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Blood pressure estimation from phonocardiographic signals recorded with a smartphone and an electronic stethoscope

Michał ŁUCZYŃSKI[1], Tomasz WALCZAK[2], Agnieszka MACIEJCZYK[2], Stefan BRACHMAŃSKI[1], Dariusz JAGIELSKI[3], Olivier MIELCZAREK[1]

[1] Wroclaw University of Science and Technology, Department of Acoustics, Multimedia and Signal Processing, Wroclaw, Poland
[2] 4th Military Clinical Hospital, Division of Cardiology, Centre for Heart Diseases, Wroclaw, Poland
[3] 4th Military Clinical Hospital, Division of Cardiology, Centre for Heart Diseases, Wroclaw, Poland and Wroclaw University of Science and Technology, Faculty of Medicine, Wroclaw, Poland

Corresponding author: Michał ŁUCZYŃSKI, email: michal.luczynski@pwr.edu.pl

Abstract Phonocardiography (PCG) is a non-invasive diagnostic method that enables the analysis of heart acoustic activity. This study investigates the feasibility of estimating blood pressure based on PCG signal parameters recorded using a smartphone microphone and an electronic stethoscope. A database of 220 ten-second heart sound fragments was created, each linked to simultaneous blood pressure measurements. Noise detection and signal segmentation were performed using a Hierarchical Segmental Hidden Markov Model (HSMM). Selected acoustic features were used to build predictive models employing machine learning algorithms, with Random Forest achieving the highest correlation with actual pressure values ($r > 0.8$). The results suggest that smartphone recordings can be as effective as those obtained with professional equipment, paving the way for mobile diagnostic tools.

Keywords: phonocardiography, blood pressure estimation, mobile health, heart sound analysis, machine learning, smartphone stethoscope, signal processing, Random Forest, non-invasive monitoring.

1. Introduction

Phonocardiography [1] (PCG) is a non-invasive diagnostic technique in cardiology that allows the recording and analysis of acoustic signals generated by the heart during its cycle. It is the process of extracting heart sounds using highly sensitive sensors, such as microphones or piezoelectric sensors, and processing them using signal processing techniques. Heart sounds are recorded to assess the function and structure of the heart and to detect possible abnormalities. During the heart cycle, valve movements and blood flow in the heart generate characteristic sounds, such as heart sounds, additional physiological and pathological murmurs. These sounds contain information about the function of the heart, the presence of valvular heart defects, and other conditions. Phonocardiography can be used as a standalone test, as a pre-test, or as a complement to other diagnostic tests such as electrocardiography (ECG) or echocardiography.

Usually, an electronic stethoscope is used to measure the PCG signal, which is an extension of the standard stethoscope with the ability to convert the acoustic signal into an electrical one. It is a professional solution aimed at medical staff, hence the price is often inadequate to the capabilities of the average patient. Therefore, it is possible to find proposals for cheaper stethoscope designs [2] or modifications of relatively cheap stethoscopes [3]. There were also proposals to use a mobile phone to record the PCG signal. The phone can be used in two ways, as a signal recorder with an external microphone connected [4–6] or by using the phone's built-in microphone [7,8]. The last method is particularly interesting due to the availability and popularity of mobile phones and the lack of need for additional devices. Independent studies carried out using various methods have shown that the quality of signals recorded by mobile phones is comparable to those recorded by electronic stethoscopes [9, 10].

The aim of the experiment presented in this paper was to investigate the possibilities of recording and analyzing the acoustic activity of the heart using different types of sensors (using a mobile phone and an electronic stethoscope). Unlike classic long-term heart monitoring (Holter ECG and ABPM – ambulatory blood pressure monitoring), the phonocardiographic signal (PCG) contains information about both heart rhythm and potentially blood pressure.

2. State of the art

In recent years, there has been a growing interest in non-invasive, cuffless methods of estimating blood pressure (BP), which could enable continuous monitoring of hemodynamic parameters at home. A promising avenue of research is the use of the heart phonocardiogram (PCG), the sound signal, as a source of information on blood pressure.

