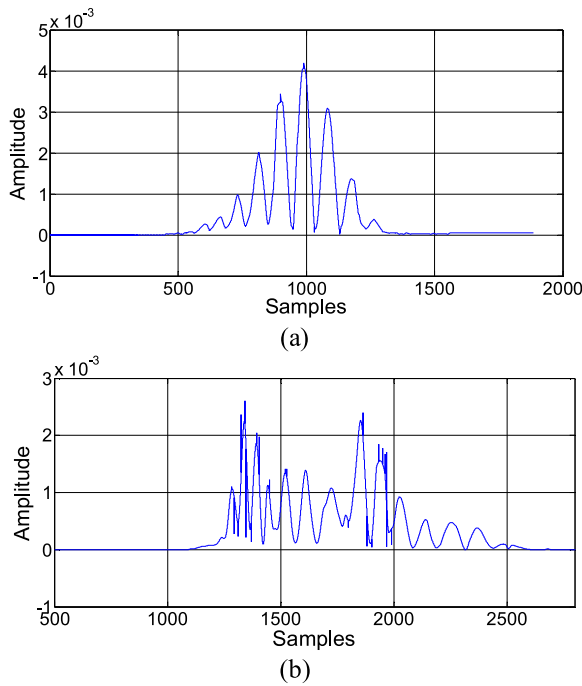


Fig. 12. Cross section of the three-dimensional signal in Fig. 10 (a) S1 with M1 (located at 899) and T1 (located at 990); (b) S2 with A2 (located at 1346) and P2 (located at 1859).

the CWT coefficients in three-dimensions is shown in Fig. 11. Dark blue and yellow represent the low and high percentage of energy, respectively. This range of colors indicates the percentage of energy that exists in each wavelet coefficient.

The cross-section of a three-dimensional graph of Fig. 11 is shown in Fig. 12. To create Fig. 12, we look at the two-dimensional scalogram [48] that shows the percentage of energy for each sample. Since the opening and closing of heart valves produce the highest amount of energy, the row with the highest percentage value will be chosen as the cross-section of the scalogram. For the S1 signal in Fig. 10(a), M1 is located at sample 899 and T1 at sample 990. For the S2 signal in Fig. 10(b), A2 is located at sample 1346

Table 2

15 Normal and 28 Abnormal Heart Sounds [29–33] used for automated measuring of Split.

Types of Cardiac Signals	No of cardiac signals	Contains split?
Normal	15	No
S1 split	2	Yes, S1
S2 split during inspiration	2	Yes, S2
S2 split with persistent splitting	3	Yes, S2
Wide S2 Split	3	Yes, S2
Paradoxical S2 split	2	Yes, S2
S1 split and S2 split	1	Yes, S1 and S2
Atrial septal defect	3	Yes, S2
Ventricular septal defect	3	Yes, S2
Mitral stenosis	3	No
Pulmonary stenosis	3	Yes, S2
Aortic stenosis	3	No

and P2 at sample 1859. In Section IV – B, we will use these sample locations to calculate the time difference between the two samples and then use it to determine the presence of split in heart sounds.

4.2. Split calculation

Once the two components of a heart sound is detected, the time interval between is calculated using the following equations:

$$S1 \text{ split} = \left| \frac{\text{Location of } T1 - \text{Location of } M1}{\text{sampling frequency}} \right| \quad (3)$$

$$S2 \text{ split} = \left| \frac{\text{Location of } P2 - \text{Location of } A2}{\text{sampling frequency}} \right| \quad (4)$$

Since locations of components are in a number of samples, the difference in the number of samples has to be divided by the sampling frequency to obtain the interval in number of seconds. From Fig. 12, the time interval between M1 and T1 for the cardiac signal of Fig. 8 is 11 milliseconds. Since the time interval is less than 30 milliseconds, this cardiac signal has a normal S1. However, the time delay between A2 and P2 is 64 milliseconds—or abnormal. Therefore, S2 has a split.

This automation technique was tested on 15 healthy individuals and 28 individuals with abnormal heart sounds obtained from online databases [29–33]. Table 2 lists the types of signals used for validating the automation. A wide variety of heart sounds have been included for the split detection.

Table 3 shows the calculated split intervals of a selected signals from Table 2. We have presented the mean and standard deviations for the heart signals from Table 2. The presence or absence of split is determined from these measured values. As we can see, our system can correctly detect the presence or absence of split in heart signals.

5. Classification of heart sounds

In this section, we describe our classification model that directly classifies processed heart sound signal as explained in Sections III and IV.

The process of automatic diagnosis of valvular heart disease started more than 50 years ago. Gerbag et al. [52] proposed an automation technique using a threshold-based method to classify phonocardiogram data. More recently, machine learning tools such as Support Vector Machine (SVM), Artificial Neural Network (ANN), and HMM have been used to classify heart sounds. ANN was one of the first widely used approaches to classify heart sounds [53]. Homomorphic filtering and k -means clustering are also used as feature extraction techniques with ANN to classify heart sounds into normal, systolic murmurs, and diastolic murmurs [55]. ANN was also used to screen innocent and pathological cases in children [56]. Turkoglu et al. [54] used wavelet entropy and STFT to extract

Table 3
Calculated Split intervals of A Sample Cardiac Signals From Each Type in Table 2.

