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Machine Learning Models for Detection of Decompensation in Chronic Heart Failure Using Heart Sounds

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Abstract. Chronic heart failure (CHF) is a complex clinical syndrome characterised by the inability of the heart to provide sufficient perfusion to meet the body's metabolic demands. It occurs primarily in the elderly and currently affects 64.3 million people worldwide. Heart failure is associated with significant morbidity and mortality as well as with prohibitive utilization of healthcare resources. Novel technologies that would improve patient management and reduce the burden of HF on healthcare resources are thus urgently needed. We assessed the performance of machine learning algorithms for predicting decompensation in CHF using heart sound data obtained by two different setups. The most accurate model was a decision tree classifier that achieved accuracy, precision, recall, F1 score, and area and the receiver operating curve of 0.896, 0.797, 0.812, 0.801, and 0.898, respectively. We also identified the most relevant predictor features extracted from different frequency bands of the recordings. Our analysis suggests that the low-frequency abnormal heart sounds do not play a critical role in detecting decompensation episodes in CHF patient cohort.

Keywords. Chronic heart failure, cardiac decompensation, heart sounds, machine learning

1. Introduction

Heart failure is a complex clinical syndrome characterised by the inability of the heart to provide sufficient perfusion to meet the metabolic demands of the body. While the acute heart failure occurs very suddenly and requires immediate medical intervention, chronic heart failure (CHF) refers to a long-term condition that is characterized by the alternating episodes of stable condition and heart failure worsening. The societal burden of heart failure is massive as approximately 64.3 million people worldwide are currently living with CHF. Moreover, in developed countries, the prevalence of heart failure could be as high as 4.2% in the general population and about 11.8% in people aged 65 years and above. Heart failure is associated with significant morbidity and mortality (50% 5-year survival) as well as with prohibitive utilization of healthcare resources [1]. In the developed systems the cost of treating this condition is reaching up to 2% of total health

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care expenditures. Although the incidence of CHF is stable, the prevalence is increasing due to the ageing of the population and improvements in treatment strategies of acute cardiac conditions (such as myocardial infarction[2]). This will likely lead to a further significant increase the burden of CHF in the coming decade [2] [3].

There are numerous risk indicators for heart failure, some of the best-known being obesity, alcohol abuse, and smoking. In addition, some cardiovascular diseases (CVDs), e.g. hypertension[3] or myocardial infarction, are known precursors of heart failure. Early detection of heart failure symptoms and assessment of CHF severity play a crucial role in CHF management and in slowing the progression of the disease, thereby improving the patient survival and quality of life as well as reducing medical costs [4]. The most successful and promising methods for early detection of heart failure today come from the field of computer science [5]. Our long-term research goal is early detection of CHF and early detection of CHF worsening. In the latter, timely and personalized treatment interventions can reverse the progression of CHF worsening episode and can thus prevent the need for unplanned outpatient or emergency room visits or even hospital admission.

The first automated detections of CHF and other CDVs were mainly performed using data from electrocardiogram (ECG) [6] [7], photoplethysmogram, heart rate variability data, and clinical data such as weight, pulse rate, age, systolic blood pressure, respiratory rate [5]. In recent years, there has been an influx of publicly available datasets of heart sound recordings, the most comprehensive being the PhysioNet (2016) dataset [8] [9]. As a result, more and more automated methods are being developed for heart sound analysis and thus CVD detection from heart sounds [8] [10] [11]. In our previous works [12][13][14], we have obtained good results in discriminating healthy and CHF patients. In this work, we improve on previous work by distinguishing between decompensated and recompensated CHF stages. We use data from additional CHF patients. In addition, we asses the importance of predictor features.

Reported algorithms for heart sound classification include artificial neural networks (NN), statistical models, and classical ML models [15]. There is only a selection of work in the literature that specifically addresses CHF. In the work by Gjoreski et al. [12], a stack of different classical ML classifiers was used to distinguish between heart failure and normal sounds. In the improved study, Gjoreski et al. [14] used a decision tree classifier (DT) to distinguish between decompensated and recompensated CHF stages, using only the first part of our current dataset. In the work of Gao et al. [16], the authors compared the gated recurrent unit, long short-term memory, fully convolutional NN, and support-vector machine (SVM) models to distinguish between the normal heart and two subtypes of CHF. In the work of Liu et al. [17], a NN and SVM were compared in classifying normal and a subtype of heart failure. Zheng et al. [18] compared the SVM, NN, and a statistical hidden Markov model in classifying normal and CHF sounds.

