Detection of heartbeat abnormalities from phonocardiography using machine learning

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***Abstract* — The paper presents the application of machine learning (MO) methods for detecting cardiovascular diseases based on phonocardiograms. Data on the high prevalence of heart disease among individuals are presented, which led to the development of models for use as additional tools for predicting heart disease. Stresses that the improvement of predictive models, development of an electronic stethoscope and their implementation in clinical practice is an important element in support of medical decision-making should be based on interdisciplinary cooperation between clinicians and specialists in the field of information technology.**

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

I. INTRODUCTION

Cardiovascular diseases (CVD) are one of the main causes of death and disability in most countries of the world [1]. The key reason for such high rates is low detection of diseases at early stages, and insufficient adherence of high-risk patients to the recommendations of doctors for prevention. In most developed countries, where much attention has long been paid to improving disease prevention rather than just treatment, there have been significant positive changes in CVD mortality rates, which has resulted in a large gap in life expectancy and the effectiveness of the fight against major chronic non-communicable diseases.

Machine learning and neural networks, as one of its varieties, is currently an actively developing branch of computer science, which is focused on and interesting to numerous research groups. The popularity of the subject of machine learning has led to the fact that at the moment any interested specialist has access to a whole set of different machine learning tools, including freely distributed ones [2-5].

Historically, the most developed machine learning tools and algorithms are those related to image recognition/processing. For example, such software products as TensorFlow (Google), Machine Learning (Amazon), Azure ML Studio (Microsoft), Firebase (Google), A platform for deploying the server part of mobile/console/web applications, are already at the start of implementation, provide mechanisms for machine learning, and even freely distributed versions support the ability to upload up to 1000 images to basic data sets. It is worth noting that the machine learning mechanisms used in the described products implement the so-called "learning with a teacher" principle, where the initial sets of images act as the "teacher" [6]. So, for example, in the case of a road sign recognition system, the initial set of values should be images of signs, since they are given in traffic regulations, and the input data for training such a neural network will be real photos of signs taken at different angles, under different lighting conditions, etc [7].

It is not difficult to imagine the potential significance of machine learning tools for medical technology. moreover, it turns out that today there are already, but are only at the implementation stage, entire platforms for analyzing medical images, such as “Botkin.ai – - a medical platform for finding cancer pathologies on x-rays [8]. However, the deployment of such systems requires a large team of specialists and developers, and the set of training data itself, when setting the task of searching for pathologies in the framework of, for example, chest images, is hardly limited to tens of thousands of images [9].

However, in addition to analyzing x-ray images, researchers have enough problems that we think it would be promising to try to solve using image recognition tools [10]. For example, information that represents sound vibrations, in particular phonocardiography, is often of diagnostic significance. it is a method for diagnosing heart diseases based on the acoustic vibrations generated by it. By themselves, acoustic vibrations recorded as an audio file, or presented, for example, as a picture in the form of a graph of changes in amplitude over time, are not very suitable as input data for the previously specified image recognition tools [11]. However, taking into account the peculiarity of the studied information, i.e. the presence of constant frequencies in the signal, as well as the possibility of presenting the audio signal in graphical form, after some transformations, image recognition systems can be used as diagnostic tools.

Further solution of the problem involves obtaining a database of "training" images by converting the freely available library of phonocardiograms for various pathologies. After training such a neural network, it is expected to get a working software model that allows you to assess the presence or absence of certain deviations from the phonocardiogram [12].

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

II. BACKGROUND

Phonocardiography (PCG) is a graphical method for recording heart sounds.a phonocardiogram is an image of heart sounds in the form of an oscillation recorded on a tape. During normal heart function and pathology, as a result of

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oscillatory movements of the myocardium, endocardium, and intracardiac blood movement, sounds occur that are characterized by a certain strength and frequency of oscillation [13]. Depending on the frequency of vibrations, heart sounds are divided into tones and noises. Tones include sounds that consist of regular and regular vibration frequencies [14]. In the case of noise, sounds are not related to each other by correct and regular relationships. For a sufficiently complete characterization of heart sounds from the frequency range in phonocardiography (PCG), a filter system is used.

When considering phonocardiography (PCG), electrocardiography (ECG) is simultaneously recorded for the accuracy of decoding the phonocardiogram (PCG) Fig. 1

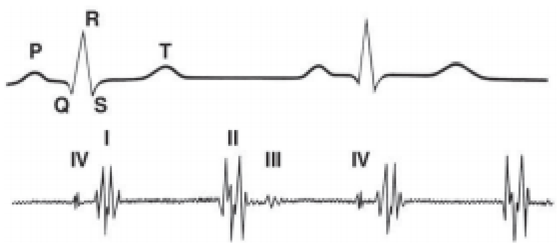

Fig. 1. Simultaneous recording of ECG and PCG

Phonocardiography is recorded using the appropriate device-a phonocardiograph. The block diagram of the device is shown in Fig. 2.

