Developing Bluetooth phonocardiogram for detecting heart murmurs using hybrid MFCC and LSTM

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ABSTRACT

Cardiovascular disease is a leading global cause of mortality. Most stethoscopes still necessitate the use of tubing, which entails direct physical contact between the healthcare provider and patient. The stethoscope can serve as a means of transmission if it is utilized on individuals who have been diagnosed with airborne and droplet-borne infectious illnesses. A prototype was created to capture heart sounds using a Phonocardiography (PCG) device over website-based Bluetooth connectivity. This approach offers the benefits of being cost-effective, facilitating computer-aided diagnostics, and being wearable. In addition, the primary significance of this study resides in the identification of heart sound irregularities caused by cardio dynamic abnormalities of the heart valves, known as murmurs. The heart sound categorization process utilizes a machine learning model that involves extracting 25 Mel frequency cepstral coefficients (MFCC) as features. The model employs a hybrid approach combining convolutional neural network and long short-term memory (CNN-LSTM) techniques. The research findings indicate that the suggested model achieves an average accuracy rate of 95.9% over five distinct categories, i.e., normal, atrial stenosis, mitral regurgitation, mitral stenosis, and mitral valves prolapse. Further study can be conducted on hardware development by incorporating an infrared sensor at the fingertip of the stethoscope.

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1. INTRODUCTION

In 2019, the World Health Organization (WHO) estimated that cardiovascular disease accounted for 32% of all fatalities worldwide, resulting in the death of approximately 17.9 million individuals. During a cardiac physical examination, a stethoscope plays a critical role in facilitating the auscultation-based detection of cardiac abnormalities. The extremely low amplitude of the heart sounds characteristics is susceptible to distortion by noise, which could result in incorrect diagnosis. Medical personnel's proficiency, alertness, and skill set are critical determinants of auscultation technique dependability. Chowdhury *et al*. [1] found that in order to perform accurate cardiac auscultation, a highly sensitive instrument is required to overcome these issues.

Acoustic stethoscopes are widely used in cardiac auscultation. Standard components of an acoustic stethoscope are a chest piece, a flexible tube, and a headpiece that includes a binaural spring and earpiece.

To execute the auscultation technique, skin contact is established between the stethoscope membrane and the region of the heart. However, present stethoscopes continue to rely on ducting, necessitating the close proximity of medical personnel and patients. Patients may be suspected of having infectious diseases that are transmitted via airborne particles or aerosols. Airborne refers to the transmission of pathogens via droplet nuclei, which are minute particulates capable of remaining suspended in the atmosphere for extended durations. Conversely, droplets denote the transmission of pathogens via sizable respiratory particles emitted by an infected individual during speech, breathing, coughing, or sneezing [2]. Diseases that are transmitted through airborne and droplet routes include severe acute respiratory syndrome (SARS), chickenpox (varicella-zoster virus), measles (measles virus), and tuberculosis (Mycobacterium tuberculosis). Airborne conditions and droplet-borne illnesses pose a significant risk to the overall well-being of the medical personnel performing examination.

While acoustic stethoscope denotes the utilization of a conventional air-coupled stethoscope in its unmodified state, devoid of any electrical transducer; electronic stethoscopes feature a variety of acoustic sensor configurations, digital signal processing capabilities, and the ability to identify heart sound abnormalities [3]. In general, an electronic stethoscope executes three primary processes: signal processing, data acquisition, and pre-processing. During the data acquisition phase, an electronic device is utilized by the electronic stethoscope to capture cardiac sound signals, which are subsequently transformed into digital signals. The amplification capability of digital signals allows them to surpass the limitations of acoustic stethoscopes. The digital signal is subsequently subjected to pre-processing to reduce interference and eliminate noise. Following the normalization of the signal, sound segmentation will occur. The subject's cardiac condition is then determined through feature extraction and sound identification using the segmented sound [4]. Bluetooth communication was then implemented as a wireless way of communication within a computer-based digital stethoscope system by Chowdhury *et al.* [1]. The study by Hirosawa *et al.* [5] provided further support for the utilization of Bluetooth, indicating that the performance of an auscultation system employing a Bluetooth-connected electronic stethoscope is equivalent to direct auscultation employing a traditional stethoscope.

