Electronic stethoscope for detecting heart abnormalities in athletes

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Abstract — **Cardiovascular diseases (CVD) are one of the main causes of death and disability in most countries of the world. As part of the fight against high morbidity, there is a clear shift in the global health paradigm towards active prevention and prevention, rather than treatment, of diseases, and a desire to reduce inpatient care in favor of outpatient treatment, home care, and self-care of patients about their own health. Most current global clinical guidelines clearly indicate the sequence of actions of the doctor to whom the patient sought help, including the obligation to evaluate objective health data, identify risk factors and based on them to determine the cardiovascular risk in a particular patient, and then take steps to reduce this risk.**

However, most countries do not currently have a comprehensive mass identification of risk factors and an overall assessment of the risk of developing CVD. Most heart diseases are related and are reflected by the sounds that the heart produces. Auscultation of the heart, defined as listening to the sound of the heart, was a very important method for early diagnosis of cardiac dysfunction. In this case, phonocardiogram (PCG) records heart sounds and noises that contain significant information about heart health. Analysis of the PCG signal has the potential to detect an abnormal heart condition. Traditional auscultation requires significant clinical experience and good listening skills. The advent of the electronic stethoscope paved the way for a new field of computer auscultation. This article discusses in detail the technology of an electronic stethoscope and the method of diagnosing heart rhythm disorders based on computer auscultation.

Keywords — Smart stethoscope, Machine learning, Classification, PCG, Abnormal heart sounds, Heartbeat

I. INTRODUCTION

Since the advent of smart devices and IoT, the amount of data and its type has increased due to collectors [1-5]. Smaller sensors that are easily accessible and accurate enough are the main benefactor of automating such a task that requires a qualified doctor. Especially useful for remote areas where skilled workers are not available. Secondly, the development of infrastructure for assessment and registration is cheaper to achieve, hence it will have a higher level of penetration and acceptance. The inclusion of ECG detectors in smart bands is a big development, although they are not very accurate, hence the detection of anomalies is also inaccurate [6]. Over time, these devices will become more accurate, which requires the development of such software.

The motivation for this task is the growing number of human victims due to cardiovascular diseases according to the world health organization (WHO) article, an estimated 17.9 million people have died from cardiovascular diseases, this population accounts for 31 percent of all global deaths [7]. In poor countries such as India, where the ratio of doctors to patients is less than 1:921, this high number means that many people are left without treatment, and queues at clinics are endless. This problem requires automatic detection and accurate treatment procedures and necessary precautions. Since PCG is a non-invasive, cheap and accurate way to monitor the heart, it is therefore preferable to any other signal.

In this paper, we consider a smart stethoscope to diagnosis heart pathologies using heart sounds based on machine learning techniques.

II. LITERATURE REVIEW

The functional state of the cardiovascular system is studied using a set of instrumental methods that allow an objective assessment of biophysical processes in the circulatory system (electrical and mechanical activity of the heart, intracardiac and General hemodynamics) [8]. A special place among these methods is occupied by phonocardiography (PCG), which allows you to control the state of the cardiovascular system, disorders in which occupy a leading place among other diseases [9]. Analysis of biomedical signals is often a difficult task for a doctor or specialist in the field of biomedical Sciences, because clinically important information in the signal is usually masked by noise and cues. In addition, the parameters of the signals most often cannot be directly perceived by the visual and sound systems of the human observer, since most of the energy of heart sounds is concentrated at or even below the threshold of sound perception by most people. Therefore, the reliability and consistency of the assessment of the phonocardiosignal (PCS) [10], as well as the understanding of the observed phenomena, are subjective factors in terms of their interpretation, depending on the qualification, experience and diagnostic capabilities of the specialist doctor. These factors determine the need not only for more advanced equipment, but also for the development of methods for objective analysis of signals in interference conditions using modern algorithms for processing and analyzing the phonocardiosignal, implemented on the basis of modern radio techniques and tools. Therefore, scientific and practical justification, development and development of methods and tools for reliable early diagnosis of heart function on the basis of modern radio engineering methods for processing and analyzing biomedical signals that contribute to increasing the volume and quality of information about the functional state of a person, and, as a result, creating more effective hardware and software tools, is an urgent problem. The main requirements for such methods are ease of implementation, information content and reliability of the results of preventive diagnostics of the cardiovascular system [11-13].