Compared to methods based on photoplethysmography (PPG), which record changes in blood volume in peripheral tissues, PCG enables the analysis of central circulatory events, such as heart valve closure (S2 sound) and cardiac cycle duration. These parameters are directly related to pressure gradients and aortic stiffness, which can provide information not available with PPG. Furthermore, PCG does not require additional optical sensors or light sources, simplifying device design and enabling the use of smartphone-based microphones.

Early work in this area has shown that the analysis of pulse wave transit times (PTT) and intervals between heart sounds (e.g. S1–S2) can provide important information about systolic and diastolic blood pressure [11]. Studies using smartphones and stethoscope microphones have shown that parameters such as stroke time (ET) or blood passage time from the heart to the finger (VTT) correlate with blood pressure values [11, 12].

Then studies focused on the analysis of the frequency spectrum of the second heart tone (S2), whose changes – both in frequency and amplitude – are associated with hypertension [12, 13]. Regression models based on S2 spectral features, such as SVM or Random Forest, achieved high agreement with reference measurements ($r > 0.9$) [13, 14].

Other approaches used geometric and temporal features of the PCG signal, such as S2 tone kurtosis or HSTT (Heart Sound Time Interval), demonstrating their effectiveness in estimating both SBP and DBP [15, 16]. Importantly, some methods eliminate the need to record PPG or ECG signals, which simplifies the measurement system and increases its availability [15, 17].

Modern solutions such as HearBP use in-ear microphones to record bone-conducted heart sounds, enabling convenient and interference-resistant blood pressure measurement [17]. On the other hand, the latest research from 2025 shows that it is possible not only to estimate BP values, but also to effectively detect hypertension based on amplitude, time and frequency characteristics of the PCG signal [18].

The development of publicly available datasets, including synchronized PCG recordings and BP measurements, such as the one presented in [19], opens new opportunities for research on predictive models and machine learning in this area.

Interesting and important research in the field of stethoscope signal analysis is also being conducted in Poland. Among others, it is worth noting the research conducted at Adam Mickiewicz University in Poznań on the segmentation of heart sound signals [20] and the development of a home stethoscope with an artificial intelligence module (StethoMe) supporting the diagnosis of lung diseases [21]. Furthermore, the AGH University of Science and Technology in Krakow conducted work on the application of the Matching Pursuit method to phonocardiographic signal analysis [22]. Considering this work allows for a better localization of this research in the national scientific context.

Research on estimating blood pressure from heart sounds is mainly focused on healthy populations, driven by the need to reduce confounding variables and ensure consistency in input data. Under physiological conditions, in people without cardiovascular diseases, the relationship between PCG signal parameters and arterial pressure is more predictable and stable. This allows estimation models to be developed and validated under controlled conditions, a necessary step before expanding the research into clinical populations.

In populations with pathologies such as atherosclerosis, arterial stenosis, aneurysms or heart valve diseases, blood flow disorders may occur that affect the distribution of pressure in the circulatory system. In these cases, despite normal heart function, the pressure measured in peripheral parts of the body (e.g. on the arm) may not reflect the actual hemodynamic condition. Therefore, pressure estimation based on the PCG signal in these groups requires separate studies and more complex models that consider additional factors.

In this study, we will focus on the healthy population to assess the effectiveness of blood pressure estimation based on heart sounds recorded using two different methods: a smartphone microphone and an electronic stethoscope. Comparing these two methods will determine whether equally precise results can be obtained using commonly available mobile devices as with specialized devices. The results of this phase will form the basis for further work on the application of this technology in clinical settings.

3. Preparing a database of recordings

The recording of cardiac sound signals was carried out using two devices: the Samsung Galaxy A25 smartphone (with the use of a built-in microphone without any additional accessories) and the 3M Littmann CORE Digital electronic stethoscope. Each recording was linked to a simultaneous blood pressure measurement taken with the Omron M7 Intelli IT upper arm blood pressure monitor.