Detecting the existence of a murmur is the most critical result derived from an examination of cardiac sounds, both in traditional and electronic cardiac auscultation. Clinical features of typical murmurs observed in children include the following: systolic onset, brief duration, absence of loudness and intermittent nature, and occasional asymptomaticity [6]. The most recent instance of this occurred in Canada involving a 9-year-old child whose mild systolic murmur was classified as benign and not pathological [7]. Furthermore, following physical activity, individuals frequently experience the manifestation of normal murmurs. Consequently, the ability to identify a murmur during the systolic phase is advantageous for distinguishing a murmur from a normal cardiac sound signal when the subject is stationary and in a tranquil environment.

A murmur in heart sound signals is typically characterized by a distinct morphology, enabling the identification of the S1 morphology, which is marginally elevated compared to the S2 morphology and complicates the differentiation between the systolic and diastolic phases [8]. As a result, a multimodal analysis was devised that typically detects cardiac ailments through the utilization of auscultation of heart sounds and electrocardiography (ECG), two prevalent non-invasive techniques employed in clinical diagnosis to monitor heart rhythm [9]. Phonocardiography (PCG) refers to the process of graphically representing audio obtained through a stethoscope. The utilization of PCG is extensive in its application for the identification of heart disease characteristics via graphical depictions of cardiac sound signals.

Prior studies have been conducted in PCG development. According to a study by Burns *et al.* [10], PCG data can serve as a more reliable indicator of cardiac disease in pediatric cardiologists compared to conventional auscultation, which has an 80% predictive accuracy. Variations in valve sounds within the PCG signal conceal a wealth of clinical information that can be utilized to diagnose cardiac conditions for which the ECG is incapable of providing information [11]. A multimodal wearable device was created to enhance the precision of current methodologies and explore novel strategies for the detection of cardiovascular disease. Prior research employed a multimodal ECG system in conjunction with PCG. Nonetheless, electrodes must be utilized to adhere to the skin on the chest's surface; this process is arduous and time-consuming, and the extensive cable requirements further diminish its usability [12]. A separate investigation implemented a modification by combining a multimodal PCG system with photoplethysmogram (PPG), which resulted in simplified instrumentation [13]. The discrete wavelet transform algorithm with Daubechies wavelets is employed to mitigate the noise present in the PCG signal in signal processing. This approach is based on the findings presented by Modak *et al.* [14]. The segmentation of S1 and S2 refers to the data presented by Cheema *et al.* [15] and Babu *et al.* [16]. The PPG signal facilitates the provision of information concerning the presence or absence of systolic and diastolic phases. The output of PCG signals can be processed into machine learning model, convolutional neural network (CNN) as in [17], and long short-term memory (LSTM) [18] to classify cardiovascular diseases. Wavelet transform, both in continuous wavelet transform (CWT) or discrete wavelet transform (DWT), has been widely used in various studies in conjunction with machine learning model for more accurate classification result [19]–[22].

In addition to minimizing the risk of transmission through airborne particles and droplets from patients with contagious diseases, a novel Bluetooth PCG system was developed in this study to produce a wireless stethoscope device that prevents the spreading of droplets to medical personnel. It also aims to reduce the possibility of medical personnel misinterpreting the sound of the mechanical activity of the heart. To reduce the possibility of medical personnel interpreting data incorrectly, this system will also be incorporated with a website that organizes patient databases and displays data graphs. The graphics that depict the morphology of the heart's mechanical activity in a different spectrum are crucial for the visualization of cardiac signals using phonocardiography. To achieve reliable feature representation for heart abnormality diagnosis, this research employed the Mel frequency cepstral coefficients (MFCC) combined with CNN-LSTM as a hybrid approach to extract significant information. The hybrid of MFCC and LSTM in PCG signal analysis has never been used in previous studies. This study seeks to provide innovative technology for medical professionals which is able to eliminate the necessity for direct patient contact while providing a diagnosis on cardiovascular diseases based on heart sounds irregularities.