In this paper, we focus on detection of decompensation in CHF from heart sound recordings using machine learning (ML) models. We use data collected from the University Medical Centre Ljubljana consisting of recordings of the decompensated CHF phase, a state in which the patient requires medical attention, and the recompensated CHF phase, in which the patient is well and is discharged from the hospital, usually recorded 2-5 days after decompensation. In addition, we explore the most important heart sound features (extracted using a well-established feature extraction tool) for predicting decompensation in CHF and investigate which is the least number of predictive features

[2] Heart attack, occurs when blood flow to a part of the heart stops
[3] Continuously raised blood pressure

for a reasonably accurate prediction. By dividing the recordings into different frequency bands, we also estimate which of the abnormal sounds are (not) important for detecting decompensation of CHF.

2. Dataset

The dataset was collected in two parts. The first part was obtained with a 3M™ Littmann Electronic Stethoscope Model 3200 digital stethoscope and consists of recordings up to 30 seconds in length, while the second part was obtained with the Eko DUO ECG + Digital Stethoscope and consists of recordings 15 seconds in length. Both devices record at a sampling rate of 4 kHz and use built-in filters to reduce ambient noise.

Table 1. Overview of the CHF sound recordings used in this study

	#Subjects	#Decompensated recordings	#Recompensated recordings	Combined duration
1st part	21	21	21	21min
2nd part	11	12	11	5min 45s
Total	32	33	32	26min 45s

The study was approved in advance by the medical ethics committee. We recorded 32 patients in both the decompensated and the recompensated phase. The average age of the patients was 51.3 ± 13.3 years. We collected 65 recordings with a total time of 26 minutes and 45 seconds. A detailed description of the dataset can be found in Table 1.

3. Methodology

The outcome of interest for the development and evaluation of the ML models was a binary variable indicating whether the patient's heart sound recording represented a decompensated or recompensated state. The main steps of the pipeline consist of: filtering the recordings, segmentation, feature extraction, aggregation, and selection and evaluation of the models. The scheme of the pipeline is shown in the Figure 1.

3.1. Filtering

In an abnormal heart sound, the main sounds, S1 and S2 caused by the closing and opening of the heart valves are accompanied by abnormal sounds such as S3, S4, gallop, murmurs, opening snaps, rubs and clicks caused by abnormalities of the heart. Detection of these abnormal sounds is crucial in identifying cardiac abnormalities from heart sound recordings [19], [20]. Heart sounds and their frequency ranges are listed in Table 2.

Table 2. Frequency ranges of heart sounds [21]

Heart sound	Frequency range
S1	10-200 Hz
S2	20-250 Hz
S3	25-70 Hz
S4	15-70 Hz
Gallop	15-50 Hz
Murmurs	Up to 600 Hz
Opening snaps	100-800 Hz
Rubs	100-800 Hz
Clicks	100-800 Hz

Although cardiovascular sounds appear in the frequency range up to 800 Hz, the most dominant frequencies are in the lower half of this range, from 20 to 400 Hz [21]. In our case, the spectral roll-off frequencies (the frequencies below which 95% of the total spectral energy lies) are 70 Hz and 190 Hz for the 1st and the 2nd part of the dataset, respectively. To isolate different groups of heart sounds, we divided each recording into nonoverlapping regions, each with its own frequency band. We tried from 3 to 9 regions, and the regions did not necessarily have to be the same size. The final regions were 25-80 Hz, 80-200 Hz, and 200-400 Hz, as they gave the most accurate predictions when tested separately. We performed the filtering using a bandpass Butterworth filter developed in Matlab R2021a [22]. Using the frequency range of 25 to 400 Hz and dividing the recordings into different frequency bands has already proven beneficial in other works when detecting cardiac abnormalities based on sounds [23] [24].