Cardiac Signal	Mean (ms)		Standard Deviation (ms)		Split Detected?
	S1 Split Interval	S2 Split Interval	S1 Split Interval	S2 Split Interval	
Normal	11.69	12.61	8.90	10.27	No
S1 split	55.96	17.99	15.46	17.27	Yes, S1
S2 split during inspiration	7.50	78.36	3.09	61.40	Yes, S2
S2 split with persistent splitting	9.47	65.98	9.76	18.04	Yes, S2
Wide S2 split	5.30	124.57	1.97	19.01	Yes, S2
Paradoxical S2 split	12.09	73.40	2.25	9.79	Yes, S2
S1 split and S2 split	45.36	70.25	–	–	Yes, S1 and S2
Atrial septal defect	9.90	65.96	8.23	29.61	Yes, S2
Ventricular septal defect	6.62	76.24	7.00	10.73	Yes, S2
Mitral stenosis	10.57	14.19	4.22	11.04	No
Pulmonary stenosis	9.95	59.22	3.35	13.51	Yes, S2
Aortic stenosis	11.38	16.70	11.48	22.06	No

features of heart sound and classify them into normal and abnormal cases.

Support Vector Machine (SVM) is another machine learning method used to classify heart sounds. Within SVM, Wu et al. [57] first use wavelet transform to extract the characteristics of PCG signals; then, they classify their results as normal, mitral stenosis, or mitral regurgitation. In another early attempt, Samjin et al. [58] propose a spectral analysis method using a normalized autoregressive power spectral density curve along with SVM to classify normal and 6 abnormal cases.

HMM is another notable method which has been proven to be effective for modeling heart sounds [59,60]. The combination of MFCC and HMM is more popular in classifying the heart murmurs [61–63]. This approach was first used in speech recognition [64–66].

One of the primary issues with the current studies in heart sound classification is data selection. These studies are limited as they often have difficulty in distinguishing between normal, abnormal cases, and murmur types. Furthermore, the heart sound recordings used do not contain any noise artifacts. We have used a combination of MFCC and HMM to design our classification model to increase our ability to distinguish between normal and abnormal heart sounds as well as to be able to identify a larger variety of murmurs. We selected this technique because of its ease of implementation in real time classification and because we would still be able to extract spectral features of a variety of heart murmurs.

Elmahdy et al. [74] have also built a classification model using HMM and MFCC coefficients as features for improved recognition of heart murmur. Chen et al. [75] use deep neural networks by *k*-mean clustering of MFCC features of heart sounds signals to recognize S1 and S2 heart sounds. Karar et al. [77] use a classification tree method to classify heart sounds into one normal and three abnormal cases – aortic valve stenosis, aortic insufficient, and ventricular septum defect.

In this study, we use 16 types of heart sounds (1 normal heart sound, S1 split, S2 split, and 13 murmurs) to build and test a classification system in a smartphone. (The types of heart murmurs that are used in this study are shown in Table 4.)

5.1. Data collection

The heart sounds were collected from online sources [29–33] and Dr. Daniel Mason's CDs, which contain a comprehensive collection of heart sounds [72]. The amount of training and test data for each type of heart sound is shown in Table 5. We added Gaussian white noise to test data to simulate a real-time signal. We preprocessed these test data as explained in Section IV before we fed them into our classification model. Since signals were recorded

Table 4
List of Murmurs used For The Presented Classification Model.

Systolic Murmurs	Diastolic Murmurs	Continuous Murmur
1. Aortic stenosis	9. Aortic regurgitation	13. Patent ductus arteriosus
2. Pulmonic stenosis	10. Pulmonic regurgitation	
3. Mitral regurgitation	11. Mitral stenosis	
4. Tricuspid regurgitation	12. Tricuspid stenosis	
5. Mitral valve prolapse		
6. Atrial septal defect		
7. Ventricular septal defect		
8. Flow murmur		

Table 5
Heart Sound Types and Number of Training and Test Data Obtained From [29–33,72,79].

Heart Sounds	Training Data	Test Data
Normal (N)	27	26
Aortic stenosis (AS)	23	22
Pulmonic stenosis (PS)	17	16
Mitral regurgitation (MR)	19	14
Tricuspid regurgitation (TR)	15	14
Mitral valve prolapse (MVP)	16	16
Atrial septal defect (ASD)	8	8
Ventricular septal defect (VSD)	7	7
Flow murmur (FM)	5	4
Aortic regurgitation (AR)	19	15
Pulmonic regurgitation (PR)	12	8
Mitral stenosis (MS)	21	15
Tricuspid stenosis (TS)	17	17
Patent ductus arteriosus (PDA)	17	17
Total	223	199

with different sampling rates, we first down sampled to 8 kHz and normalized. (We selected 8 kHz for the sampling rate because the live audio recorded from our customized external microphone was sampled at this rate.) Next, we extracted features of the signals using MFCC and used the training data to train the HMMs with a forward-backward algorithm.