2. METHOD

Two components comprise the system design for this study. The first part is the hardware design and data acquisition. The second part is the classification of cardiac sounds. Figure 1 illustrates the comprehensive block diagram, while subsequent subsections provide detail on each individual block.

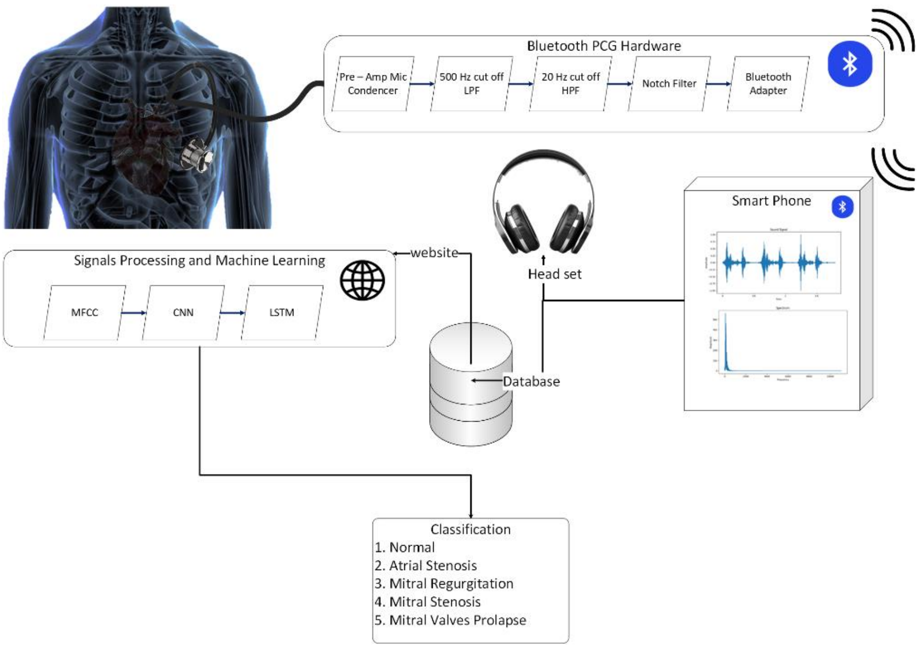


Figure 1. A prototype for hardware and software design

2.1. Hardware design

Hardware development commenced with Riester acoustic stethoscope modifications. A preamplifier circuit will receive the cardiac sound captured by the stethoscope and transmit it to the condenser microphone. The objective of this process is to transform analog sound waves detected by the stethoscope into electrical signals using a microphone as the sensor. The purpose of pre-amplifier circuit is to enhance the intensity of faint cardiac sound signals, thereby enabling the microphone to detect them. Electrical signals from the condenser microphone will be received by the low pass filter (LPF) circuit, which has a cut-off frequency of 500 Hz, and the high pass filter (HPF), which has a cut-off frequency of 20 Hz [23], [24], in order to restrict the bandwidth of the signals. The purpose of this frequency bandwidth restriction is to eradicate unnecessary data.

The electrical signal data obtained from the hardware must be converted into audio format (WAV) in order to facilitate processing on the website. This procedure is executed by employing Bluetooth transmitter and receiver components to transmit data from the hardware and receive data on the smartphone in the form of audio waveform audio file format (WAV). The transmission of this data occurs at a sample rate of 16 kHz.

The hardware featured an ON/OFF switch that activates Bluetooth, and the pairing procedure may be completed using a smartphone. To initiate the recording of heart sounds, one must push the record button on the voice recording application installed on the smartphone. This action activates the microphone, which captures the sound and transmits it to the smartphone using Bluetooth. Upon the completion of the sound recording procedure, the outcomes can be directly listened to and subsequently uploaded to the website.

