Chronic Heart Failure Detection from Heart Sounds Using a Stack of Machine-Learning Classifiers

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***Abstract*—Chronic heart failure represents a global pandemic, currently affecting over 26 million of patients worldwide. It is a major contributor in the death rate of patients with cardiovascular diseases and results in more than 1 million hospitalizations annually in Europe and North America. Methods for chronic heart failure detection can be utilized to act preventive, improve early diagnosis and avoid hospitalizations or even life-threatening situations, thus highly enhance the quality of patient's life. In this paper, we present a machine-learning method for chronic heart failure detection from heart sounds. The method consists of: filtering, segmentation, feature extraction and machine learning. The method was tested with a leave-one-subject-out evaluation technique on data from 122 subjects, gathered in the study. The method achieved 96% accuracy, outperforming a majority classifier for 15 percentage points. More specifically, it detects (recalls) 87% of the chronic heart failure subjects with a precision of 87%. The study confirmed that advanced machine learning applied on real-life sounds recorded with an unobtrusive digital stethoscope can be used for chronic heart failure detection.**

I. Introduction

Cardiovascular diseases (CVDs) encompassing heart attacks and chronic heart failure, rheumatic heart disease, acute myocardial ischemia, cerebrovascular disease, arterial hypertension, peripheral artery disease and congenital heart disease, have shown to be the cause of death for 17.5 million people according to the World Health Organization report in 2014 [1]. Beside the well known risk factors, such as smoking, obesity, diabetes and hyperlipidemia, the main reason accounted to be in high correlation with the CVDs is the population aging (older population is more prone to CVDs), especially prominent in the developed countries [2].

Changing the lifestyle and focusing on preventive rather than on curative medicine can significantly reduce the incidence of CVD. The preventive medicine itself basically relies on a continuous monitoring of the person's health. There is a trend of developing sensors for physiological signals (Phonocardiogram - PCG, Electrocardiogram - ECG, Electromyogram - EMG, Electroencephalography - EEG, Capnogram, Electrodermal activity - EDA, etc.) monitoring [3] in a relatively cheap and efficient way, providing the opportunity of a continuous health control without interfering with the person's every day activities.

Most heart diseases can not be simply detected by using ECG [4]; however, they cause changes to the heart sounds that can be very useful in aiding the accurate diagnosis [5]. Those changes that may result from a turbulent blood flow, valvular abnormalities or changes in ventricular compliance, are known as heart murmurs [2]. The detection of the murmurs and other abnormal heart sound changes is a problem that requires high-skilled physicians with deep knowledge obtained by a long term clinical training process. Phonocardiography is one of the tools for heart auscultation. The recorded PCG signal carries even more information that can be heard by the human ear, even though in the past it has not been very popular due to the deficiency of methods for appropriate analysis of the signal features [6]. One of the basic tools in aiding the clinical diagnosis of heart failure is the determination of plasma levels of NT-proBNP. In this paper, we focus on chronic heart failure (CHF), a condition that is currently affecting over 26 million people worldwide [7]. In CHF, the heart is unable to pump sufficiently to maintain blood flow to meet the body's needs. A trained physician can recognize CHF from heart sounds (a third tone S_3 being a strong but not exclusive indication), however, currently the only reliable diagnostic tool is the NT-proBNP [8] test.

The continuous technological advancement enables computing-power increase which allow researchers to improve existing, and come up with new artificial intelligence methods, which significantly influences our everyday life. Using state-of-the-art techniques (e.g., deep learning) computers are able to perform human tasks (e.g., speech recognition, emotion recognition, object recognition, etc.) just by analyzing real-life signals (e.g., pictures, videos and sounds).

Following this trend towards real-life signal analysis, we are proposing an original methodology for chronic heart failure detection based on Machine Learning (ML) analysis of PCG sounds. The sounds are recorded using a professional digital stethoscope presented in Figure 1, which can transfer recorded sounds via Bluetooth. We have used a total of 152 heart sounds obtained from 122 different subjects - 23 of which were previously diagnosed by a physician to have heart abnormalities. The methodology consists of four procedures: filtering, segmentation, feature extraction and stacking of ML classifiers. The applied methodology resulted in an overall accuracy of 96%, obtaining F-score of 0.97 for the negative (healthy) class and 0.87 for the positive (unhealthy) class.