5.2. Classification model

Mel-frequency Cepstral Coefficient (MFCC), a highly popular method used in extracting features in automatic speech recognition, allows identification of audio signal components such as frequency and energy intensity while discarding redundant data such as noise artifacts. MFCC, first introduced by Bridle and Brown in 1974 [67], resembles the human auditory system. Mel scale is a logarithmic scale because human perception of frequency contents is non-linear. Since heart sounds are also heard by humans, MFCC becomes a good candidate algorithm to extract features of the heart sounds.

A Hidden Markov model is a Markov process in which the system has hidden discrete states. The model also provides transition probabilities of moving from one state to another. In this system, a sequence of emissions is observed without knowing the sequence of the hidden states or whether there is a one-to-one correspondence between the emission and the hidden state [68–71]. To compute the maximum likelihood estimates for the HMM parameters, the forward-backward algorithm is used. HMM is commonly used in pattern recognition or as a classification tool in automatic speech recognition and gesture recognition.

Our classification model is built with 8 HMMs: normal systolic, midsystolic, late systolic, holosystolic, normal diastolic, early diastolic, mid/late diastolic, and holodiastolic, where the first four models are systolic murmur models and the latter four are diastolic murmur models.

The following list shows how each murmur is associated with a model:

- ASD-midsystolic and split detected in S2.
- AS/PS- midsystolic and normal diastolic.
- MVP-late systolic and normal diastolic.
- FM-late systolic and normal diastolic.
- MR/TR-holosystolic and normal diastolic.
- N-normal systolic and normal diastolic.
- VSD-holosystolic and split detected in S2.
- AR/PR-normal systolic and early diastolic.
- MS/TS –normal systolic and mid/late diastolic.
- PDA-holosystolic and holodiastolic.

After training the HMMs, we use the test data results from Table 5 to validate our classifier. In this initial step the normalized heart sound is segmented into first (S1) and second (S2) heart sounds. Next, we feed the S1 into systolic murmur models and the S2 into diastolic murmur models. Next, our computational model calculates the likelihood of each model. Finally, our model classifies the heart sound based on the maximum likelihood of systolic and diastolic murmurs.

The maximum likelihood estimate may sometimes lead to two classified signals. For example, maximum likelihood in midsystolic and normal diastolic leads to AS and PS. To distinguish between the two, the auscultation area is used for further classification. For example, for AS the auscultation point is the aortic area whereas for PS the auscultation point is the pulmonic area. Depending on which auscultation point was used to acquire the heart sound, the signal can be correctly classified.

5.3. Accuracy of the classification model

The classification model used for this study is associated with several parameters such as number of states in HMMs, frame size of the signal while extracting the Mel-frequency Cepstral Coefficient (MFCC), and number of MFCCs used per frame. For the purpose of extensive testing, these parameters were varied with all possible combinations as follows:

1. States of each Hidden Markov Model (HMM): 2, 3, and 4.
2. Frame size of a signal (number of samples used in one frame): 128, 256, and 512.
3. Number of MFCCs picked per frame: 8, 12, and 16.

The accuracy of our classification model with various combinations of parameters is shown in Table 6. From the table, HMM with 2 states, frame size of 512 samples and 8 MFCCs per frame is the best combination with an accuracy of 92.52%, the highest in the table.

Table 6

Accuracy of classification model with all possible combinations of HMM States, Frame Size and No. of MFCCs.

HMM states	Frame size (samples)	No. of MFCCs		
		8	12	16
2	128	85.09	82.61	85.09
2	256	84.47	86.96	78.26
2	512	92.52	84.47	87.58
3	128	79.50	85.09	81.37
3	256	91.30	85.09	88.82
3	512	80.75	80.75	75.78
4	128	83.85	78.88	81.37
4	256	85.71	85.09	86.34
4	512	80.12	79.50	78.26

Table 7

Accuracy in classifying each type of heart sounds from Table 5.

Heart sounds	Accuracy	Accuracy without Auscultation area
Normal (N)	76.92	61.53
Aortic stenosis (AS)	72.72	45.45
Pulmonic stenosis (PS)	81.25	43.75
Mitral regurgitation (MR)	78.57	35.71
Tricuspid regurgitation (TR)	71.42	27.27
Mitral valve prolapse (MVP)	100.00	81.25
Atrial septal defect (ASD)	87.50	–
Ventricular septal defect (VSD)	100.00	–
Flow murmur (FM)	75.00	50
Aortic regurgitation (AR)	66.66	26.66
Pulmonic regurgitation (PR)	80.00	50.00
Mitral stenosis (MS)	86.66	73.68
Tricuspid stenosis (TS)	100	88.23
Patent ductus arteriosus (PDA)	88.24	47.05

Table 8

Number of heart sounds classified as normal or abnormal from test data in Table 5.