2.1.1. Pre-amplifier mic condenser

A condenser microphone preamplifier is an electronic circuit designed to amplify sound signals with greater sensitivity than operational amplifiers (Op-Amp). The pre-amplifier employs an active NPN transistor component to amplify the amplitude of the incoming signal. In general, the utilization of this circuit can effectively preserve the integrity of the sound signal prior to its entry into the subsequent primary amplification phase. The Op-Amp circuit will offer supplementary amplification prior to signal recording and processing. This amplifier facilitates the generation of an optimal signal for subsequent processing. The Op-Amp functions to regulate the amplification, manipulate the frequency response, and deliver the intended signal attributes.

2.1.2. Filter circuits

The filter circuit of a PCG comprises a LPF, HPF, and notch filter. The LPF circuit in the PCG hardware design serves to attenuate signals with a frequency exceeding 500 Hz that stems from radio frequency (RF) wave interference. The LPF circuit is constructed utilizing a Sallen-Key topology, with the cut-off frequency set at 500 Hz to match the maximum frequency spectrum of the PCG signal [25]. The purpose of the HPF circuit on the PCG is to attenuate signals below a frequency of 20 Hz that are caused by interference from lung sound waves [26]. The notch filter, also known as a band stop filter, is designed to attenuate signals caused by network interference at a specific frequency of 50 Hz [27].

2.2. Software design

Heart sound signals typically span a frequency range of 20-500 Hz. According to the Nyquist theorem [28], in order to accurately record a signal, the minimum sampling frequency should be at least twice the maximum frequency. Thus, the sampling frequency was selected as 4,000 Hz, considering that a higher sample frequency can yield greater frequency resolution and more precise temporal information.

The Python programming language will be used to develop software for signal processing. This software will analyze heart sound data captured by a stethoscope to detect the first heart sound signal (S1) and the second heart sound signal (S2), and also to diagnose heart disease. PCG signal processing involves multiple phases. In order to achieve a reliable feature representation for heart abnormality diagnosis, this research employed the MFCC approach to extract significant information in the form of 25 MFCC coefficients [29]. These coefficients serve as indicators of changes in the spectrum energy of the signal. When the MFCC coefficient is positive, most of the spectral energy is focused on the low frequency range. Conversely, when the MFCC coefficient is negative, most of the spectral energy is concentrated in the high frequency range.

Multiple phases must be executed in order to acquire the MFCC coefficient. Initially, it is necessary to encapsulate the signal within a compact frame. This stage is employed to gather data regarding frequency variations in the signal and can employ the short time Fourier transform (STFT) technique [30]–[31]. STFT is commonly employed due to the dynamic nature of signal frequency, which undergoes continuous changes over time. By recording data from a narrow frame, the likelihood of losing information is minimized. The framing method is executed by choosing a specific number, N, of time samples. Assuming that the signal is divided into frames of 25 milliseconds, a signal with a frequency of 16 kilohertz will have 0.025 seconds multiplied by 16,000 hertz, resulting in 400 frames. After determining the frame length, each frame will be subjected to multiplication by a window function. The process is referred to as the windowing stage. Subsequently, the power spectrum of the discrete signal $x[m]$ can be computed using the SSTFT method, employing (1) to generate a spectrogram from the STFT,

$$STFT[n,k] = X[n,k] = \sum_{m=n}^{n+(N-1)} x[m]\, e^{-j\frac{2\pi k}{N}m} \quad (1)$$

where n and m are sequence in time, k is sequence in frequency, N is amount of data, and j is imaginary part of Fourier function.

The resulting STFT spectrogram will subsequently be processed with Mel-filter bank. Additionally, the Mel-filter bank application process must complete a number of steps. Commencing with the determination of the quantity of bands (25 in this instance) and applying (2) to convert the frequency into Mel representation. This stage yields a spectrogram from the MFCC in which time is represented along the *y*-axis and Mel frequency is plotted along the I-axis. As an input signal, the logarithmic function applied to the MFCC spectrogram will be utilized prior to the inverse Fourier transform stage. This stage generates twenty-five MFCC coefficients that are deemed prepared for further processing. The comprehensive procedure for deriving the MFCC coefficient is represented by (3) [32],

$$m = 2595 \cdot \log\left(1 + \frac{f}{700}\right) \tag{2}$$

$$C\big(x(t)\big) = F^{-1}\left[\log\Big(F\big(x(t)\big)\Big)\right] \tag{3}$$

where $C(x(t))$ denotes the cepstrum of the signal $x(t)$, and F, F^{-1} represent the phases, respectively, of the Fourier and inverse Fourier transformations.