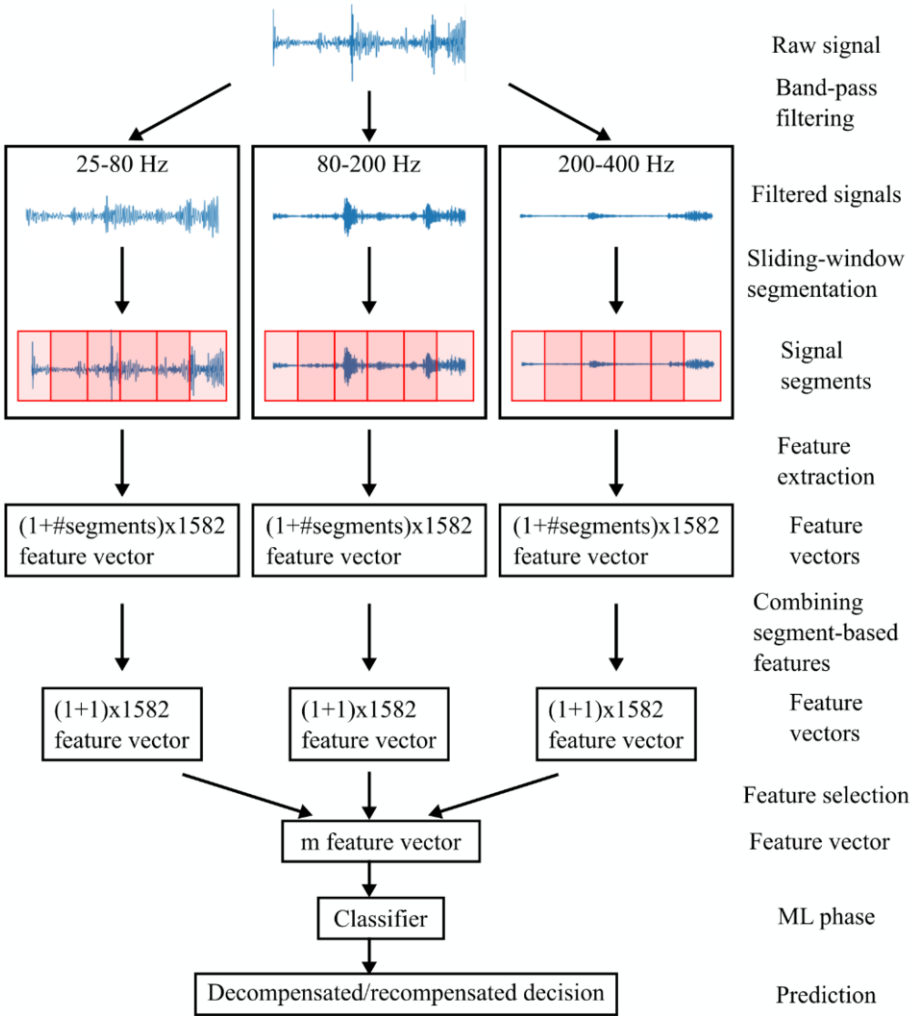

Figure 1. Scheme of the methodology pipeline.

3.2. Segmentation

The purpose of segmentation is to divide each recording into cardiac cycles and allow subsequent feature extraction to extract the features of the possible abnormal sounds [25]. We segmented each of the filtered recordings using a sliding window technique with a window length of 2s and 50% overlap. Thus, we obtain segments that span at least one cardiac cycle.

3.3. Feature Extraction and Selection

The goal of signal feature extraction is to find a small set of features that represent the entire signal, with the idea that the features are then used to train the classification model. Training the classification model is much more accurate and efficient when done using extracted features rather than the raw signal itself. For feature extraction, we used the openSMILE tool [26], which extracts numerical features from an audio signal. The tool extracts 1582 features from a variety of feature groups such as waveform (zero-crossing, extremes), signal energy, loudness, fast Fourier transform spectrum, cepstrum, Mel/Bark spectrum, semitone spectrum, cepstral, pitch.

We extracted the features from each of the filtered recordings and each of the segments. The features of the segments of the same filtered recording were then combined using the mean. Because we created 3 filtered recordings with different frequency bands for each raw recording, we thus obtained 6×1582 numerical features for each of the 65 raw recordings in our database. The features were normalized patient-wise and, because the features were of different magnitudes, the were also scaled to the range (0, 1). The scaling of the features is important because the features with a higher range of values usually dominate, as most ML algorithms use the distance between data points in their calculations.

