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AI-Based Heart Monitoring System

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***Abstract*— Heart sounds convey imperative physiological and neurotic proof about well-being. AI-based Heart monitoring system offers a distant heart sound classification device for a person without manual medical care administrations. In this paper, a Heart monitoring device based on AI (artificial intelligence) is proposed to screen and identify heart sounds, which transfers the data to the parental figure as a clinical specialist using the Internet of Things (IoT). Without any planning for data transfer via IoT and sign inspection, a coordinated system for heart sound protection, storage, and offbeat investigation has been developed. The AI-based Heart monitoring system has been intended to screen the heart pulse rate of a person. Wi-Fi connection is utilized to offer force proficiency and moderate information the rate of transmission. To remove obstruction signs and to help extricate the heart tone symbol highlights, active noise canceling and the Fast-Fourier transform are used. Long short-term memory (LSTM) architecture is used for the classification of the Heart sound as Normal, Murmur, and Artifact. Hence, patients can analyze their heart sound by themselves. Mel Frequency Cepstral Coefficient (MFCC) is by a wide margin the best element utilized in sound Processing. Prepossessing, division and grouping strategies were performed for data understanding. The AI-based Heart monitoring system may provide a novel approach to coronary illness self-management in medicine 4.0 to support the development of a society 5.0.**

Keywords —Heart sound classification, Active noise canceling, Deep Learning, Recurrent Neural Network (RNN), Fast-Fourier transform, Mel Frequency Cepstral Coefficient (MFCC), Personalized Medicine, Telemedicine, Medicine 4.0, Society 5.0

I. INTRODUCTION

A big cause of mortality all over the world is heart disease. According to the world health rankings, the death rate per 100000 is 160.86 in India, 79.21 in the US, and 123.79 in Sri Lanka [1]. With the development in the extents of the grown-up and older populace, because of the ups and downs of lifestyle, much like the rise of chronic diseases and conditions, there has been a need to track people's well-being status in their day-to-day lives to keep away from deadly conditions.

Doctors, Physicians, and other medical officers have to face a certain amount of risk when dealing with patients, especially when observing their symptoms. During the coronavirus outbreak, a lot of medical officers infected the virus from the patients. So it makes a huge problem in health services in the world. Also, in modern society, a lot of people using e-medicine services. But there isn't any proper way to collect a patient's physical readings in e- Medicine. So it makes some limitations when providing e-medicine services.

The adoption of remote health checking is urging to support the nature of life expectancy for ongoing wiped out patients and the elderly individuals, just as solid one. Besides, unnecessary hospitalizations can stay away by far-off health care checking, which lessens the expense of care and increments the nature of care [2]. The long-term monitoring of actual work encourages the improvement of interdisciplinary medical services research. With the use of the Internet of Things, the transition of social systems, shifting from the traditional well-being of managers to additional personalized medical treatment structures, benefits human well-being.

The basic expressive method for a fundamental evaluation of the state of a patient is an ordinary stethoscope. It is problematic to translate heart sounds, chest sounds, or intestinal sounds using a stethoscope, requiring comprehension and relying on the specialist's hearing limit. Different stethoscopes correct for the inability of the human ear to detect low frequencies of distinct behaviors. It is significant, for example, that changing the length of the tubing of a regular stethoscope affects the audible consistency of heart sounds [3]. Also, it is often difficult for cardiologists to have cardiac sounds that are an extraordinary occasion and to realize the progression of the cardiac ailment without a way to monitor the heart sounds of patients. What's more, heart sound and ECG checking is a normally utilized indicative technique. This strategy can get indispensable physiological and obsessive proof about patients. For long-haul complex heart sound testing, many existing techniques are not rational. Because of the scale, considerable cost, and sophistication to run. Considering these perspectives, it is important to improve the innovation of the heart monitoring system, and the advantages of the electronic stethoscope can be significant.