The machine learning model was trained using CNN and LSTM as classifiers. The resulting data points were categorized into five distinct groups: normal, atrial stenosis, mitral regurgitation, mitral stenosis, and mitral valve prolapse, as illustrated in Figure 2. The convolution stage, represented by the yellow block, was executed three times in conjunction with maximum pooling. The model produced at this stage is a (.h5) file format version that is prepared for evaluation using audio data containing extracted features of heart sound signals.

The dataset shall consist of two distinct components: training data and testing data, organized in an 8:2 ratio. The training procedure for the model is conducted on training data utilizing the k-fold cross validation technique, where k equals three. A k value of 3 results in the division of 1,118 training data into three folds, where each fold comprises 372 data points. This approach is utilized during the training phase to prevent overfitting, which occurs when the model predicts a value that is satisfactory for the training accuracy but is unable to do so when presented with new data distinct from the training set.

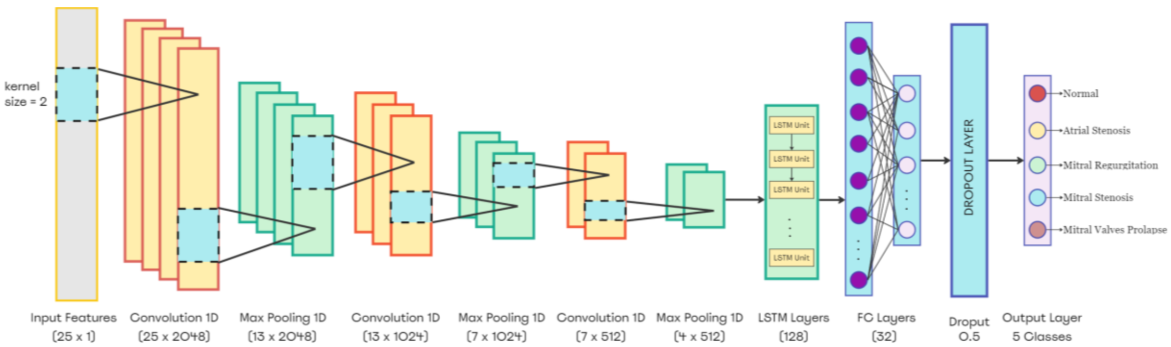


Figure 2. Architecture model of CNN-LSTM

2.3. Dataset

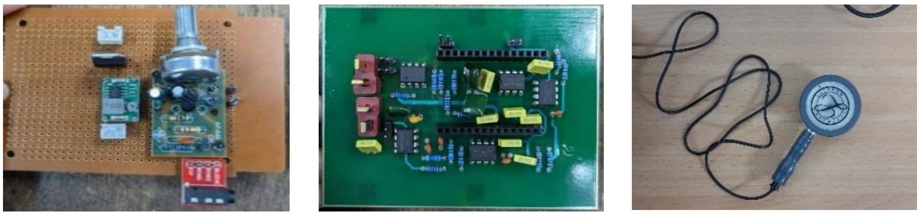
In order to train and validate the machine learning models that will be developed, datasets serve as the primary material. Two distinct secondary sources were consulted for the data. Bentley *et al.* [33], the "classifying heart sound challenge" provided the initial dataset. Dataset A and dataset B constitute the two substantial subsets of this dataset. For model training in this innovative endeavor, solely the normal and extrasystole classes from dataset A and B are utilized. Thus, from the initial dataset, this research extracted 397 WAV audio files of the normal class. The subsequent dataset was acquired from a compilation of data from multiple sources by Yaseen *et al.* [22]. After validating and filtering the data, the heart sounds will be classified into five distinct classes: normal atrial stenosis, mitral regurgitation, mitral stenosis, and mitral valve prolapse (each class contains two hundred waves of audio data). The machine learning model that has been developed will be trained and evaluated using 597 data points from the normal class and 800 data points from the abnormal class.