To avoid overfitting and to keep the models as transparent and explainable as possible, we performed feature selection, keeping only a small subset of the features used for training. Features were selected by calculating the mutual information between each feature and the outcome variable. The mutual information score between two variables is zero if the two variables are independent, and higher values mean higher dependency. The features with the highest dependencies on the outcome variable were then selected as predictors for the classification models.

3.4. Evaluation of the Models

The goal of classification is to feed the selected features into a ML classifier that learns the differences between the outcome variables. In our case, we distinguished between the stage of decompensated and recompensated CHF.

Since our dataset is relatively small and NNs tend to overfit smaller datasets, we focused on some classical ML algorithms. We implemented: logistic regression (LR), decision tree classifier (DT), random forest classifier (RF), Gaussian naive Bayes (GNB), C-support vector classifier (SVC), stochastic gradient descent classifier (SGD), gradient boosting classifier (GB), light gradient boosting machine classifier (LGBM), and extreme gradient boost (XGB) classifier. We implemented the models and evaluation methods using the Python scikit version 0.24.2 [27] and lightgbm version 3.3.1 [28] libraries.

4. Results

The models were evaluated in a leave-one-subject-out (LOSO) approach, a type of k-fold cross-validation, where k corresponds to the number of patients in the dataset and each test set consists of the records of a single patient. We compared the models based on accuracy, precision, recall, and area under the receiver operating characteristic curve (ROC AUC). We chose accuracy as the main metric of performance evaluation.

4.1. Model Performance

We evaluated the models using 15 selected predictor features. The performance measures of the models are given in Table 3. The results were averaged across 32 LOSO folds.

Table 3. Performance measure for prediction of decompensation in CHF.

Model	Accuracy	Precision	Recall	F1	ROC AUC
DT	**0.896**	0.797	0.812	0.802	0.898
GB	0.880	**0.812**	**0.844**	**0.823**	**0.953**
RF	0.833	0.766	0.781	0.771	0.859
XGB	0.818	0.797	0.812	0.802	0.844
GNB	0.755	0.734	0.750	0.740	0.734
LR	0.740	0.703	0.719	0.708	0.766
LGBM	0.740	0.672	0.719	0.688	0.750
SGD	0.714	0.625	0.750	0.667	0.703
SVC	0.708	0.672	0.688	0.667	0.672

The most accurate model is DT, which misclassified a total of 7 out of 65 recordings and achieved an accuracy of 0.896. For each patient (fold), DT misclassified no more than 1 recording. On the other hand, the GB model achieved the highest values for other metrics studied. Specifically, GB achieved a recall of 0.844, an F1 of 0.844, and a ROC AUC of 0.953. It is important to note here that the models perform well even though the recordings were obtained with two different recording devices with slightly different characteristics.

4.2. Feature Importance

To understand which features are most important for the classification, we calculated the mutual information score of each feature with the outcome variable and sorted the features by score. The list of the 15 most important features can be found in Table 4, along with their mutual information score, whether the feature is from the unsegmented filtered recording or from the segments, and the identifier indicating to which of the 3 selected frequency bands of the recording the feature belongs.

The first part of the feature name corresponds to low level descriptor (LLD), while the last part corresponds to the functional type. In our case, the relevant LLDs are *mfcc,* which corresponds to Mel-frequency cepstrum coefficients (0-14), *lspFreq* which corresponds to 8 linear spectral pair frequencies computed from 8 linear prediction filter coefficients, and *logMelFreqBand,* which means the logpower of 8 Mel-frequency bands (0-7) distributed between 0 and 8 kHz. The suffix *_sma* appended to the names of the LLDs indicates that they have been smoothed by a moving average filter, while the suffix *_de* indicates that the current feature is a 1st order delta coefficient of the smoothed LLD. For the functional types, *quartile1* and *quartile2* correspond to the 1st and the 2nd quartiles,

respectively, *pctlrange0-1* corresponds to the outlier robust signal range "max-min" represented by the range of the 1% and the 99% percentile, *linregc2* corresponds to the offset of a linear approximation of the contour, *upleveltime75* corresponds to the percentage of time the signal is above (0.75×range + min), *linregerrQ* and *linregerrA* are the quadratic and linear error computed as the difference between the linear approximation and the actual contour, and *iqrl1-3* corresponds to the interquartile range: quartile3-quartile1.

Table 4. Selected predictor features.