Many devices in the market can record heart sounds digitally. 3M Littmann electronic stethoscope, CORE digital stethoscope, Isteso-D2, Thinklabs One, Cardionics E-Scope, and Stemoscope are some of the branded electronic stethoscopes in the medical field [4]- [5]. 3M Littmann and Thinks lab one use the Ambient Noise Reduction (ANR) technique for de-noising. Some of these E-stethoscope have a 40x time amplification ability. However, most high-end devices such as 3M™ Littmann® Electronic Stethoscope Model 3200, 3M™ Littmann® Electronic Stethoscope Model 4000, Thinklabs One cost around $200-$900 [6]. So that it is not affordable for a typical family of a 3rd world country, most of the commercial products target data collecting rather than accuracy and classification. But very few can record heart sounds and classify them using Machine Learning.

Heart auscultation can be collected through a heart sound sensor that has been made by connecting a condenser mic to the rubber tube of an ordinary stethoscope. The stethoscope's diaphragm vibrates according to the skin vibration, a result of mechanical activity that forms by contracting the atrial and ventricular of the Heart. From an engineering point of view, there are three stages to automatic heart sound analysis, including prepossessing, extraction of features, and classification. Collected data from the condenser mic must need to remove unwanted background noises. This research presents active noise canceling and Fast Fourier Transform (FFT) for de-noising the signals. Mel Frequency Cepstral Coefficient (MFCC) was used for the classification and segmentation of heart sounds. A heart pulse sensor detects the pulse rate of the bloodstream using an optical mechanism. This paper introduces a heart monitoring system that can record heart sounds and classify them and obtain the beats per minute (BPM) value of the user. Then take the advantages of wireless technology implemented via WIFI; the user and physician can obtain that information through a web interface.

II. RELATED WORK

Heart sound auscultation depends heavily on a cardiologist's listening capacity, ability, and expertise. To aid the cardiologist, a computerized examination of the sound of the Heart is also necessary. It is important to segment the heart sounds into their components before any automated processing can be done. The sound of the Heart consists of four parts: S1, S2, S3, and S4. The first sound of the Heart (S1) and the second sound of the Heart are the principal components of heart tone (S2). S1 occurs during ventricular systole and contributes to the 'lub' function of the 'lub-dub' that each heartbeat can be heard. Closures of the mitral and tricuspid valves cause it. Ventricular diastole leads to the S2 development of the 'dub' just after S2, S3 occurs and has a relatively low energy material. S4 follows S1 and has a lesser amplitude than the other cardiac sounds. The mechanical events of the cardiac cycle include the opening and closing of heart valves, as well as the sounds they create. The electrical activities of the heart cycle precede them. Noises associated with injury to the valves and the improper closing of the valves are heart murmurs. Fig. 1 shows the interaction of the phonocardiogram (PCG) and electrocardiogram (ECG) in the time domain. S1 is 0.04s-0.06 s after the start of the QRS complex, S2 appears at the end of the T wave, and the fourth heart tone S4 begins after the P wave [7].

There are two significant difficulties in building up a computerized heart sound examination instrument: categorization and segmentation. Locating the borders of heart sound segments and separating the component group S1, S2, S3, and S4 are the basic segmentation tasks. Notwithstanding, the vast majority of the strategies center around either component identification or boundary detection. Furthermore, numerous strategies apply to ordinary heart sounds, so those obstacles seriously restrict the use of these techniques [8].

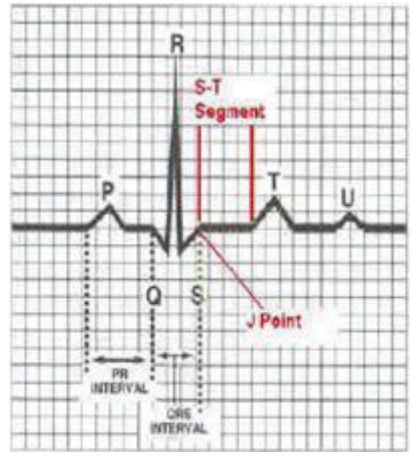


Fig. 1. QRS points

Moukadem et a. [9] developed a methodology of S-transform-based heart sound division; however, traditional heart sounds must be added to this approach. Liang et a. [10] suggested a technique of heart tone segmentation based on Shannon-entropy to interpret S1 and S2, but they did not contemplate S3, S4, and murmurs. Kumar et al. [11] introduced an S3 identification calculation dependent on wavelet transform; in any case, this strategy couldn't recognize the boundaries of the heart sound segments.