Input	Results		
	Normal	Abnormal	Correctly Classified
Normal	20	6	76.92%
Abnormal	2	171	98.84%

Another problem that must be addressed is accurately identifying whether a murmur is normal or life-threatening. As with abnormal heart valve movement, murmurs can be difficult to identify, complicated by the wide variance in types. Our model needed to accurately identify not only that the murmur occurs, but also what type it might be so physicians can determine necessary actions. The accuracy for each murmur is shown in Table 7. The number of available patients with murmurs such as ASD, VSD, FM, and PR is low and, thus, we do not have as many samples as we have for the other murmurs. Nevertheless, we have been able to achieve good accuracy overall across all murmurs as shown in Table 8. In Table 8, a confusion matrix is shown, which classifies heart sounds as normal or abnormal. The abnormal heart sounds include all the heart murmurs. 20 out of 26 normal heart sounds and 171 out of 173 abnormal heart sounds were correctly classified. As shown in the table, the probability of incorrectly classifying an abnormal heart sound as normal is very low (i.e., false negatives accounted for only 1.16%). This demonstrates the high overall accuracy of the presented system.

6. Software design of heart sound application

In this section, we describe the mobile application software that implements the methodologies described in Sections III, IV, and V for detection and classification of heart sounds.

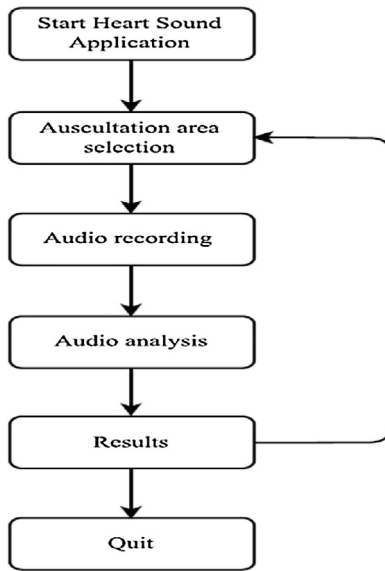


Fig. 13. High level architecture of the heart sound application.

The heart sounds software (App) is smartphone software to record and analyze heart sounds. It provides a low-cost, portable solution to remotely monitor the functioning of a heart. Using the App requires an external customized microphone and a smartphone with an Android 5.0 and above operating system. The external microphone requires a 3.5 mm adapter for mobile phone, 50–18000 Hz frequency response, –54 dB sensitivity, 1000 ohm impedance, and an analog stethoscope. Using this application, the users can (i) record, (ii) localize, (iii) view, (iv) listen to, (v) classify, (vi) detect split in, (vii) generate electronic records of heart sounds, and (viii) share electronic medical records.

6.1. Software design

The high-level architecture of the application is shown in Fig. 13. Once the Start button is pressed, the heart sound starts appearing on the screen. When the Record button is pressed, the microphone starts recording the heart sounds from the stethoscope. The recording automatically stops after 10 s and the recorded signal is made available for analysis on the results screen. A sample recording is shown in Fig. 14. The blue signal represents the live audio signal being recorded while the green dots represent the potential S1 or S2 peaks.

The App selects the best S1–S2 pairs from the whole recording based on the peak selection method (discussed in Algorithm 1) for further analysis. The signals are simultaneously used for split calculation and filtering as explained in earlier sections.

After the signals are processed, the results are displayed as shown in Fig. 15. The user interface of the results has two sections. The upper section displays a visualization of the analyzed heart sounds. The displayed signal is segmented into two parts—S1 in pink and S2 in red. Blue indicates other signals that were not selected for analysis. The x-axis is time in milliseconds while the y-axis is the normalized amplitude. The lower section shows the initial diagnosis of the signal with details such as patient's name, and date and time of the recording, along with the auscultation area selected by the user. Next, the screen's table shows all the selected signals along with their split timings and the classification. The results of split calculation are displayed in milliseconds. If the split(s) is/are more than 30 ms, the App will indicate the presence of a split in the first and/or second heart sound. Finally, the result of the classification is displayed. As shown in Fig. 15, the Share button

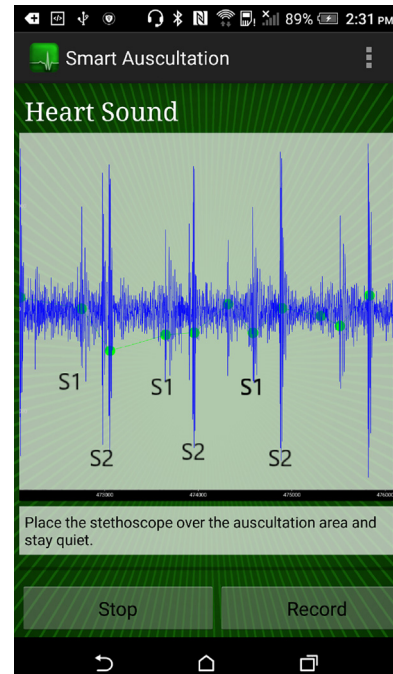


Fig. 14. Screenshot of live record of heart sounds.