The analysis of wave forms is performed by calculating the correlation coefficient, determining the amplitude and duration of the wave, and evaluating the phase characteristics of the wave. A more detailed analysis requires the use of several features. For morphological analysis of the shape of the PCG, the following steps must be implemented: detection of the PCG tones (S1 and S2) - segmentation; determination of their boundaries and calculation of parameters that characterize the shape of the tones; form analysis (Fig. 1).

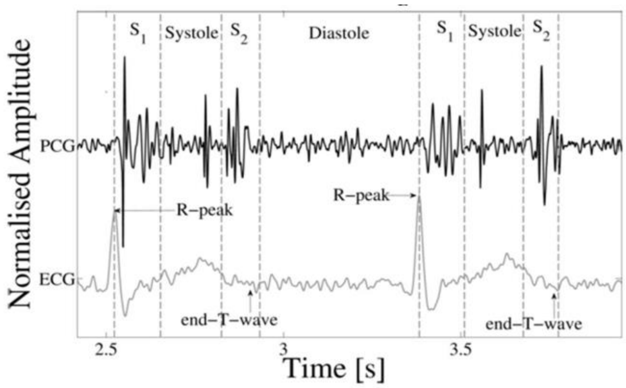

Fig. 1. PCG signal labelled with ECG. Showing states S1 phase, Systolic phase, S2 phase and Diastolic phase

Thus, the PCS analysis includes such important parameters as: a) calculating the duration of tones and identifying additional tones (III, IV, V); b) conducting a comparative assessment of the shape and amplitude of the I and II tones at different points of registration; C) detecting splitting, bifurcation of tones, clicking the opening of the mitral valve, etc.; d) detecting and analyzing the characteristics of heart noise in different frequency ranges; e) determining the relationship between electrical, mechanical and Electromechanical systoles. To perform a morphological analysis, it is necessary to perform pre-processing of the signal: filtering to eliminate noise and interference created by the environment. Other noise and interference may also be present on the FCS: network interference, internal physiological interference, etc.to suppress them, additional filtering is necessary, which is carried out in the second filter block based on low and high frequency filters. Next, PCS segmentation is performed, which is an important stage of processing when analyzing the PCG signal, as well as for extracting informative features and highlighting the main components of the signal. A fundamental step in the analysis of the heart is to identify conditions in the heart cycle, such as diastolic and systolic periods. The first heart sound (S1) and the second heart sound (S2) are the dominant sound reflections and indicate the beginning of the systole and diastole, respectively. Segmentation of the main components of the PCS provides an increase in the information content and reliability of diagnostic information about the state of the CCC. Thus, the use of heart rate as an integral indicator of regulation processes makes it possible to assess the state of adaptation of the body as a whole, and the functioning of the autonomic nervous system.

III. Electronic Stethoscope Hardware

This is a stethoscope that connects to the smartphone's TRS (mini-jack 3.5) connector and uses the mobile app to predict your condition. The developed intelligent stethoscope is a simple battery-free system incorporated into an audio-microphone interface providing power and signal transmission. A block diagram summarizing the method is illustrated in Fig. 2.

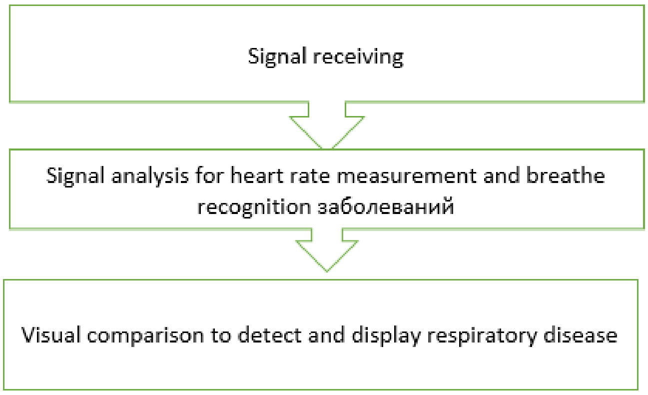

Fig. 2. Working principle of the smart stethoscope

The device is designed as simple as possible using the smallest components: a stethoscope, a mobile application and a small device. An electret microphone is inserted into the stethoscope tube to produce sound. The hose is blocked at all other ends except the reception area to eliminate the noise factor. Fig. 3 illustrates components of the smart stethoscope.