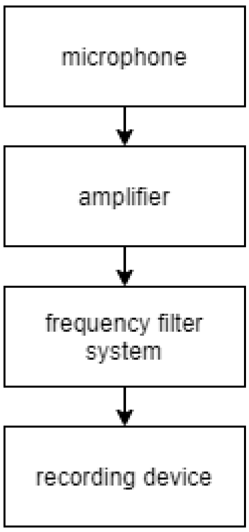

Fig. 2. Block diagram of a phonocardiograph

The microphone is placed on the chest wall at the common points of auscultation of the heart. Sound vibrations converted by the microphone into electrical ones are amplified and transmitted to a system of frequency filters that select a particular group of frequencies from all sounds and pass them to various recording channels [15]. This allows you to selectively record low, medium, and high frequency sounds. For clear transmission of all fluctuations of heart sounds that reach 800-1200 Hz in frequency. Audio signals are transmitted through the microphone to the MU microphone amplifier, where the signal is amplified, and then to the filter block, where frequency filtering is performed using various types of filters [16]. The recording device receives a signal that was filtered by frequency and removed the frequencies where the interference could have passed.

III. ANALYSIS OF INTELLIGENT SYSTEMS FOR PREDICTING DISEASES

Intelligent systems based on machine learning and artificial intelligence technologies have shown great promise in predicting and identifying threats to public health, as well as improving the results of managing high-risk patients. As they continue to improve, healthcare professionals will increasingly use this powerful tool to provide patients with more accurate, timely preventive care [17]. According to the Sloan Kettering Institute, which has studied the effectiveness of diagnosis and treatment of cancer patients, doctors use only 20% of the available information. Using advanced algorithms that can process huge amounts of data and provide the doctor with a comprehensive assessment of available medical information within a few seconds, you can significantly improve the efficiency of the doctor's work, while not extending the time of admission and even reducing the load.

There are the following prerequisites for this approach:

1. Worldwide, there is a massive transition to maintaining electronic medical records (EHRs).

2. The initial data necessary to determine the risk at least by known methods such as the Score scale are available in the vast majority of systems used for maintaining the patient's electronic medical record.

Thus, one of the most promising ways to improve the effectiveness of preventive methods to reduce morbidity and, as a result, mortality, is to create systems for supporting medical decision-making (DSS), which could be integrated into medical information systems with an electronic medical records management system (EHR). Built as centralized services for the analysis of EMCS and the identification of risk factors or suspicions of diseases at an early stage, such DSSS could take some of the preventive work on their own shoulders, and in a fully automatic mode.

IV. HARDWARE

In this section we describe a hardware to get PCG signals. In order to do this, we developed an electronic stethoscope. This is a stethoscope that connects to the TRS (mini-jack 3.5) connector of a smartphone and uses a mobile app to predict your condition. The developed intelligent stethoscope is a simple battery-free system built into an audio-microphone interface that provides power and signal transmission. A block diagram summarizing this method is shown in Figure 3.

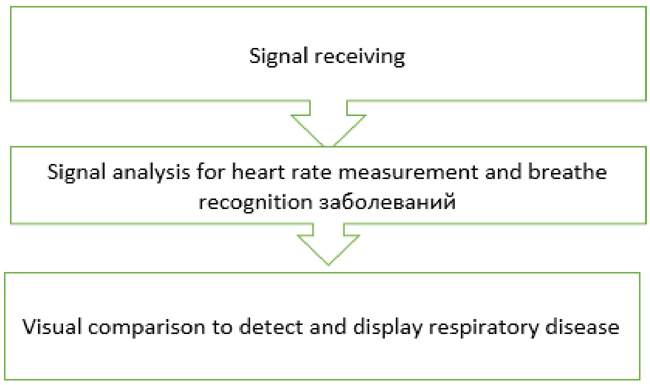

Fig. 3. Working principle of the smart stethoscope

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. 4 illustrates components of the smart stethoscope.