3. RESULTS AND DISCUSSION

This section consists of two main parts. The first part presents the findings and analysis of the hardware system. The second part presents the classification of heart sound signals. Every part will undergo evaluation in each of the following subsections.

3.1. Hardware and data acquisition

The results of phonocardiograph circuits that consist of amplifiers and filters are shown in Figure 3. The pre-amplifier circuit wiring is illustrated in Figure 3(a), whereas the printed circuit board (PCB) for the filter circuit, including the LPF and HPF, is depicted in Figure 3(b). The modifications to the stethoscope depicted in Figure 3(c) involve the elimination of the majority of the tubes and ear tips. By positioning the microphone in the remaining brief segment of the tube, it is brought into closer proximity to the stethoscope membrane. A sequence of pre-amplifiers, filters, and stethoscopes has been assembled to generate heart sound signals. We tested our device to one healthy subject, male, aged 22 years old, with no murmurs. Our developed device successfully acquired the data, with the cardiac sound image result shown in Figure 4(a).



(a) (b) (c)

Figure 3. Realization of; (a) pre-amplifier, (b) filters circuit, and (c) modified stethoscope

3.2. Classification for heart sounds

The results of signal processing and feature extraction from heart sounds are illustrated in Figure 4. The outcomes of contrasting normal and abnormal heart sound signals are illustrated in Figures 4(a) and 4(b), respectively, for the purpose of comparison. Comparative audio data labelled mitral valve prolapse serves as the anomalous sample. The graphs representing aberrant data exhibit distinct S1 and S2 morphologies, as illustrated in Figure 4(c) and Figure 4(d), which pertain to morphological results. There seems to be an undetected signal, particularly in the S1 segment. Mitral valve prolapse may arise due to an inadequate closure of the mitral valve.

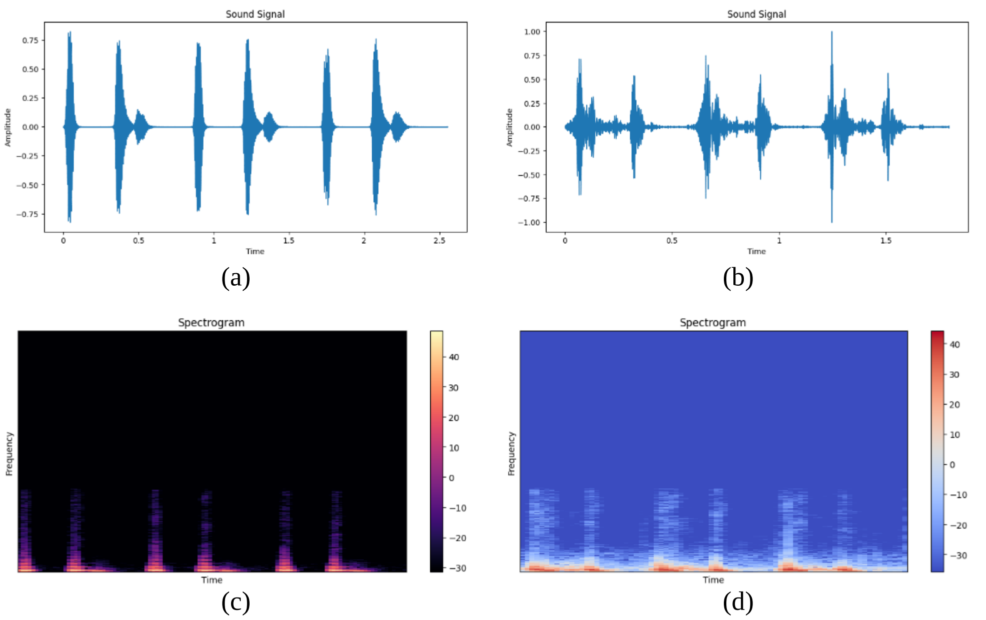


Figure 4. Result of heart sound; (a) normal signal, (b) abnormal signal, (c) normal spectrogram of MFCC, and (d) spectrogram of mitral valve prolapse