Heart Sound Signals were analyzed in two groups for the feature extraction. The entire signal was analyzed in both the time and frequency domain in the first group of extractions. The second group uses significant parts of the signal as a whole to extract Features. S1 and S2 are significant parts of the signal. Eighteen different features were extracted, seven of which are based on the entire signal according to the literature by Angela Chao, Shirley Ng, and Linda Wang [12]. In the time domain, the first set of features are zero crossings, momentum, and energy entropy. Spectral distribution, spectral entropy, spectral flux, and Mel Frequency Cepstral Coefficients in the frequency domain (MFCCs) are used in the frequency domain. All characteristics, except MFCCs, have been extracted using Py Audio Analysis, a python library for analyzing audio signals. Zero crossings capture frequency and intensity information used for speech recognition tasks.

Several numbers of advantages can be taken using lung sounds of patients in medical technology and medical treatments. Lung sounds are mostly used to diagnose disorders

such as wheezing, crackling, and lung cancer, et. [13]. Lung sounds, also called breath sounds, can be heard across the anterior and posterior chest walls.

- rhonchi (a low-pitched breath sound)
- crackles (a high-pitched breath sound)
- wheezing (a high-pitched whistling sound caused by narrowing of the bronchial tubes)
- stridor (a harsh, vibratory sound caused by narrowing of the upper airway)

When a doctor uses an electronic stethoscope to identify lung disorders, the stethoscope stores the lung sound signals and transmits them to the machine. The lung sound signals can be recognized by studying the time-frequency features of the signals and creating an identification model. The health state of the lungs can also be estimated. Therefore, by using AI technology to interpret and classify the lung sound obtained by the stethoscope, it can increase not only diagnostic precision but also improve diagnostic performance. It is important for the prevention and treatment of pulmonary diseases. [14]. The frequency range is also more condensed. Because the frequency band of lung sound signals is 100HZ to 2000Hz, it may be assumed that there are no lung sound signals below 100Hz.

Thinking about the principal clients and application situations, the framework ought to be convenient and rearrange the control of the Application. Finished heart auscultation observing. The framework incorporates obtaining a module inserted with a heart sound sensor, a presentation unit, and an examination framework with the capacity of criticism. The idea plan of observing the framework appears underneath Figure 2. A microcontroller and a Bluetooth 4.0 device compose the acquisition module, which measures the heart tone signals and transfers the information to the mobile phone that is also equipped with Bluetooth 4.0. The ability off far-reaching use and low energy of Bluetooth 4.0improves the similarity and diminishes the force utilization of this framework. Along these lines, the Android phone gets the Heart sound information and plots the sign bends progressively. The versatile Application goes about as the showcase gadget and can transfer information to a cloud stage for additional investigation. The cloud stage incorporates information for concentrated handling and capacity. Therefore, by any fringe gadgets that are equipped with explicit programming, licensed pathologists and specialists will obtain access to the cloud stage to get the data set and results. Also, the clients can acquire the analysis results, and the proposed framework understands e-medicine in the long run [15].

III. SYSTEM DESCRIPTION

The Heart monitoring system consists of sensors, which obtains Sound and pulse signal from the chest. Then the sensor data is transmitted to the RasberryPi. Then input data classify using a deep learning model. And displays classification details of heart sound using a touch screen display. Finally, data sent to a remote user through a web interface.

The first component of the system is a sound sensor, which can record the heart sound of a patient. An electret condenser microphone is used as the sound sensor. It is a type of electrostatic capacitor-based microphone. Electret types need no polarizing voltage, unlike other condenser microphones, but it includes an integrated preamplifier that requires a small amount of power. So this is an ideal microphone for our task because of the small size and can have the ability to grab law intensity sounds.