Name (openSMILE label)	Score	Seg./unseg.	Frequency band
pcm_fftMag_mfcc_sma[14]_quartile2	0.423	Seg.	80-200 Hz
pcm_fftMag_mfcc_sma[13]_linregc2	0.405	Seg.	200-400 Hz
pcm_fftMag_mfcc_sma[8]_upleveltime75	0.395	Seg.	80-200 Hz
pcm_fftMag_mfcc_sma[10]_kurtosis	0.377	Unseg.	200-400 Hz
pcm_fftMag_mfcc_sma[5]_linregerrQ	0.376	Seg.	25-80 Hz
lspFreq_sma[2]_iqr1-2	0.365	Unseg.	200-400 Hz
logMelFreqBand_sma[0]_pctlrange0-1	0.364	Unseg.	80-200 Hz
pcm_fftMag_mfcc_sma[14]_quartile1	0.358	Seg.	80-200 Hz
pcm_fftMag_mfcc_sma[14]_quartile1	0.352	Unseg.	80-200 Hz
logMelFreqBand_sma_de[4]_pctlrange0-1	0.342	Seg.	25-80 Hz
pcm_fftMag_mfcc_sma[9]_linregerrA	0.334	Unseg.	200-400 Hz
lspFreq_sma_de[1]_upleveltime75	0.334	Unseg.	80-200 Hz
pcm_fftMag_mfcc_sma[9]_iqr1-3	0.329	Seg.	200-400 Hz
pcm_fftMag_mfcc_sma[7]_quartile2	0.327	Unseg.	200-400 Hz
pcm_fftMag_mfcc_sma[9]_linregerrQ	0.323	Unseg.	200-400 Hz

We see that the selected top features are distributed approximately equally between the unsegmented and segmented recordings. On the other hand, only 2 (13%) of the selected features belong to the 25-80 Hz frequency band, which suggest that the low-frequency abnormal sounds (S3, S4, and gallop) most likely do not play a major role in discriminating between the decompensated and recompensated stages of CHF.

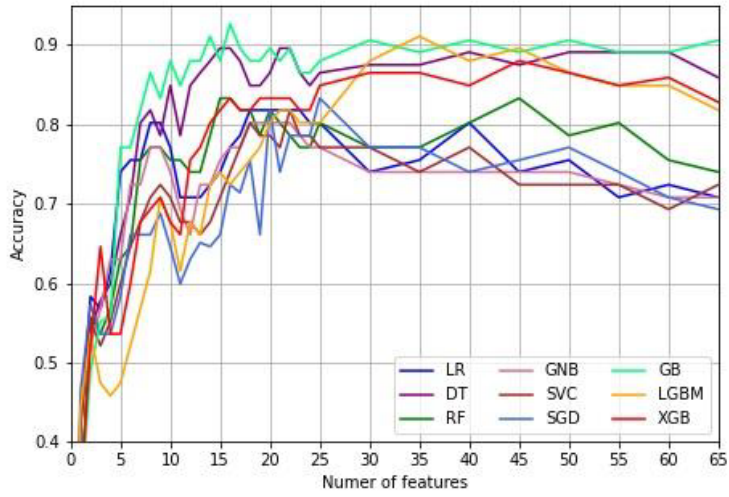

Figure 2. Accuracy as a function of the number of predictor features.

4.3. Investigating the Number of Features

We examined the performance of the models with different numbers of predictor features. This is relevant as a small number of features makes the models more robust, as well as more appropriate to integrate on the hardware level. For this experiment, we iteratively added features, starting with the most important, and estimated performance using LOSO. To prevent overfitting, we chose the maximum possible value of the features to be 65, as this is the number of recordings in our dataset. The results are shown in Figure 2. We see that increasing the number of features to over 15 does not improve the performance of the best models, GB, DT, RF, and XGB. Also, we see that the models are able to achieve accuracy of 0.880 and 0.771 with 10 and 5 features, respectively.

5. Discussion and Conclusion

In this study, we used 9 ML models to discriminate between decompensated and recompensated stages of CHF based on heart sounds, as a step in the long-term project to detect worsening of the condition using telemedicine. We used data collected from the University Medical Centre Ljubljana. The data contain 33 recordings of decompensated and 32 recordings of recompensated stages of CHF obtained from 32 patients and correspond to a total duration of 26min and 45 seconds. A simple classical machine learning algorithm, the decision tree classifier, proved to be the best method in terms of accuracy. We found that the least number of predictor features to achieve maximal performance was 15. Equally important, we demonstrated that using only 10 and 5 of the most important features based on mutual information with the outcome variable, the models achieved an accuracy of 0.880 and 0.771, respectively. It is important to note that the models performed well, although our dataset is somewhat heterogeneous because the two recording devices use slightly different built-in filters to remove ambient noise, resulting in different spectral roll-off points for the two parts of the dataset.