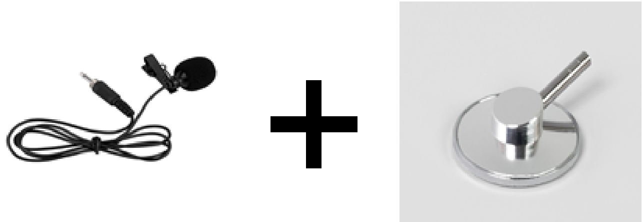

Fig. 3. Components of the smart stethoscope

Fig. 4 illustrates the smart stethoscope as a device that connect to a smartphone.

Fig. 4. Smart stethoscope as a device that connected to a smartphone

IV. Electronic Stethoscope Software

A. Abnormal heart sound detection

An observed PCG signal S(n) can be modeled as

$$\Sigma(\nu) = \Phi(\nu) + \mathrm{O}(\nu) = \Phi(\nu) + \mathrm{X}(\nu) + \mathrm{N}(\nu) \quad (1)$$

where F(n) denotes the fundamental components of heart sound (FHS), first (S1) and second (S2) heart sounds, and O(n) represents a mixture of other signals including other heart sound components (C(n), such as murmurs) and noise components N(n).

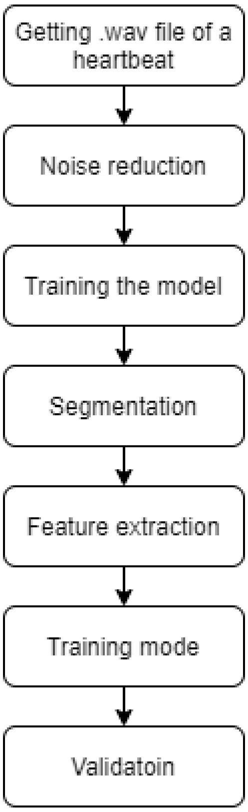

Fig. 5. Process Flow for heartbeat abnormality detection

Fig. 5 demonstrates process flow for heartbeat abnormality detection. To detect the first heart sound in noisy environment, a two-stage framework is developed. In the first stage, the fundamental components F(n) are separated from background signals O(n) by using an adaptive sublevel tracking module. Shannon energy tracking is applied to detect peaks of S1/S2 from noisy interference, followed by a knowledge-based S1 identification procedure.

B. Dataset

For the experiment, the PhysioNet database that contains ECG measurements, Phonocardiogram and respiration was used [14-16]. In order to train a machine-learning model, we used 400 PCG records that divided into two types. Half of all the records were belong to people with health abnormality in heart sounds and the other part were belong to healthy people. Dataset was divided into two parts as 80% to 20%. 80% of all data were used to train, and the remaining 20% were utilized to test the machine learning model.

V. Results

Fig. 6 shows heart abnormality detection process using smartphone after getting the heartbeat sounds through the stethoscope. The first is a smart stethoscope that studies the sound received from the stethoscope. The second is a trained algorithm that analyzes extraneous noise. The third is the classification process. Moreover, the output shows your potential diagnosis.

After processing and eliminating the noises in signals, we start to identify heat sounds. After detecting normal and abnormal heart sounds, the result were given in Table 1 and Table 2. As we notified before, we divided the dataset into two parts, as 200 abnormal to 200 normal heart sounds. In addition training and testing data divided in 80% to 20% proportion.