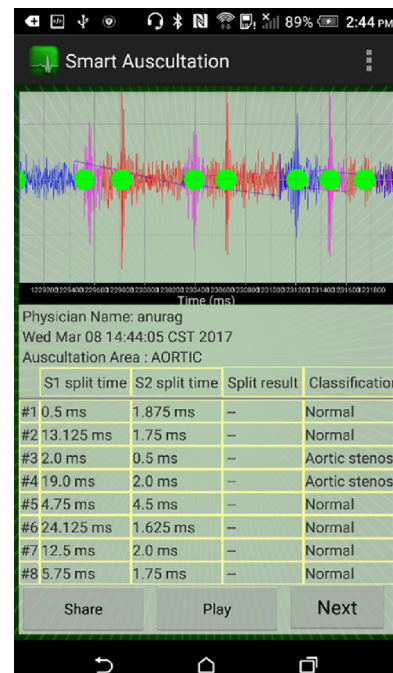


Fig. 15. Screenshot showing Detection of S1 and S2.

will produce an electronic record of the heart sound that can be shared with medical practitioners via e-mail, while the Play button replays a filtered and amplified audio signal for the user.

A video demonstrating the presented system is available at <https://youtu.be/4chBot2lrVY>. This video shows the use of the modified stethoscope to record heart sounds and the user-interface of the software in a smartphone to process and classify the recorded heart sounds.

6.2. Performance analysis

To analyze the App performance, heart sounds are collected from patients visiting the clinic at UT Southwestern, Dallas. The

Table 9

Accuracy of Heart Sounds collected from Clinical Trials of Patients at UT Southwestern, Dallas.

Heart sounds	Accuracy (%)
Normal	76.19
S2 Split	83.33
Aortic stenosis	68.00
Mitral regurgitation	75.00
Flow murmur	87.00
Aortic regurgitation	66.00

Table 10

Number of heart sounds from Table 9 correctly identified as normal or abnormal case.

Input	Results		
	Normal	Abnormal	Correctly Classified
Normal	21	5	80.76%
Abnormal	3	38	92.68%

classification accuracy results obtained with the available data are shown in Table 9. Sufficient data was not available for some types of murmurs. The test data can be segmented into 21 normal and 41 abnormal heart sounds. The classification of normal and abnormal heart sounds is shown in Table 10.

7. Conclusion and future work

In this paper, we have presented a detailed description of a smartphone-based electronic stethoscope that can record, process, and identify 16 types of heart sounds. The presented solution is portable, low-cost, and does not need a highly trained medical practitioner to operate. Therefore, this system will have incredible application as an initial diagnosis tool in non-hospital environments such as homecare, rural areas, and urban clinics. Furthermore, as shown in the results, our method is very accurate and reliable in the detection of abnormal murmurs in heart sounds.

A comparison of our system with previous studies and existing products (Appendix: Table A.1 and Table A.2) shows that our system can detect and classify more types of heart sounds than any other previously published work. Also, our system is one of only two systems built on the smartphone platform, making it more portable and easy to use. Furthermore, our sample size for testing is one of the highest, making our presented data more reliable. Compared to other commercial products, our system is a low-cost, portable, and efficient solution, with visualization and playback features not available in all products. Furthermore, our system can provide instant and accurate classification of heart sound that is not available with most other available products.

Future work focuses on enhancing the current model to detect more abnormal heart sounds such as open snap, gallops, and atrial fibrillations. The model can also be improved to detect multiple murmurs per heart sound. Similar methodologies can also be used to detect more body sounds such as from lungs and bruits. In this study, due to the source of collected data samples, results are biased towards the local Dallas, TX population. We propose analyzing a wider variety of data collected from a worldwide population to train the classification model that will make this an excellent initial screening tool that can be used reliably throughout the world.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.bspc.2018.05.008>.