We divided each recording into three frequency regions, 25-80 Hz, 80-200 Hz, and 200-400 Hz, and extracted the features from each of three frequency bands. Examination of the feature importance showed that the most important features were mainly from the two upper frequency bands, whereas only 2 of the 15 selected most important features were from the 25-80 Hz frequency band. This indicates that the low-frequency abnormal sounds, S3, S4, and gallop, are most likely not of critical importance in distinguishing between decompensated and recompensated state in CHF.

This study has some limitations. Due to the nature of data collection in a clinical setting, the dataset contains only recordings of 32 patients, which prevents us from developing more sophisticated predictive models. A small dataset could also be the reason that the best performing model was a decision tree, which is extremely simple and tends not to overfit on smaller datasets, unlike more complex models (such as NNs) that can easily overfit if the dataset is too small.

In future, we plan to expand our dataset to include recordings from additional patients and also to use electrocardiogram data recorded simultaneously with the audio. The use of electrocardiogram data could also help us detect the main heart sounds and thus assist in segmenting the recordings into separate cycles rather than sliding windows. Detecting the locations of the main sounds is important because their removal will help feature extraction to extract only the features of the abnormal sounds, which is what we are interested in.

References

[1] Groenewegen A, Rutten FH, Mosterd A, Hoes AW. Epidemiology of heart failure. European Journal of Heart Failure. 2020; 22(8): 1342-560.

[2] Ponikowski P, Voors AA, Anker SD, Bueno H, Cleland JGF, Coats AJS, Falk V, González-Juanatey JR, Harjola VP, Jankowska EA, Jessup M, Linde C, Nihoyannopoulos P, Parissis JT. 2016 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure: The Task Force for the diagnosis and treatment of acute and chronic heart failure of the European Society of Cardiology (ESC). European Heart Journal. 2016; 37(27): 2129-200.

[3] Savarese G, Lund LH. Global Public Health Burden of Heart Failure. Cardiac Failure Review. 2017; 3(1): 7-11.

[4] Ford I, Robertson M, Komajda M, Böhm M, Borer JS, Tavazzi L, Swedberg K. Top ten risk factors for morbidity and mortality in patients with chronic systolic heart failure and elevated heart rate: The SHIFT Risk Model. International Journal of Cardiology. 2015; 184: 163-9

[5] Tripoliti EE, Papadopoulos TG, Karanasiou GS, Naka KK, Fotiadis DI. Heart Failure: Diagnosis, Severity Estimation and Prediction of Adverse Events Through Machine Learning Techniques. Computational and Structural Biotechnology Journal. 2017; 15: 26-47.

[6] Jahmunah V, Oh SL, Wei JKE, Ciaccio EJ, Chua K, San TR, Acharya UR. Computer-aided diagnosis of congestive heart failure using ECG signals – A review. Physica Medica. 2019; 62: 95-104.

[7] Bhurane AA, Sharma M, San-Tan R, Acharya UR. An efficient detection of congestive heart failure using frequency localized filter banks for the diagnosis with ECG signals. Cognitive Systems Research. 2019; 55: 82-94.

[8] Liu C, Springer D, Li Q, Moody B, Juan RA, Chorro FJ, Castells F, Roig JM, Silva I, Johnson AEW, Syed Z, Schmidt SE, Papadaniil CD, Hadjileontiadis L. An open access database for the evaluation of heart sound algorithms. Physiological Measurement. 2016; 37: 2181-213.

[9] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, CK, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. Circulation. 2000; 101(23): 2015-20.

[10] Clifford GD, Liu C, Moody B, Millet J, Schmidt S, Li Q, Silva I, Mark RG. Recent advances in heart sound analysis. Physiological Measurement. 2017; 38(8):10-25.