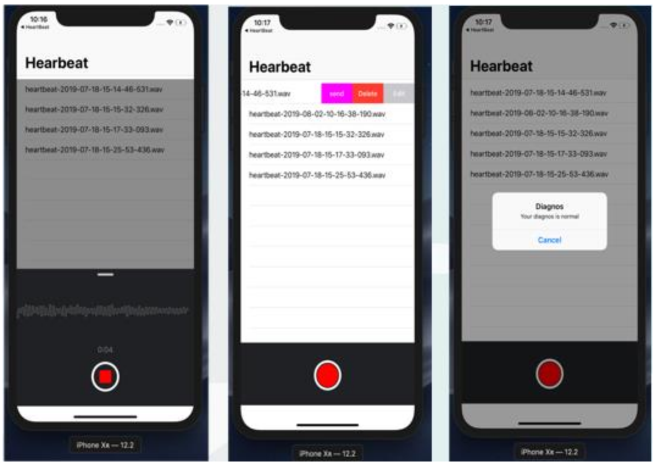

Fig. 6. Heartbeat abnormality detecttion process

The results of detecting heartbeat abnormalities using machine learning techniques are concidered true positive (TP), false positive (FP), false negative (FN), and true negative (TN). A true positive means the total number of abnormalities in heart sounds that are actually identified, while a false positive represents the total number of heartbeat abnormalities that are incorrectly detected by the model. A false negative value is the total number of heartbeat abnormalities that are not identified at all. These results are used to calculate the results of evaluating the detection of heart rhythm disorders using various machine learning classifiers, which include sensitivity (SN), positive Predictivity (PP), and overall accuracy (OA). The equations below show the calculation for SN, PP, and OA.

$$SN = \frac{TP}{TP + FN} \times 100 \quad (2)$$

$$PP = \frac{TP}{TP + FP} \times 100 \quad (3)$$

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (4)$$

Table 1 and Table 2 demonstrate segmentation result of normal and abnormal heart sounds.

TABLE I. SEGMENTATION OF NORMAL CARDIAC SOUNDS

Normal sounds	True positive	True negative	False negative	False positive	Sensitivity	Accuracy
S1	187	2	6	5	96.89	94.5
S2	185	3	5	7	97.37	92.5
Total	372	5	11	12	97.12	93

TABLE II. SEGMENTATION OF ABNORMAL CARDIAC SOUNDS

Normal sounds	True positive	True negative	False negative	False positive	Sensitivity	Accuracy
S1	188	3	4	5	97.91	94
S2	185	4	5	6	97.36	92.5
Total	373	7	9	11	97.64	93.25

VI. DISCUSSION AND CONCLUSION

The paper presents a model for detecting pathological patterns on the PCG for detecting heart obstruction and electronic stethoscope to use the model for athletes.

Audio signal analysis is mostly related with problems such as signal weakness, narrow band bandwidth, contamination by various types of noise, randomness, the need to separate the combined signals into a single signal, and etc. Heart sounds as complex signals are also subject to that rule. Heart valve sounds, the filling and emptying of ventricles and arteries, and the interference between these sounds and a narrow frequency range make it difficult to detect heart-related problems based on sound analysis.

On the other hand, the presence of reliable signals, such as ECGs, has led experts to rely on them for the diagnosis of heart disease. While the PCG signal can be used as an independent method to detect many improper disorders and cardiac arrest functions in an inexpensive and fast way. Although there have been several algorithms for detecting heart sounds in recent years, each of them has some barriers because of the nature of audio signals.

To be able to use the phonocardiogram signal as a diagnostic tool in the field of heart disease, we must first provide a method for segmenting and detecting heart sounds as clinically significant segments and identifying their correspondence to heart cycles. The value of this algorithm and method increases when the signal is independently used as a diagnostic method, rather than still affecting the ECG signal. Of course, sometimes it is necessary to use either of these methods, since the complementary method is used together.

In this paper, before describing our proposed algorithm, we reviewed at some common and traditional signal processing methods used to detect heart sounds and discuss their problems. The reason for this was to examine the strengths and weaknesses of these methods and highlight the fact that there is still a need for methods that can provide more accurate segmentation of heart sounds. Some of the problems these methods face are the uncertainty of threshold-based methods, potential confusion and error in envelope-based methods (hemorrhoids, Hilbert transform, and energy envelope), and inefficient removal of background noise and heart noise even in visual representation methods such as CWT.

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In our proposed algorithm, we did not use approximation methods and threshold values, and the results obtained depend on the nature of the signals and the choice of the best IMF corresponding to the main PCG signal, which is one of the advantages of the algorithm. Thanks to these advantages, the algorithm also succeeds in detecting abnormal sounds that are slightly different from normal sounds. If we were using methods based on threshold level or approximation due to the unpredictable nature of abnormal behavior, the sounds might not be at the threshold or distance that was expected; this will cause an error to be detected. The proposed algorithm allows us to avoid such errors.