The rest of the paper is organized as follows. An overview of the recently developed methods and achievements in the CVDs prediction is presented in Section II. The data gathering procedure is presented in Section III. The proposed methodology is presented in Section IV. Section V presents the experimental setup and the analysis of the obtained results. In the final Section VI, the paper is concluded with a short discussion.

II. Related Work

Failure in the presentation of heart sound frequencies and the differentiation between them, the identification of the energy variations, the process of signal de-noising, and the determination of the heart sound components [9] are only few of the issues that the researchers often confront with when analyzing the PCG signals. Some of them we address in the research presented in this paper.

Mainly, the authors distinguish three parts when analyzing PCG signals. The first part is the segmentation process where the signals are segmented into S_1 and S_2 components. S_1 represents the events related to ventricular contraction, and S_2 marks the end of S_1 (the closure of the aortic and pulmonary valves) and the beginning of ventricular relaxation [5]. In order to ease the segmentation process, some researchers apply de-noising techniques (mostly wavelet-based [10]) to remove the noise caused by the human body itself or by the environment where the experiment has been performed.

Fig. 1. The digital stethoscope used in the study.

The segmentation process can be either direct or indirect (by using ECG signal as a reference) [11]. Another segmentation categorization is by envelope (direct), or by ML (applying external medical knowledge). Normalized average Shannon energy [12], [13]; the Hilbert transform; the cardiac sound characteristic waveform (CSCW) [13]; autoregressive moving average spectral methods; power spectral density; energy of wavelet coefficients; complexity signatures; Wigner-Ville distribution [14], are some of the methods usually used for direct segmentation. In [15] the authors have used the segmentation method based on the Matching Pursuit algorithm proposed in [16] to determine the time location of the beginning and the end of each cardiac cycle in the signal (the onset and the offset). The algorithm has shown accuracy of 97.5% for the onset and 96% for the offset detection [16]. Sometimes manual segmentation is necessary to find the boundaries [17]. In that case, envelope-based approaches can be avoided and ML techniques as Hidden Markov Models [18] and Time-delayed Neural Networks can be applied [19].

Feature extraction is usually the second part in PCG signal analysis and is crucial to achieve successful classification. There are two types of features, the first type are those based on medical knowledge, and the second are based on time-frequency signal representation. The second type is suitable for PCG signals due to their non-stationarity, meaning their frequency changes in time [14]. Peak frequency, peak amplitude, total power, total harmonic distortion, bandwidth, Q-factor, cepstrum peak amplitude, zero crossing rate, and a few time duration characteristics considering S_1 and S_2 components, are some of the proposed time-frequency features found to be useful for PCG signal classification (the third and final part in PCG signal analysis) [20]. Wavelet-based algorithm has been used to extract some statistical characteristics of the PCG signal and have been aided by Artificial Neural Network (ANN) and statistical classifier to select the most appropriate subset [21].

Variety of ML techniques have been used to classify PCG signals [22]. Support Vectors Machine (SVM) has been applied on 198 heart sounds with the purpose of identifying various types of murmurs. The reported results have shown a total accuracy of 76.48% for the systolic diseases, and 77.94% for the diastolic diseases. Back-propagation Neural Networks as well as KNN and Naive Bayes have also been used, but they have shown a lower performance compared to the SVM-based approach [23]. On the contrary, in another study [20] Naive Bayes has been found to be the best classifier with 93.33% accuracy when compared to other ML methods. Probabilistic approach based on Hidden Markov Models has been proposed [24] where the classification resulted in 96.25% correctness for systolic murmurs and 90% for diastolic murmurs. Abnormality detection system based on SMOTE and AdaBoost algorithm has achieved 83.33% overall accuracy and 84.92% precision when classifying the abnormal heart sounds [25]. Similar to the approach proposed in this paper, in [26] the authors propose a methodology where the PCG signal is broken into small overlapping windows. The SVM-based classification of 25 subjects produced overall 80% accuracy [26]. Regularized logistic regression has been applied on PCG signals from 151 subjects obtained from both mobile phone and electronic stethoscope [27]. The results showed a sensitivity/specificity of 77.8%/86.7% for the mobile phone measurements and a sensitivity/specificity of 81.9%/91.2% for the electronic stethoscope source. The ability of KNN and fuzzy KNN has been reported in [28] where a highest accuracy of 99.6% has been achieved on subset of features extracted by using fisher discriminant ratio (FDR) feature reduction technique.