Each time, the pressure was measured on the left arm, above the elbow. Two blood pressure measurements were taken: the first was assigned to a recording made with a phone, and the second – to a recording with a stethoscope. In order to avoid acoustic interference, the recording of the heart sound was started immediately after the end of pumping the blood pressure monitor cuff. The recordings were made at the Erb's auscultation point, by placing the telephone microphone or the head of the stethoscope against the chest wall. The sample duration was 30 seconds. A total of 44 recordings were recorded (22 with a telephone, 22 with a stethoscope). Each recording is associated with the measurement of systolic and diastolic blood pressure and pulse. The recordings were recorded for one person (a man, 32 years old, without diagnosed heart disease). To obtain a variety of values in the database, measurements were taken at different times of the day and different physical states (resting state, after mild physical exercise, under mental stress).

Files recorded with a stethoscope were saved in WAV format with a sampling frequency of 4 kHz and a resolution of 16 bit (PCM). The files recorded with the phone were initially 44.1 kHz and 16 bits (PCM), but in order to standardize the parameters, they were resampled to 4 kHz.

The subject was informed about the details of the experiment and signed a consent to participate in the study and to the processing of personal data, in accordance with the requirements of the bioethics committee that approved the research project.

According to the results presented in the previous publication [11], effective estimation of arterial pressure based on the PCG signal requires the presence of at least 10 complete heart cycles in the analysed part of the signal. In the study [19], concerning the construction of the PCG recording database, an approach was used to divide 60-second recordings into 10-second fragments with 50% overlapping. Assuming a heart rate ≥ 60 beats per minute (BPM), each 10-second fragment contained at least 10 heart cycles.

This study takes a similar approach. All 30-second recordings were divided into five 10-second fragments with an offset every 5 seconds (i.e. with a 50% overlap). A schematic illustration of the division method is shown in Figure 1.

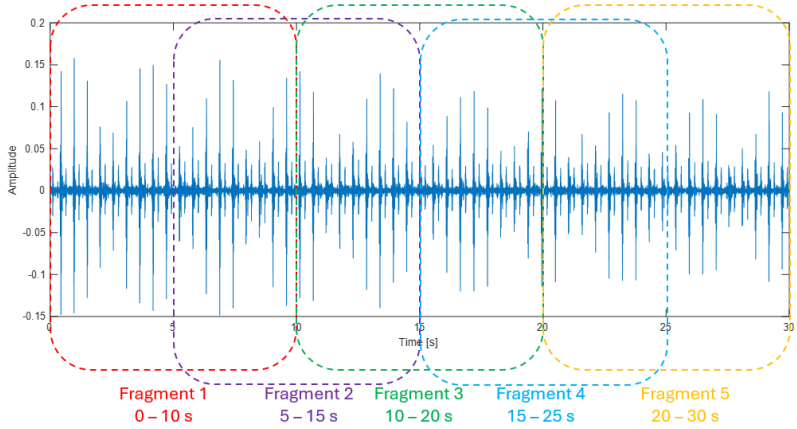

Figure 1. Diagram of dividing the recording into 10-second fragments.

The above procedure allowed us to create a database containing a total of 220 10-second fragments, including:

- 110 fragments from recordings made with a phone,
- 110 fragments from recordings made with a stethoscope.

The signal database prepared in this way was used to analyse signal parameters and build predictive models.

Due to the nature of the recorded PCG signal, some of the recordings contained interference that negatively affected the quality of the analysis and the segmentation process. To identify these interferences, a simple algorithm based on spectrum analysis of the signal was developed.

Many noises – such as mechanical noise, sounds resulting from the phone being placed or moved away from the body – have a wide frequency band, which is different from the typical heartband contained in the 20-200 Hz band.

The algorithm works in an iterative manner, in the steps outlined below:

- Splitting the signal (vector y) into fragments with a length of N samples.
- Calculation of the spectrum for each signal fragment
- Deciding whether the analysed part of the signal is disturbed or not
  - when the spectral energy concentrated in the range of 20–200 Hz the signal is undisturbed,
  - when the spectrum is wider, the analysed fragment is considered disturbed and is removed from the database.

This algorithm is effective at detecting interference with a distinctly different spectrum, but some types of interference – e.g. fragments of speech or phone movements on the body – may not be detected because their maximum spectrum is still in the range of 20-200 Hz. An example of such interference is shown in Figure 2.