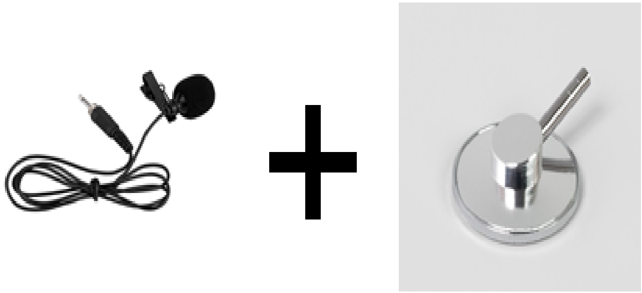

Fig. 4. Components of the smart stethoscope

Fig. 5 illustrates the smart stethoscope as a device that connect to a smartphone.

Fig. 5. Smart stethoscope as a device that connected to a smartphone

V. SOFTWARE

A. *Abnormal heart sound detection*

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

$$\Sigma(\nu) = \Phi(\nu) + O(\nu) = \Phi(\nu) + X(\nu) + N(\nu) \qquad (1)$$

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).

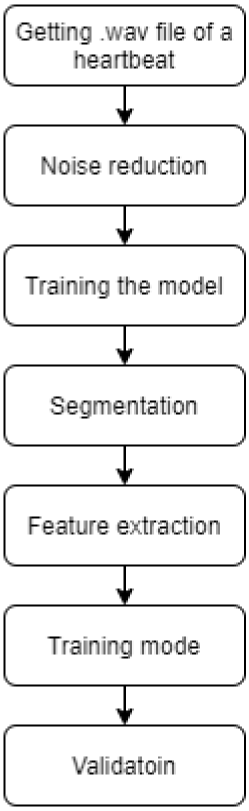

Fig. 6. Process Flow for heartbeat abnormality detection

Fig. 6 shows the process flow for detecting heartbeat abnormalities. A two-stage structure has been developed to detect the first heart sound in a noisy environment. In the first stage, the fundamental components F (n) are separated from the background signals O(n) using an adaptive sublevel tracking module. Shannon energy tracking is used to detect S1/S2 peaks from noise 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.

VI. RESULTS

Fig. 7 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 noise in the signals, we begin to identify thermal sounds. After detecting normal and abnormal heart tones, the results were shown in Table 1 and table 2.As we reported earlier, we divided the data set into two parts, as 200 abnormal and 200 normal heart sounds. In addition, training and testing data is divided in a ratio of 80% to 20%.

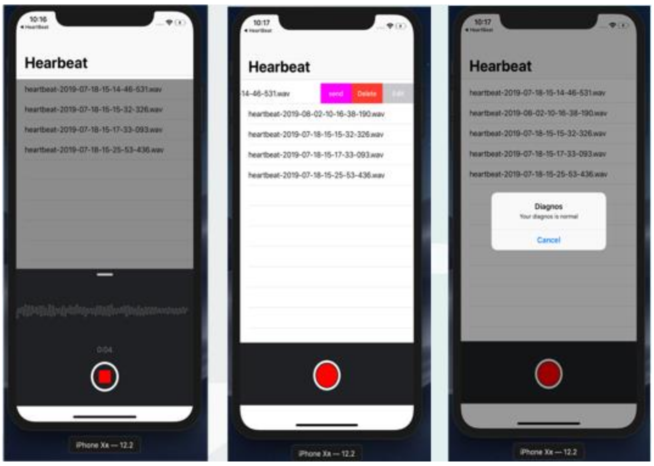

Fig. 7. Heartbeat abnormality detecttion process

The results of detecting heartbeat abnormalities using machine learning methods are considered true positive (TP), false positive (FP), false negative (FN), and true negative (TN). A true positive represents 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 evaluation results for detecting heart rhythm disorders using various machine learning classifiers that include sensitivity (SN), positive Predictivity (PP), and overall accuracy (OA). The equations below show the calculation.

$$SN = \frac{TP}{TP + FN} \times 100 \tag{2}$$

$$PP = \frac{TP}{TP + FP} \times 100 \tag{3}$$

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{4}$$

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

VII. DISCUSSION AND CONCLUSION

The electronic stethoscope has a sensitive microphone that picks up a wider range of frequencies than the human ear. At the same time, doctors are able to increase the volume of audible noises. This is important when working with a complete patient, since the sound gets worse through the thick fabric of the man. Plus, the function is relevant for older health workers who have a hearing acuity that is not the same as in their youth.

The smart stethoscope is paired with a smartphone. The app provides users with recommendations regarding diagnostics, saves and processes records, and displays measurement results. Thanks to this, the device can be used by people who do not have a medical education.

However, the development is not aimed at replacing the doctor. The main purpose of the "smart stethoscope" will be screening. Based on auscultation data and a special questionnaire, the device will be able to determine whether the patient should be concerned about the presence of a serious pathology. If there is a high risk of the disease, the mobile app will offer to conduct a remote medical consultation.

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