III. Dataset

The PCG data in this study has been recorded using a professional digital stethoscope 3M^{TM} Littmann Electronic Stethoscope Model 3200. We collected the recordings of 23 people with a diagnosed CHF condition and of 99 people, treated as "healthy" - meaning they did not have any medical condition that would manifest itself in abnormal heart sound. PCG was always recorded at Erb's point. The stethoscope allows recordings of up to 30 seconds long segments. For some people, more than one segment was recorded in order to increase the amount of data for the study. The approval of the medical ethics committee was obtained prior to the study. The basic demographics of both groups is shown in Table 1, including the comorbidity factors, pre-existing medical diagnoses, and pre-existing medications.

TABLE I
Basic demographic data for both groups of people in the database. Age, height and weight are given as mean value $\pm$ standard deviation.

	Healthy (99)	**CHF (23)**
Gender	55 F + 44 M	3 F + 20 M
Age	35 ± 11	51 ± 13
Height (cm)	173 ± 9	173 ± 18
Weight (kg)	71 ± 13	80 ± 16
Smoking	11	2
Overweight	9	1
Alcohol	1	0
Any medical condition	19	23
Any medications used	10	23

IV. Methodology

The proposed methodology is presented in Figure 2. It consists of: filtering, segmentation, segment-based feature-extraction, segment-based machine-learning, recording-based feature-extraction and recording-based machine-learning phase. The last three phases implement stacking, a ML technique for combining multiple ML models. Each of these phases is described in the following subsections.

A. Filtering and segmentation

The raw audio files are filtered using low-pass Butterworth filter with a threshold 1 kHz. This technique was chosen based on the study by Choi et al. [13] in which they proposed a methodology for cardiac sound abnormality detection based on Shannon energy. The threshold is set to 1 kHz since the majority of cardiovascular sounds are most likely to occur in the frequencies below 1 kHz [13]. In addition, noise in audio recordings usually appears in high frequencies.

For segmentation of the filtered audio signal, we used a sliding window of 1s with an overlap of 0.5s. This provides audio segments with a duration of 1s. In addition, for each segment we calculate the energy in the segment and remove the audio segments with energy lower than the median energy in the recording in which the segment belongs. This technique usually is used in speech processing to discard audio segments which contain no information [29], but might hurt a machine-learning method by introducing noise in the data.

B. Segment-based feature extraction

In the segment feature-extraction phase we used feature brute-forcing, since there are no generally known features in the field of CVDs detection from raw audio recordings. From each audio segment, 1582 features are computed. These features contain information extracted in frequency (e.g., cepstral coefficients) and time-domain (e.g., position of maximal loudness). For extracting the features we used OpenSmile [30], a tool for extracting numerical features from audio recordings. OpenSmile first computes low-level descriptors from the audio signal (e.g., pitch, loudness and audio quality) and different representations of the audio signal (e.g., cepstrum and linear predictive coding). Then, it applies statistical functions and regression analysis over the descriptors to generate final feature vector, which can be used by ML algorithms. The statistical functions that OpenSmile applies are: extremes (position of mix/min value), statistical moments (first to forth), percentiles and duration (e.g., percentage of time the audio signal is above threshold). After the segment feature-extraction phase, each segment is represented by a 1582 feature vector which is used as input to the segment-based ML models. OpenSmile was previously also used by some of the authors of this paper when dealing with classification of buzzing sounds of various species and types of bumblebees [31].

C. Stacking

The stacking module consists of tree phases: segment-based ML phase, recording-based feature-extraction phase and recording-based ML phase.