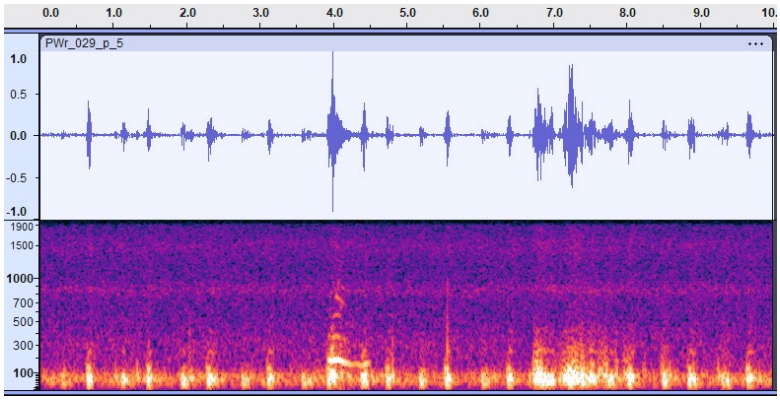

Figure 2. Interference in the form of a fragment of speech and a shift of the phone.

In such cases, an additional criterion was required: the proportion of the total signal energy in the 20-200 Hz band was calculated.

Based on these principles, an algorithm was developed that analysed each 10-second fragment of the signal and classified it as correct or distorted. Fragments considered disturbed were eliminated from further analysis so that they did not adversely affect the process of segmentation and extraction of parameters.

It should be emphasized that the developed algorithm is preliminary and not without limitations. In the future, it is planned to be further developed and improved, i.a. through the use of more advanced methods of spectral analysis and machine learning.

To determine the parameters that describe heart sounds, it was necessary to perform PCG signal segmentation. Segmentation allowed to determine the position of the first (S1) and second (S2) heart tone and to assign the corresponding phases of the heart cycle: systole and diastole.

Traditional threshold-based segmentation methods show moderate efficacy; hence the probabilistic model approach was used in this study. In particular, the Hierarchical Segmental Hidden Markov Model (HSMM) was used, which considers a priori information about the expected duration of individual states [23, 24]. This method allows for a more precise and stable separation of the phases of the heart cycle, which is crucial for further analysis of the parameters. The result of the heart sound separation algorithm is shown in Figure 3. For each 10-second fragment, 4 sound files were created containing tones S1, systole, tones S2 and diastole.

An additional condition has been introduced to verify the correctness of the segmentation. For each sound file containing S1 tones, the signal was band-filtered (20-150 Hz), enveloped and thresholded. Based on the autocorrelation of the binary signal, the interval between heart tones was estimated, from which the pulse in BPM was calculated. In addition, pulse was calculated based on the number of S1 tones detected in the signal. These two values were compared. If the values did not differ by more than 10%, it was considered that the segmentation was performed with satisfactory correctness.

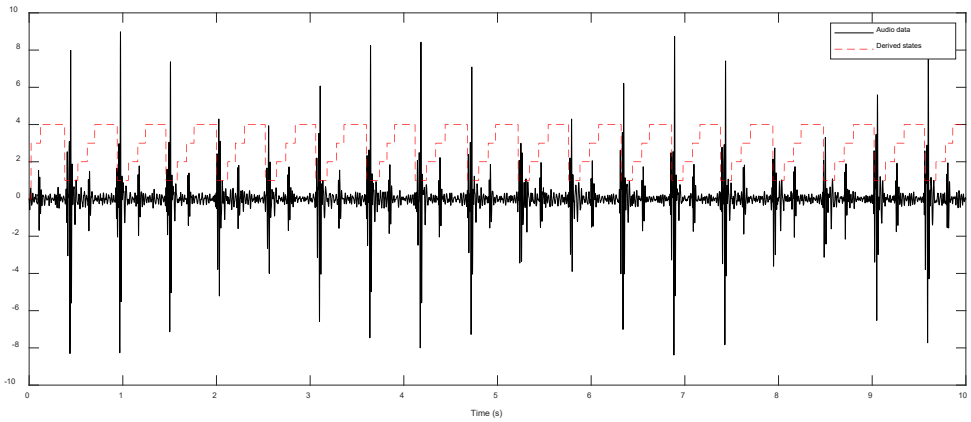

Figure 3. Result of separation of cardiac sound components with segments marked.