Main advantages of the proposed stethoscope are speed – 10 seconds is enough for analysis. Locality – Smart stethoscope does not send data to servers, so everything is stored in your phone. Sound recording can be provided to the doctor without problems. Accuracy – Accuracy reached about 90%. In conclusion, we would like to say that such technologies are quite convenient and practical. In further, we are going to improve an accuracy of the stethoscope and increase the heart disease count that can be diagnosed by the smart stethoscope.

REFERENCES

[1] Dorri, A., Kanhere, S. S., Jurdak, R., & Gauravaram, P. (2017, March). Blockchain for IoT security and privacy: The case study of a smart home. In 2017 IEEE international conference on pervasive computing and communications workshops (PerCom workshops) (pp. 618-623). IEEE.

[2] Omarov, B., & Altayeva, A. (2018, January). Towards intelligent IoT smart city platform based on OneM2M guideline: smart grid case study. In 2018 IEEE International Conference on Big Data and Smart Computing (BigComp) (pp. 701-704). IEEE.

[3] Shyam, G. K., Manvi, S. S., & Bharti, P. (2017, February). Smart waste management using Internet-of-Things (IoT). In 2017 2nd international conference on computing and communications technologies (ICCCT) (pp. 199-203). IEEE.

[4] Saravanan, M., Das, A., & Iyer, V. (2017, June). Smart water grid management using LPWAN IoT technology. In 2017 Global Internet of Things Summit (GIoTS) (pp. 1-6). IEEE.

[5] Ejaz, W., Naeem, M., Shahid, A., Anpalagan, A., & Jo, M. (2017). Efficient energy management for the internet of things in smart cities. IEEE Communications Magazine, 55(1), 84-91.

[6] Mahdy, L. N., Ezzat, K. A., & Tan, Q. (2018, November). Smart ECG Holter Monitoring System Using Smartphone. In 2018 IEEE International Conference on Internet of Things and Intelligence System (IOTAIS) (pp. 80-84). IEEE.

[7] https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

[8] Sundaram, D. S. B., Shivaram, S., Balasubramani, R., Muthyala, A., & Arunachalam, S. P. (2019, May). Discriminating Normal Phonocardiogram From Artifact Using a Multiscale Entropy

Technique. In 2019 IEEE International Conference on Electro Information Technology (EIT) (pp. 542-545). IEEE.

[9] Maitra, S., & Dutta, D. (2019, March). A Systemic Review on the Technological Development in the Field of Phonocardiogram. In 2019 Devices for Integrated Circuit (DevIC) (pp. 161-166). IEEE.

[10] Dia, N., Fontecave-Jallon, J., Gumery, P. Y., & Rivet, B. (2019, May). Heart Rate Estimation from Phonocardiogram Signals Using Non-negative Matrix Factorization. In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1293-1297). IEEE.

[11] Banerjee, R., Biswas, S., Banerjee, S., Choudhury, A. D., Chattopadhyay, T., Pal, A., ... & Mandana, K. M. (2016, September). Time-frequency analysis of phonocardiogram for classifying heart disease. In 2016 Computing in Cardiology Conference (CinC) (pp. 573-576). IEEE.

[12] Durand, L. G., & Pibarot, P. (2017). Most Recent Advancements in Digital Signal Processing of the Phonocardiogram. Critical Reviews™ in Biomedical Engineering, 45(1-6).

[13] Clifford, G. D., Liu, C., Moody, B., Millet, J., Schmidt, S., Li, Q., ... & Mark, R. G. (2017). Recent advances in heart sound analysis. Physiological measurement, 38(8), E10-E25.

[14] Moody, G. B., Mark, R. G., & Goldberger, A. L. (2001). PhysioNet: a web-based resource for the study of physiologic signals. IEEE Engineering in Medicine and Biology Magazine, 20(3), 70-75.

[15] Moody, G. B., Mark, R. G., & Goldberger, A. L. (2000, September). PhysioNet: A research resource for studies of complex physiologic and biomedical signals. In Computers in Cardiology 2000. Vol. 27 (Cat. 00CH37163) (pp. 179-182). IEEE.

[16] Alday, E. A. P., Gu, A., Shah, A., Robichaux, C., Wong, A. K. I., Liu, C., ... & Li, Q. (2020). Classification of 12-lead ecgs: the physionet/computing in cardiology challenge 2020. medRxiv.