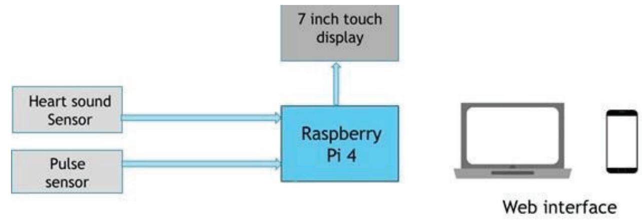


Fig. 2. System architecture

And to record the sound with more power, we use a conventional stethoscope chest component.

The next sensor is a plug-and-play heart-rate sensor called Pulse Sensor Amped. It effectively incorporates a simple optical heart rate sensor with circuits for amplification and noise cancellation, making it quick and easy to obtain precise pulse readings[16]. It even sips power at 5V with just a 4mA current pulled, so it's perfect for smart devices.

The data sensed from those two sensors is sent to a RaspberryPi module. RaspberryPi module is the main processor of the system that interconnects inputs and outputs and facilitates the processing power to deep learning analysis. Since the deep learning process requires an additional amount of computing power, a module with 4 GB Ram and Raspberry Pi 4 using a quad-core ARM Cortex-A72 processor was used by Raspberry Pi. A 1.5 GHz 64-bit quad-core ARM Cortex-A72 CPU, 802.11ac onboard Wi-Fi, Bluetooth 5, full gigabit Ethernet B 2.0 ports, two USB 3.0 ports, and dual-monitor connectivity with a pair of micro HDMI ports are included with Raspberry Pi 4. The Raspberry Pi 4 is also operated by a USB-C port, allowing downstream peripherals to be given more power.

Our design uses a USB sound card to connect the microphone and earphone to the Raspberry Pi. And GPIO ports to connect the pulse sensor. Micro HDMI ports to connect the display. And connect this module to the internet using Wi-Fi as depicted in Fig. 2.

The recorded sound then goes through a noise cancellation process before the deep learning analysis[17]. The deep learning model used has several layers, including Input, LSTM, Dropout, Thick, and Softmax. RNN (Recurrent Neural Network) architecture was selected to implement the classification of heart sounds. By the aforesaid deep learning model, heart sound is classified into three categories. Those are normal, murmur, and artifact.

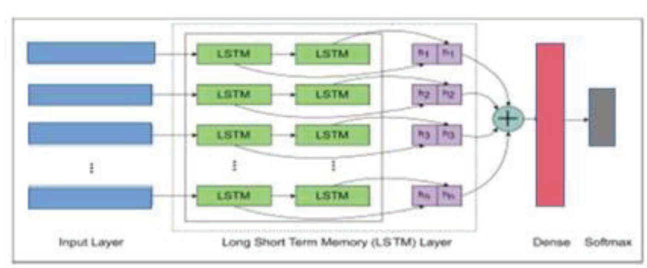


Fig. 3. Overall Architecture of Recurrent Neural Network (RNN).

A 7-inch Touch screen unit displays the type of heart sound and the heart pulses using a GUI. The GUI provides a detailed report of analyzed heart sounds and pulse rates. A user can also send the report to a remote location by using the same GUI. The remote user also can view the detailed report and listen to sounds using a web application we designed for the purpose.