The results of the above criterion were compared with the interference detection criterion and on this basis a database of recordings considered to be undisturbed was obtained (189 recordings – 103 from the stethoscope, 86 from the telephone). It was found that 7 recordings made with the use of a stethoscope and as many as 24 recordings made with a phone were excluded. This may indicate that your phone recordings are more prone to noise and interference.

In this study, PCG signals from a single healthy participant without heart murmurs were analyzed. The interference detection algorithm was based on analysis of the signal spectrum and energy ratio in the 20–200 Hz band, which allowed for the elimination of mechanical interference and artifacts. Future work plans to expand the algorithm to include the classification of pathological murmurs and assess their impact on the quality of pressure estimation.

4. Prediction model

In this part of the work, the focus is on the analysis of selected acoustic parameters of cardiac sound, determined from 10-second fragments of the PCG signal. The aim was to identify the features most closely associated with pressure and use them in a predictive model.

For each fragment, a set of features describing ~~its~~ temporal, amplitude and frequency structure of tone S1 and S2 was calculated. Parameters of time relationships between tons S1 and S2 are also included. Among the features analysed, the highest correlation with the values of the measured pressure were:

- tone duration (average),
- kurtosis and amplitude skewness,
- DCT kurtosis – a measure of the "pointiness" of the energy distribution in the frequency domain,
- kurtosis and FFT envelope skewness – describe the structure of the frequency spectrum of a tone,
- maximum FFT envelope value – informs about the dominant energy in the spectrum,
- time between tone S1 and S2 (median) and time between tone S2 and S1 (median),
- duration of systole and diastole (mean and median),
- tone energy (RMS values of S1 and S2 tone).

The sounds of the heart, and in particular the tones S1 and S2, arise as a result of the closing of the heart valves and the accompanying mechanical phenomena. Their characteristics – duration, shape, rising and falling dynamics, as well as frequency spectrum – reflect the physiological conditions in the heart and circulatory system at any given time. The following are the reasons why individual parameters may be related to blood pressure:

Duration of tone: depends on the resistance of the blood to the closure of the valves and the dynamics of their closure. High blood pressure can cause the valves to close more quickly and abruptly, which can result in shorter tone duration. Conditions of low pressure or increased vascular compliance, closure may be slower and more protracted.

Signal shape and envelope: may reflect the uneven distribution of forces acting on the valve. Rapid build-up may indicate abrupt valve closure, which is typical of a high-pressure gradient between the heart cavities and vessels. Slower rise or fall may indicate decreased contraction force or increased vascular compliance

Frequency spectrum (tone sound): The spectrum of heart tone depends on the rigidity of the heart and vascular structures and on the strength and speed of valve closure. High pressure can generate higher frequency tones with higher energy in the high band.

Tone Energy (RMS): Tone energy is an indirect indicator of the mechanical force of valve closure. High energy can be associated with a large pressure gradient, and low energy can be associated with a weakened systolic function or low system pressure.

To assess the generality and robustness of the models, tests were carried out in different scenarios:

- Model 1: trained and tested on all selected data recorded with both a stethoscope and a phone;
- Model 2: trained and tested only on data recorded with a stethoscope;
- Model 3: trained and tested only on data recorded with the phone;
- Model 4: Trained and tested on all data but limited to half of the data for better comparison with models made on data registered with only one device type. Half of the data was removed from the model 1 dataset so that the data volume was similar to that of model 2 and model 3, while maintaining the distribution of systolic and diastolic blood pressures.

The data for the training and test sets have been selected in such a way that the distribution of pressure values in both sets is similar. Table 1 shows the minimum, average, and maximum values of systolic and diastolic pressure for the sets analyzed in each model. The data was manually separated into training and test data sets to avoid different parts of the same recording from being in two sets.

Table 1. Range of pressure values in training and test sets of analysed models.