References

- [1] Cardiosleeve, The world's first stethoscope attachment to provide ECG, Digital Auscultation and Instant Analysis, Rijuven Corporation [Online] Available: <https://cardiosleeve.myshopify.com/> [Accessed: 4.25.2018].
- [2] Sencardiac, A way to provide quantitative heart screenings [Online] Available: <https://sencardiac.com/> [Accessed: 4.17.2018].
- [3] Eko Devices, Eko Core Digital Stethoscope [Online] Available: <https://ekodevices.com/> [Accessed: 4.17.2018].
- [4] R.S. Patel, J. Schwarz, V. Danesh, A.M. Einhorn, D. Bello, Clinical Performance of The HeartBuds, an Electronic Smartphone Listening Device, Compared to FDA Approved Class I and Class II Stethoscopes, American Heart Association, Inc., 2015 (Print ISSN. 0009-7322 Online ISSN. 1524-4539).
- [5] One Digital Stethoscope, Thinklabs Medical LLC [Online] Available: <http://www.thinklabs.com/> [Accessed: 4.17.2018].
- [6] Stethaid, Parker H. Petit Institute for Bioengineering and Bioscience [Online] Available: <http://atlanticpediatricdeviceconsortium.org/stethaid> [Accessed: 4.17.2018].
- [7] H.K. Walker, W.D. Hall, J.W. Hurst, Clinical Methods: The History, Physical, and Laboratory Examinations, Butterworths, 1990.
- [8] M.A. Chizner, Cardiac auscultation: rediscovering the lost art, *Curr. Prob. Cardiol.* 33 (7) (2008) 326–408.
- [9] A.K. Abbas, R. Bassam, Phonocardiography signal processing, in: Synthesis Lectures on Biomedical Engineering, Morgan and Claypool Publishers, 2009.
- [10] S.M. Debbal, F. Bereksi-Reguig, Computerized heart sounds analysis, *Computers in Biology and Medicine, Comput. Biol. Med.* 38 (2) (2008) 263–280.
- [11] T. Biancaniello, Innocent murmurs, *Circulation* 111 (3) (2005) e20–e22.
- [12] B. Wells, The graphic configuration of innocent systolic murmurs, *Br. Heart J.* 19 (1) (1957) 129–134.
- [13] B. Erickson, Heart Sounds and Murmurs: A Practical Guide, Mosby Year Book, 1991.
- [14] A.C. Guyton, J.E. Hall, Textbook of Medical Physiology, Guyton Physiology Series, Elsevier Saunders, 2006.
- [15] N.O. Fowler, Diagnosis of Heart Disease, Springer, New York, 2012.
- [16] R.M. Rangayyan, R.J. Lehner, Phonocardiogram signal analysis: a review, *Crit. Rev. Biomed. Eng.* 15 (3) (1986) 211–236.
- [17] P. Heintzen, The genesis of the normally split first heart sound, *Am. Heart J.* (1961) 332–343.
- [18] P. Kincaid-Smith, J. Barlow, The atrial sound and the atrial component of the first heart sound, *Br. Heart J.* 21 (4) (1959) 470–478.
- [19] J.J. Kelly, Diagnostic value of phonocardiography in mitral stenosis: mode of production of first heart sound, *Am. J. Med.* 19 (6) (1955) 862–868.
- [20] I.R. Gray, Paradoxical splitting of the second heart sound, *Br. Heart J.* 18 (1) (1956) 21–28.
- [21] J.M. Barber, O. Magidson, P. Wood, Atrial septal defect: with special reference to the electrocardiogram, the pulmonary artery pressure and the second heart sound, *Br. Heart J.* 12 (3) (1950) 277–292.
- [22] J.K. Perloff, W.P. Harvey, Mechanisms of fixed splitting of the second heart sound, *Circulation* 18 (5) (1958) 998–1009.
- [23] L. Huiying, L. Sakari, H. Iiro, A heart sound segmentation algorithm using wavelet decomposition and reconstruction, IEEE, in: Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 4, 1997, pp. 1630–1633.
- [24] S.M. Debbal, F. Bereksi-Reguig, Automatic measure of the split in the second cardiac sound by using the wavelet transform technique, *Comput. Biol. Med.* 37 (3) (2007) 269–276.
- [25] Z. Dokur, T. Olmez, Heart sound classification using wavelet transform and incremental self-organizing map, *Digital Signal Process.* 18 (6) (2008) 951–959.
- [26] G.G. Mendoza, B.Q. Tran, In-home wireless monitoring of physiological data for heart failure patients, IEEE, in: Proceedings of the Second Joint Engineering in Medicine and Biology, vol. 3, 2002, pp. 1849–1850.
- [27] Z. Jiang, S. Choi, A cardiac sound characteristic waveform method for in-home heart disorder monitoring with electric stethoscope, *Expert Syst. Appl.* 31 (2) (2006) 286–298.
- [28] S. Mandal, L. Turicchia, R. Sarpeshkar, A battery-free tag for wireless monitoring of heart sounds, in: 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks, IEEE, 2009, pp. 201–206.
- [29] CWRU: Physical Diagnosis, The Cardiac Exam, Case Western Reserve University [Online] Available: <http://casemed.case.edu/cardiaceexam/> [Accessed: 4.25.2017].