When the model was evaluated using 279 experimental data points, confusion matrix of classification is illustrated in Figure 5. The label representing the model's predictions appears on the y-axis, whereas the x-axis represents the label of the actual data. The prediction classes exhibit the subsequent accuracy values: 100% for normal, 93.3% for atrial stenosis, 91% for mitral regurgitation, 91.8% for mitral stenosis, and 100% for mitral valve prolapse. The overall average accuracy of each prediction class is 95.9%, showing that the hybrid model proposed can classify the heart sounds correctly, but still can be further improved for more accurate PCG signals classification.

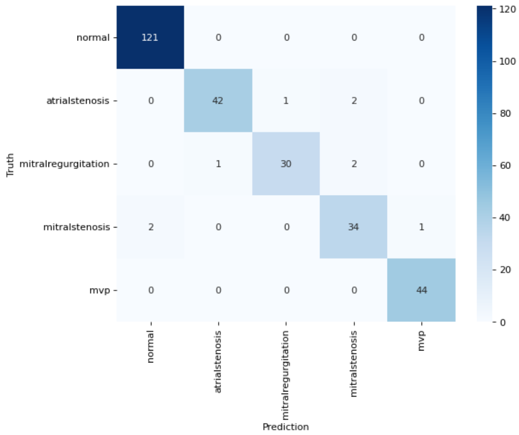


Figure 5. Confusion matrix

We compared the overall accuracy result of this model with previous studies, including CNN and other classifier methods. The comparison is shown in Table 1. It is shown that the proposed hybrid MFCC-LSTM method achieved relatively better accuracy result compared to others, except for MFCC-DWT still achieving the best performance in 97.9% accuracy.

Table 1. Result comparison with other studies

Methods	Overall accuracy (%)
CNN [17]	85
DWT [22]	92.3
LSTM [18]	93.5
MFCC [22]	91.6
MFCC-DWT [22]	97.9
Proposed method (MFCC-LSTM)	95.9

LSTM deep learning model for cardiac arrythmia classification was proposed in [18], achieving 93.5% in accuracy. As LSTM is an improved model of CNN, LSTM accuracy is higher than accuracy of CNN proposed in [17], which is 85%. Other classifier methods utilized MFCC and DWT for cardiovascular disease classification done by Yaseen *et al.* [22]. MFCC achieves 91.6% accuracy and DWT achieves 92.3%. When combined, MFCC-DWT gives the best accuracy result at 97.9%. Our proposed method combines MFCC with LSTM as a hybrid approach, giving 95% accuracy. This number is not the best accuracy compared to other methods, but still better than most as expected. However, among other prior studies, our proposed method is the only one that utilizes Bluetooth for PCG as a wireless stethoscope device in the design. Further research can be done to further improve the system's accuracy. This study was evaluated with readily available datasets. Clinical testing with real patients can be done in the future to justify the system's readiness for clinical practice.

4. CONCLUSION

By integrating Bluetooth technology into the phonocardiogram, proficient medical personnel can mitigate the transmission of droplets, thereby potentially surpassing the level of droplet-borne diseases that occur during cardiac examinations. The incorporation of heart examination findings into the website is capable of mitigating the potential for medical personnel to erroneously interpret mechanical heart activity sounds. This is achieved via the implementation of machine learning algorithms to identify heart abnormalities, which are visually represented on the website interface. The proposed Bluetooth PCG system was tested and proven successful in acquiring heart sounds signals. For the purpose of classifying cardiac sounds, a machine learning model is employed, with 25 MFCC being features extracted. The model uses a CNN-LSTM hybrid strategy, which combines deep learning and CNN. The model under consideration achieves an average accuracy of 95.9% across all five classifications. Compared to other studies, the proposed method performs better. Future studies still need to be conducted to further improve accuracy. Clinical trials can be done in the future to assess the readiness of the system for clinical practice. This research contributes positively to the surveillance of the health of patients with heart defects and is an encouraging development in the effort to enhance the quality of medical services.

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