	Train set				Test set			
Model number	Samples number	Minimum SBP/DBP	Mean SBP/DBP	Maximum SBP/DBP	Samples number	Minimum SBP/DBP	Mean SBP/DBP	Maximum SBP/DBP
Model 1	107	115 / 78	134 / 87	165 / 109	82	117 / 80	135 / 89	170 / 109
Model 2	58	115 / 78	132 / 86	154 / 100	45	117 / 80	132 / 89	158 / 107
Model 3	49	122 / 82	137 / 88	165 / 109	37	117 / 80	138 / 90	170 / 109
Model 4	54	115 / 78	134 / 87	165 / 109	41	117 / 80	135 / 89	170 / 109

The study tested various machine learning algorithms to estimate blood pressure values. Among the models considered were: Decision Tree, Gradient Boosting, KNN, Linear Regression, Random Forest, SVM [25, 26].

5. Results

For all selected data recorded with both a stethoscope and a phone (model 1) and with the same division into training and test data, an analysis of systolic pressure prediction was performed using various machine learning models. The results of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Maximum Error, Coefficient of Determination (R2), and correlation of test values and values predicted by the model are shown in Table 2 for systolic pressure and Table 3 for diastolic pressure.

Table 2. Comparison of six regression models in the same dataset (Model 1) for systolic pressure.

Model	RMSE	MAE	Max Error	R^2	Correlation
Random Forest	8.1	6.6	20.8	0.66	0.82
Gradient Boosting	6.3	5.2	14.1	0.36	0.68
KNN	7.8	6.2	24.0	0.01	0.44
Linear Regression	8.3	6.8	20.6	-0.14	0.52
Decision Tree	8.8	7.0	23.0	-0.27	0.54
SVM	9.8	6.7	25.4	-0.56	0.29

The Random Forest model is far superior to the other models in terms of coefficient of determination (R2) and correlation with systolic pressure. A detailed summary of the values from the test set and the corresponding predicted values for systolic and diastolic pressure is shown in Figure 4. The blue color indicates the measured pressure value, the gray color indicates the pressure value predicted by the model. Dashed lines indicate trend lines.

Table 3. Comparison of six regression models in the same dataset (Model 1) for diastolic pressure.

Model	RMSE	MAE	Max Error	R^2	Correlation
Random Forest	5.1	4.0	13.3	0.58	0.81
Gradient Boosting	5.9	4.9	14.0	0.34	0.66
KNN	7.5	6.1	22.0	0.02	0.44
Linear Regression	8.2	6.7	19.0	-0.11	0.51
Decision Tree	8.7	6.9	21.0	-0.24	0.52
SVM (RBF)	9.6	6.6	24.0	-0.54	0.28

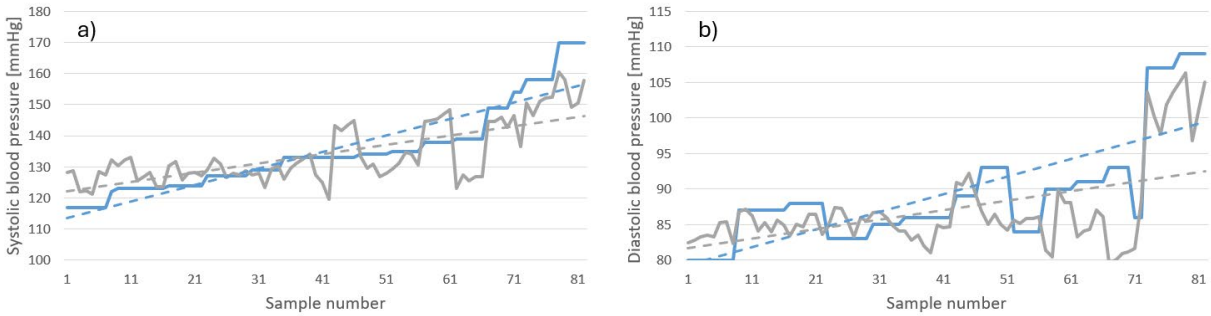

Figure 4. Actual values (blue line) vs values predicted (gray line) by the Random Forrest model for the model set 1, a) systolic pressure, b) diastolic pressure.

Table 4 shows how selected features of the model, pulse and pressure values predicted by the model correlate with the measured systolic pressure. Table 5 presents analogous data for the correlation with diastolic pressure.