[11] Sidra G, Ammara N, Taimur H, Bilal H, Ramsha A. Fully Automated Identification of Heart Sounds for the Analysis of Cardiovascular Pathology. In: Khan F, Jan MA, Alam M, editors. Applications of Intelligent Technologies in Healthcare, Springer, Cham; 2018, p. 117-129.

[12] Gjoreski M, Simjanoska M, Gradišek A, Peterlin A, Gams M, Poglajen G. Chronic Heart Failure Detection from Heart Sounds Using a Stack of Machine-Learning Classifiers. In: Jason J, editor. The 13th International Conference on Intelligent Environments; 2017 Aug 23-25; Seoul, Korea. Danvers: IEEE = Institute of Electrical and Electronics Engineers. 2017, p. 14-19.

[13] Gjoreski M, Gradišek A, Budna B, Gams M, Poglajen G. Toward Early Detection and Monitoring of Chronic Heart Failure Using Heart Sounds. In: Muñoz A, Ouhbi S, Minker W, Echabbi L, Navarro-Cía M, editors. Intelligent environments 2019: Workshop Proceedings of the 15th International Conference on Intelligent Environments in conjunction with the 15th International Conference on Intelligent Environments (IE19); 2019 Jun 24-27; Rabat, Morocco (Ambient intelligence and smart environments, 26). Amsterdam: IOS Press. 2019, p. 336-343

[14] Gjoreski M, Gradišek A, Budna B, Gams M, Poglajen G. Machine Learning and End-to-End Deep Learning for the Detection of Chronic Heart Failure From Heart Sounds. IEEE Access. 2020; 8: 20313-24.

[15] Dwivedi AK, Imtiaz SA, Rodriguez-Villegas E. Algorithms for Automatic Analysis and Classification of Heart Sounds–A Systematic Review. IEEE Access. 2019;. 7: 8316-45.

[16] Gao S, Zheng Y, Guo X. Gated recurrent unit-based heart sound analysis for heart failure screening. BioMedical Engineering OnLine. 2020; 19.

[17] Liu Y, Guo X, Zheng Y. An Automatic Approach Using ELM Classifier for HFpEF Identification Based on Heart Sound Characteristics. Journal of Medical Systems. 2019; 43.

[18] Zheng Y, Guo X, Qin J, Xiao S. Computer-assisted diagnosis for chronic heart failure by the analysis of their cardiac reserve and heart sound characteristics. Computer Methods and Programs in Biomedicine. 2015; 112: 372-83.

[19] Groenewegen A, Rutten FH, Mosterd A, Hoes AW. Epidemiology of heart failure. European Journal of Heart Failure. 2020; 22(8): 1342-56.

[20] Kaniusas E. Sensing by acoustic biosignals. Biomedical signals and sensors. Springer, Berlin, Heidelberg; 2016. p. 1-90.

[21] McGee S. Auscultation of the Heart: General Principles. Evidence-Based Physical Diagnosis (4th Edition). Elsevier; 2018. p. 327-32.

[22] MATLAB. version 9.10.0 (R2021a). Natick, Massachusetts: The MathWorks Inc.; 2021.
[23] Potes C, Parvaneh S, Rahman A, Conroy B. Ensemble of feature-based and deep learning-based classifiers for detection of abnormal heart sounds. 2016 Computing in Cardiology Conference (CinC), 2016, p. 621-24.
[24] Singh SA, Meitei TG, Majumder S. Short PCG classification based on deep learning. Deep Learning Techniques for Biomedical and Health Informatics. Elsevier; 2020; 141–64.
[25] Li S, Li F, Tang S, Xiong W. A Review of Computer-Aided Heart Sound Detection Techniques. Research International. Hindawi Limited; 2020. p. 1–10.
[26] Eyben F, Wöllmer M, Schuller B. "openSMILE - The Munich Versatile and Fast Open-Source Audio Feature Extractor", Proc. ACM Multimedia (MM), ACM, Florence, Italy, ISBN 978-1-60558-933-6, 2010; 1459-62.
[27] Pedregosa F, Varoquaux G, Gramfort A, et al. Scikit-learn: machine learning in Python. J Mach Learn Res. 2011;12:2825-2830
[28] Ke G, Meng Q, Finley T, et al. LightGBM: A Highly Efficient Gradient Boosting Decision Tree. In: Jordan MI, LeCun Y, Solla SA, editors. Advances in Neural Information Processing Systems. Curran Associates, Inc. 2017; 30.