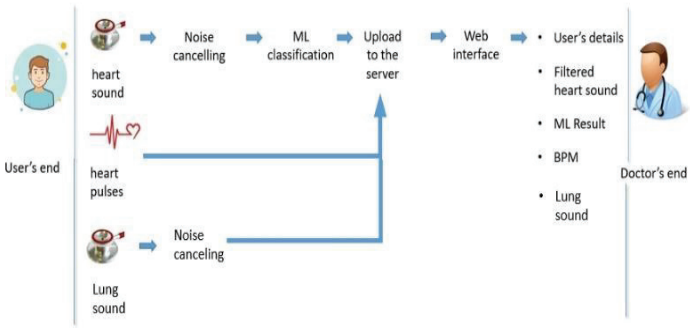


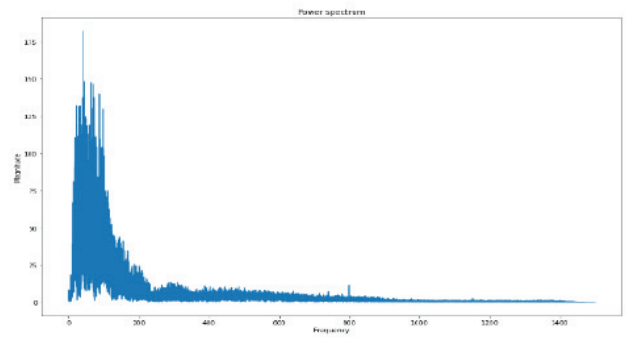
Fig. 4. System description

IV.TESTING

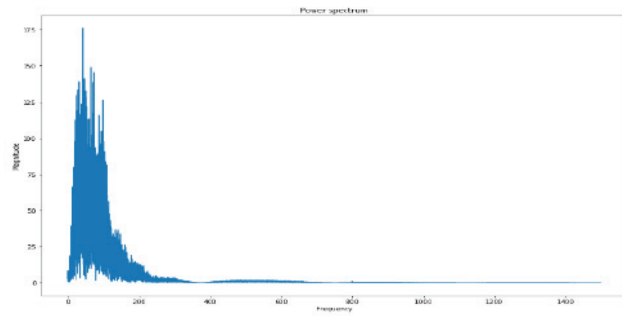
The performance testing of the AI-based Heart monitoring system includes performance testing of all components involving stethoscope, microphone, heart pulse sensor, and Raspberry Pi units. This was a non-clinical study that was carried out on healthy people using a non-invasive method. Thus, no ethical approval was requested in the execution of this investigation. The information was gathered by the proposed heart sound checking framework, with a sampling rate of 44100Hz. The ordinary heart sound information was gathered from 10 understudy volunteers. The Physio Net/Computing in Cardiology (CinC) Challenge 2016 irregularity heart sound data set was used to verify the grouping accuracy [16]. Here we mainly considered the performance testing related to sound processing, ML, and BPM measuring. All testing was carried out at the university hospital.

The main purpose of our endeavor was to construct a device that can identify multiple heart sounds, obtain heartbeats per minute, and store data on a server to help the doctors to diagnose the relevant conditions. In this study, a filtering method was applied to the input heart sound for de-noising, and a deep learning model was used to classify Heart sounds into three categories, i.e., Normal, Murmur, and Artifact.

Heart sounds were recorded at the same bit rate 16kb/s, and the sample rate was 44100 Hz. Recorded heart sounds were polluted with noise. The noises are generated because of electronic noises on the ground wire of the electronic circuit. Raw test sounds are recorded by Thinklabs Phonocardiography software using a condenser microphone. In the study of sound and acoustics estimation, the Fast Fourier Transform is an important estimation technique. It transforms into individual unearthly fragments over a signal and then generates recurrence details about the symbol. Fig. 5 shows the frequency spectrum of raw heart sound and filtered heart sound.



a). The frequency spectrum of raw audio



b). The filtered audio frequency spectrum

Fig. 5. a). The frequency spectrum of raw audio. And b) Filtered audio frequency spectrum

By filtering the audio, the high frequencies that above 200HZ could be removed that are not within an instrument's frequency range. So it can be identified using fig5.

IV. RESULTS

The pulse is the flood of blood that is pushed through the corridors when the heartbeats. The pulse rate is how often one can feel a heartbeat consistently. MAX30102 is a very sensitive sensor since very small movements can affect it. While reading BPM the sensor must be stable and the gap between skin and reflector shouldn't change. The reflection method was used throughout this project. Count 10 seconds and get pulse count (c) using the finger top. The digital pulses are given to the Raspberry Pi as an input for calculating the heartbeat rate, given by the following formula:

Ten pulse time = T2 – T1

Single-pulse time = Ten pulse time /10

Rate = 60000/ Single-pulse time;

Where T1 is the first pulse counter value

T2 is list pulse counter value

Rate is final heart rate (BPM)

TABLE I. AN ERROR RATE OF HEART PULSE SENSOR WITH COMPARING MI BAND BPM

MI band	Heart pulse sensor(MAX30102)	Error (in %)
69	69	0
72	72	0
72	72	0
75	76	1.33
79	80	1.26
75	72	4.0
82	85	3.65
75	80	6.66
77	79	2.59
75	77	2.66

In the Categorizing process, we explored two machine learning algorithms and three deep learning algorithms with the data set.