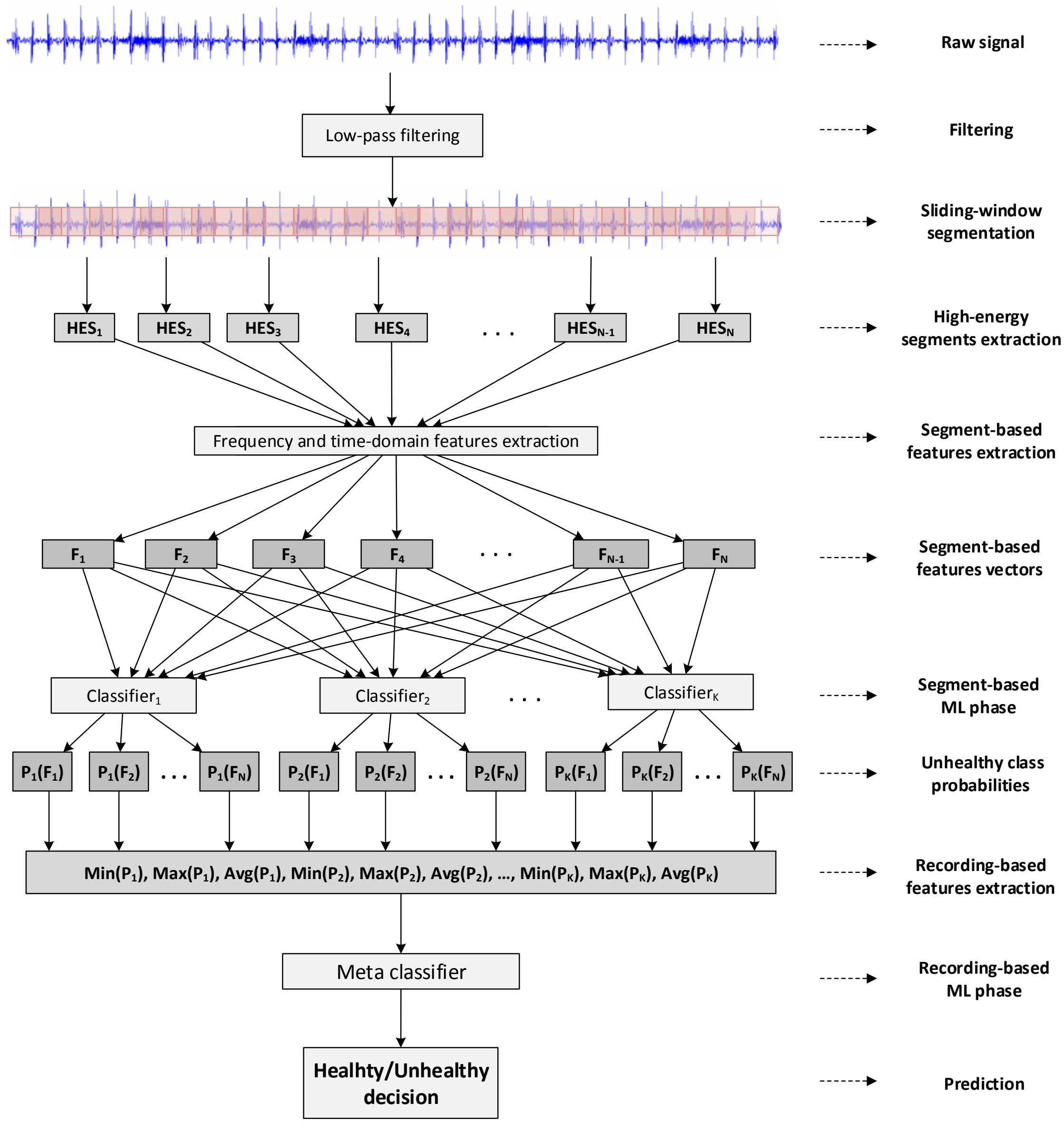

Fig. 2. The methodology overview.

In the segment-based ML phase, several ML models are build using the algorithms: J48, Naive Bayes, KNN, SVM, Random Forest, Bagging, and Boosting. The idea behind combining variety of algorithms is that different algorithms can model different structures in the data. Each of the seven ML models takes as input the feature vectors extracted in the segment feature-extraction phase and outputs a probability for a segment to be unhealthy.

In the recording-based feature-extraction phase, the output of the segment-based ML models is aggregated and provided as input for the recording-based ML phase. The aggregation is performed using min, max and average over the predictions of the segment-based ML models. For example, if we use seven segment-based ML models and if one recording is split into dozen 1-second segments, for each segment the segment-based ML models output probability to be unhealthy. The outputted probabilities are aggregated into 21 features (three functions - min, max and average are applied over the output of the seven segment-based ML models, thus 21) for the recording-based ML phase.