- [30] Heart Sounds Lessons, Quizzes and Reference Guides, MedEdu LLC [Online] Available: <http://www.easysauscultation.com/heart-sounds> [Accessed: 4.17.2018].
- [31] Advanced Physical Diagnosis, University of Washington, Department of Medicine [Online] Available: <http://depts.washington.edu/physdx/heart/demo.html> [Accessed: 4.17.2018].
- [32] Heart Sound and Murmur Library, University of Michigan [Online] Available: http://www.med.umich.edu/lrc/psb_open/html/repo/primer_heart_sound/primer_heart_sound.html [Accessed: 4.17.2018].
- [33] The Auscultation Assistant-Hear Heart Murmurs, Heart Sounds and Breath Sounds [Online] Available: <http://www.wilkes.med.ucla.edu/inex.htm> [Accessed: 4.17.2018].
- [34] Elite™ Electronic Stethoscope, Welch Allyn [Online] Available: https://www.welchallyn.com/content/welchallyn/americas/en/products/categories/discontinued-products/physical-exam/stethoscopes/elite_electronic_stethoscope.html [Accessed 4.17.2018].
- [35] JABES Life Sound System [Online] Available: <http://telehealthtechnology.org/toolkits/electronic-stethoscopes/assessment-process/product-cut-sheets/jabes> [Accessed 4.17.2018].
- [36] Littman Stethoscopes [Online], Available: <http://www.littmann.com/3M/en.US/littmann-stethoscopes> [Accessed 4.17.2018].
- [37] A.P. Yoganathan, R. Gupta, F.E. Udawadia, J.W. Miller, W.H. Corcoran, R. Sarma, J.L. Johnson, R.J. Bing, Use of the Fast Fourier Transform for frequency analysis of the first heart sound in normal man, *Med. Biol. Eng.* 14 (1) (1976) 69–73.
- [38] A.P. Yoganathan, R. Gupta, W.H. Corcoran, Fast Fourier Transform in the analysis of biomedical data, *Med. Biol. Eng.* 14 (2) (1976) 239–245.
- [39] M. El-Seaiger, O. Lilja, S. Lukkarinen, L. Sornmo, R. Sepponen, E. Pesonen, Computer-based detection and analysis of heart sound and murmur, *Ann. Biomed. Eng.* 33 (7) (2005) 937–942.
- [40] A. Djebbari, F.B. Reguig, Short-time Fourier transform analysis of the phonocardiogram signal, The 7th IEEE International Conference on Electronics, Circuits and Systems Vol. 2 (2000) 844–847.
- [41] C.C. Balili, M.C.C. Sobrepena, P.C. Naval, Classification of heart sounds using discrete and continuous wavelet transform and random forests, in: 3rd IAPR Asian Conference on Pattern Recognition (ACPR), IEEE, 2015, pp. 655–659.
- [42] T.-H. Chen, P.-Y. Guo, S.-X. Xing, Y. Zheng, A new method of sorting of heart sound signal based on wavelet transform and parameter model method, 4th International Conference on Bioinformatics and Biomedical Engineering (ICBBE) (2010) 1–4.
- [43] H. Liang, S. Lukkarinen, I. Hartimo, Heart sound segmentation algorithm based on heart sound envelopegram, IEEE, in: *Computers in Cardiology*, 1997, pp. 105–108.
- [44] V. Chandrasekaran, R. Dantu, S. Jonnada, S. Thiyagaraja, K.P. Subbu, Cuffless differential blood pressure estimation using smart phones, *IEEE Trans. Biomed. Eng.* 60 (4) (2013) 1080–1089.
- [45] S.R. Thiyagaraja, J. Vempati, R. Dantu, T. Sarma, S. Dantu, Smart phone monitoring of second heart sound split, in: 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2014, pp. 2181–2184.
- [46] S. Jonnada, Cuffless Blood Pressure Measurement Using a Smart Phone, University of North Texas, 2012.
- [47] D. Kumar, P. Carvalho, M. Antunes, J. Henriques, A. Sa e Melo, R. Schmidt, J. Habetha, Third heart sound detection using wavelet transform-simplicity filter, 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2007).
- [48] S.R. Thiyagaraja, Detection and Classification of Heart Sounds using a heart-mobile interface, in: A Dissertation, Univ. of North Texas, 2016.
- [49] Q. Zhang, H. Wang, Y. Fang, X. Xu, An adaptive heart murmur detection method based on SVD, *J. Comput. Inf. Syst.* 8 (21) (2012) 9085–9092.
- [50] S. Winder, Analog and digital filter design, in: *EDN Series for Design Engineers*, Elsevier Science, 2002.
- [51] B.A. Sheno, Introduction to Digital Signal Processing and Filter Design, Wiley, 2005.
- [52] D.S. Gerbarg, A. Taranta, M. Spagnuolo, J.J. Hoer, Computer analysis of phonocardiograms, *Prog. Cardiovasc. Dis.* 5 (4) (1963) 393–405.
- [53] I. Cathers, Neural network assisted cardiac auscultation, *Artif. Intell. Med.* 7 (1) (1995) 53–66.
- [54] I. Turkoglu, A. Arslan, E. Ilkay, An expert system for diagnosis of the heart valve diseases, *Expert Syst. Appl.* 23 (3) (2002) 229–236.