Those deep learning algorithms are Multi-Layer Perceptron (MLP), Convolution Neural Network (CNN), and Recurrent Neural Network (RNN). Random forest and decision tree are machine learning models. The accuracy of differential algorithms is depicted in Fig 6.

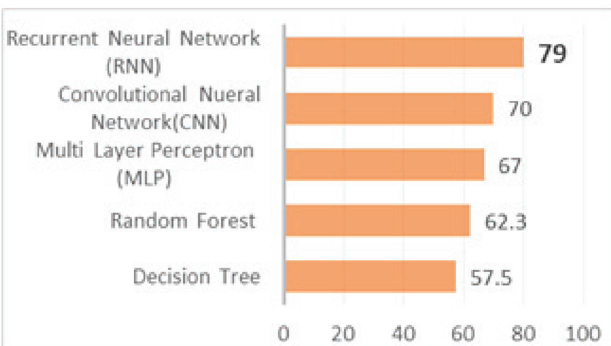


Fig. 6. Accuracy for different algorithms

By this Fig6 also we can clearly see the RNN LSTM model got the highest accuracy. That is the main reason for choosing the RNN model for the deployment process in our device.

And we also use hyper parameter tuning to further improve the validation accuracy of the model. So by using 100 epochs and 32 as the batch size we ended training our model.

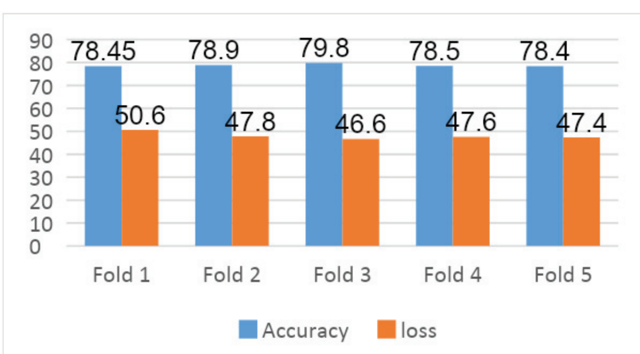


Fig. 7. Performs of RNN & LSTM models

K-Fold Cross Validation is a re-sampling method used to validate the classification model on limited data sets. And it estimates the performance of the model. When compared to other approaches, K-Fold CV delivers a model with less favoritism. The parameter called 'k' in K-Fold CV is the parameter determines how many folds the dataset will be divided into. Every single fold allows the model to perform (k-1) times in the training set, confirming that every sample in the dataset appears in the dataset and allowing the model to understand the underlying data spread. We choose 5 folds to validate and check the performance of the model because the value of k is generally between 2 to 10 and not too high and not too low. So this figure shows how Our RNN LSTM model performs in each fold.

V. CONCLUSION

This Heart monitoring system was designed, specifically on the basis of long short-term memory (LSTM) architecture. According to the results shown in Fig 6. RNN LSTM model has the best accuracy. As a result of this, the RNN LSTM model can be used for the deployment procedure. The novelty of this exploration incorporates the heart monitoring system for the home environment for the investigation of the heart-related issues and passing of the information to a doctor at the remote end. Hence the proposed design is advantageous over the conventional stethoscope. It is suitable for the home environment, checking the cardiovascular well-being of an occupant through the auscultation sound observing of an occupant. The information has been gathered and examined through a deep-learning algorithm to characterize heart sounds into groups. And our developed device mainly focused on heart monitoring, but it also can be used to monitor lungs as well. So we hope with further improvements to the deep learning model by hyper parameter tuning and hardware component, this device can be used to deploy for the healthcare industry on approval of the National Medicines Regulatory Authority (NMRA). Further research is in progress to devise a framework that will incorporate more advanced tests under various definite oddity coronary illnesses and provide more precise and in-depth outcomes to support the development of a society 5.0. The proposed scheme shall provide a novel approach to coronary illness self-management in medicine 4.0.

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