In the recording-based ML phase, a recording-based ML model is trained. The recording-based ML model gets min, max, and average probability for the segments in one recording to be unhealthy from seven different ML models and provides

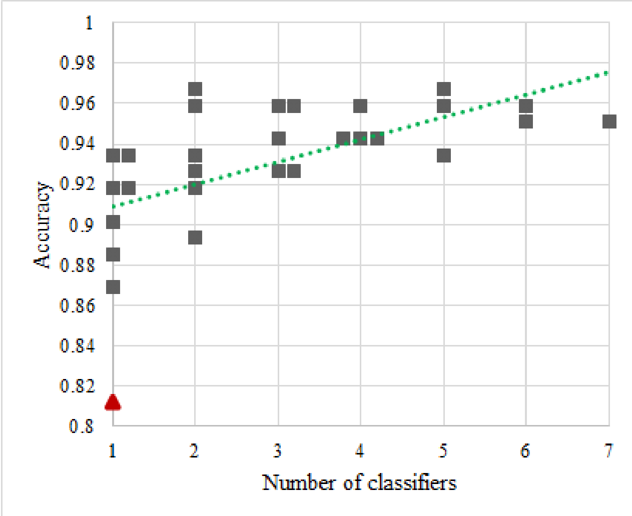

Fig. 3. LOSO evaluation - classification accuracy vs. the number of classifiers

the final prediction whether the recording belongs to a healthy or an unhealthy subject. All ML algorithms are used as implemented in the WEKA machine-learning toolkit [32].

V. Experimental results

For evaluation of the method, experiments were performed using a leave-one-subject-out (LOSO) cross-validation. That is, the ML models are built using the data of all subjects except one, which is left out for testing. This procedure is repeated as many times as there are subjects in the dataset (122) and the results are averaged. In addition, experiments were performed with combinations of different types of models in the segment-based ML phase, from single models to combinations of seven models built with the algorithms: J48, Naive Bayes, KNN, SVM, Random Forest, Bagging and Boosting. The algorithms' parameters were default.

Figure 3 represents the result for the LOSO evaluation. On the y-axis is the accuracy of the method, and on the x-axis is the number of classifiers used in the segment-based ML phase. The red triangle represents the majority class in the dataset (i.e., 81% of the subjects are healthy). Each gray dot represents the performance of the method for different combinations of models in the segment-based ML phase. From the results it can be seen that the proposed method outperforms the majority classifier for any combination of ML models. In additions, the trend line (green dotted line) depicts that in general the more models in the segment-based ML phase, the better the performance of the method. However, if chosen smartly, good performance can be achieved with only two models in the segment-based ML phase.

Table 2 presents the confusion matrix and performance metrics (accuracy, precision, recall and F1-score) for the best performance achieved by the method. The best performance is achieved by using combination of five ML models (Boosting, SVM, KNN, Naive Bayes, and J48) in the segment-based ML phase and Random Forest as meta learner. The rows in the confusion matrix represent the true class and the columns represent the predicted class by the method. The numbers in the confusion matrix represent fractions of the overall number of instances per class. In addition, it can be seen that both precision and recall for the "unhealthy" class are 87%, and the F1-score 0.87.

TABLE II
Confusion Matrix and Performance metrics

Acc = 96%	**Healthy**	**Unhealthy**	**Precision**	**Recall**	**F1-score**
Healthy	0.97	0.03	96.97	96.97	0.97
Unhealthy	0.13	0.87	86.96	86.96	0.87

VI. Conclusion

We presented a method for chronic heart failure detection from heart sounds by using a stack of ML classifiers. The experimental evaluation showed promising results as the method achieves 96% accuracy for a LOSO evaluation. In addition, it detects (recalls) 87% of the "unhealthy" instances with a precision of 87%. This confirms that chronic heart failure can be detected using real-life sounds recorded with an unobtrusive digital stethoscope.

In future, the method will be tested on a larger dataset gathered by the medical professionals in the study, and also on an open access database for evaluation of heart sounds algorithms [9]. In addition, the method will be exploited to develop personalized models for monitoring patients with chronic heart failure which would predict when a patient is supposed to modify the medication treatment in order to prevent the deterioration of medical condition and thus avoid the hospitalization. The final application will employ wearable sensors (e.g., a microphone) connected to a smartphone application, that will act as an interface between the patient and the doctor, thus enabling easier management of the medical condition.

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