- [55] C.N. Gupta, R. Palaniappan, S. Swaminathan, S.M. Krishnan, Neural network classification of homomorphic segmented heart sounds, *Appl. Soft Comput.* 7 (1) (2007) 286–297.
- [56] Z. Guo, L.-G. Durand, H.C. Lee, L. Allard, M.-C. Grenier, P.D. Stein, Artificial neural networks in computer-assisted classification of heart sounds in patients with porcine bioprosthetic valves, *Med. Biol. Eng. Comput.* 32 (3) (1994) 311–316.
- [57] J.-B. Wu, S. Zhou, Z. Wu, X.-M. Wu, Research on the method of characteristic extraction and classification of phonocardiogram, in: *International Conference on Systems and Informatics (ICSAI)*, IEEE, 2012, pp. 1732–1735.
- [58] S. Choi, Z. Jiang, Cardiac sound murmurs classification with autoregressive spectral analysis and multi-support vector machine technique, *Comput. Biol. Med.* 40 (1) (2010) 8–20.
- [59] M. El-Hanjouri, W. Alkhalidi, N. Hamdy, O.A. Alim, Heart diseases diagnosis using HMM, in: 11th Mediterranean Electrotechnical Conference, 2002. MELECON, IEEE, 2002, pp. 489–492.
- [60] R. Saraçoğlu, Hidden Markov Model-based classification of heart valve disease with PCA for dimension reduction, *Eng. Appl. Artif. Intell.* 25 (7) (2012) 1523–1528.
- [61] S. Chauhan, P. Wang, C.S. Lim, V. Anantharaman, A computer-aided MFCC-based HMM system for automatic auscultation, *Comput. Biol. Med.* 38 (2) (2008) 221–233.
- [62] L. Zhong, J. Wan, Z. Huang, G. Cao, B. Xiao, Heart murmur recognition based on hidden markov model, *J. Signal Inf. Process.* 4 (2) (2013) 140–144.
- [63] P. Wang, C.S. Lim, S. Chauhan, J.Y.A. Foo, V. Anantharaman, Phonocardiographic signal analysis method using a modified Hidden Markov Model, *Ann. Biomed. Eng.* 35 (3) (2007) 367–374.
- [64] C.-T. Do, D. Pastor, A. Goalic, On the recognition of cochlear implant-like spectrally reduced speech with MFCC and HMM-based ASR, *IEEE Trans. Audio Speech Lang. Process.* 18 (5) (2010) 1065–1068.
- [65] G. Talwar, R.F. Kubichek, H. Liang, Hiddenness control of Hidden Markov Models and application to objective speech quality and isolated-word speech recognition, *Fortieth Asilomar Conference on Signals, Systems and Computers*, IEEE (2006) 1076–1080.
- [66] D. O'Shaughnessy, Invited paper: automatic speech recognition: history, methods and challenges, *Pattern Recognit.* 41 (10) (2008) 2965–2979.
- [67] J.S. Bridle, M.D. Brown, An experimental automatic word recognition system, *JSRU Rep.* 1003 (5) (1974).
- [68] A.M. Fraser, *Hidden Markov Models and Dynamical Systems*, Society for Industrial and Applied Mathematics, 2008.
- [69] W. Zucchini, L.L. MacDonald, *Hidden Markov Models for time series: an introduction using R*, in: *Monographs on Statistics & Applied Probability*, Chapman & Hall/CRC Press, 2009.
- [70] R.J. Elliott, L. Aggoun, J.B. Moore, *Hidden markov models: estimation and control*, in: *Stochastic Modelling and Applied Probability*, Springer, New York, 2008.
- [71] L.R. Rabiner, A tutorial on Hidden Markov Models and selected applications in speech recognition, *Proc. IEEE* 77 (2) (1989) 257–286.
- [72] D. Mason, *Listening to the Heart: A Comprehensive Collection of Heart Sounds and Murmurs*, Davis, 2000.
- [73] E. Sejdic, J. Jiang, Selective regional correlation for pattern recognition, *IEEE Trans. Syst. Man Cybern. – Part A Syst. Humans* 37 (1) (2007) 82–93.
- [74] H.N. Elmahdy, K. Rajoob, M.A. Refaey, M.A. Kotb, Improving the recognition of heart murmur, *Int. J. Adv. Comput. Sci. Appl. (IJACSA)* 7 (7) (2016) 1–10.
- [75] T.E. Chen, S.I. Yang, L.T. Ho, K.H. Tsai, Y.H. Chen, Y.F. Chang, Y.H. Lai, S.S. Wang, Y. Tsao, C.C. Wu, S1 and S2 heart sound recognition using deep neural networks, *IEEE Trans. Biomed. Eng.* 64 (2) (2017) 302–308.
- [76] K.L. Kuan, A Framework for Automated Heart and Lung Sound Analysis Using a Mobile Telemedicine Platform, 2010 [Online] Available: <http://hdl.handle.net/1721.1/62658> [Accessed: 4.17.2018].
- [77] M.E. Karar, S.H. El-Khaffif, M.A. El-Brawany, Automated diagnosis of heart sounds using rule-based classification tree, *J. Med. Syst.* 4 (2017) 1–7.
- [78] S.R. Thiyagaraja, R. Dantu, P.L. Shrestha, M.A. Thompson, C. Smith, Optimized and secured transmission and retrieval of vital signs from remote devices, *IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)* (2017).
- [79] *Cardiac Auscultatory Recording Database* [Online] Available: <http://murmurlab.org/card6/> [Accessed 4.17.2018].