Table 4. Correlation of systolic pressure predicted by the model, pulse and selected features of the model with the measured systolic pressure value.

		Model feature name										
Predicted systolic blood pressure	Pulse	Diastole duration	S2 peak to S1 peak time	Systole duration	Kurtosis of FFT envelope	Kurtosis of DCT coefficients	S1 duration	S1 peak to S2 peak time	Skewness of FFT envelope	S2 duration	S1 energy (RMS)	Max of FFT envelope
0.82	0.74	0.68	0.67	0.55	0.46	0.44	0.43	0.43	0.42	0.36	0.35	0.31

Table 5. Correlation of the value of the diastolic pressure predicted by the model, pulse and selected features of the model with the measured value of diastolic pressure.

		Model feature name									
Predicted diastolic blood pressure	Pulse	S2 peak to S1 peak time	Diastole duration	Kurtosis of DCT coefficients	Median of S1 envelope	Skewness of S1 envelope	Kurtosis of S1	Entropy of S2 envelope	Kurtosis of FFT envelope	S1 energy (RMS)	S2 energy (RMS)
0.81	0.62	0.45	0.44	0.39	0.37	0.35	0.34	0.33	0.32	0.32	0.31

It can be seen that the pressure values predicted by the model correlate with the measured pressure better than the pulse and then each of the features of the model separately (both for the systolic and diastolic pressure).

Next, the effectiveness of the pressure prediction model was compared for sets limited only to data recorded with a stethoscope (model 2), only with a telephone (model 3) and for a set with recordings recorded with both methods. In the third case, the number of data was halved so that the number of data sets was comparable. This is how the 4 model was created. The results of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Maximum Error, Coefficient of Determination (R2), and the correlation of test values and values predicted by the analyzed models are presented in Table 6 for systolic pressure and Table 7 for diastolic pressure.

Table 6. Results of systolic pressure prediction models.

Model	RMSE	MAE	Max Error	R^2	Correlation
Model 1	8.1	6.6	20.8	0.66	0.82
Model 2	8.2	6.7	17.0	0.47	0.73
Model 3	9.6	7.4	22.9	0.62	0.87
Model 4	8.9	7.4	22.6	0.60	0.79

Table 7. Results of diastolic pressure prediction models.

Model	RMSE	MAE	Max Error	R^2	Correlation
Model 1	5.1	4.0	13.3	0.58	0.81
Model 2	5.0	3.9	10.6	0.52	0.88
Model 3	6.5	5.5	13.4	0.41	0.67
Model 4	5.6	4.2	13.8	0.50	0.76

In the case of prediction of systolic blood pressure, the model trained and tested only on data recorded with a phone (model No. 3) achieved a greater correlation with the measured systolic pressure than the model trained and tested on data from the stethoscope (model No. 2). In the case of diastolic pressure prediction, the situation was reversed. As expected, a model trained and tested on mixed data with a cardinality similar to models 2 and 3 (model No. 4) obtained values between models with data constrained to a single data capture method.

6. Summary

The pressure values predicted by the model correlate with the measured pressure better than the pulse and then each of the features separately. The correlation of the values predicted by the model in the case of systolic pressure was 0.80 and in the case of diastolic pressure 0.82. Meanwhile, the correlation with pulse alone is 0.74 and 0.62 for systolic and diastolic pressure, respectively. The results of the model's work are satisfactory at this stage, but there is room for improvement.

In the case of systolic pressure prediction, a very good agreement of the results (correlation) was obtained using data recorded only with the phone. With the prediction of diastolic pressure, this agreement was lower. However, it can still be considered that recordings made with a phone can be used to analyze the sound of the heart. Also, phone data can be considered the same as stethoscope data. This conclusion was obtained by comparing it with a model created using data from a stethoscope and with a model created using data from both devices. However, the smartphone recordings were more susceptible to noise, resulting in 24 fragments being rejected. In practice, this requires the use of procedures to improve recording quality, such as phone stabilization and acoustic environment control. Future work plans to implement additional noise reduction methods and signal quality assessment mechanisms in the mobile app.

It is important to emphasize that this study included data from a single healthy individual, allowing for control of measurement conditions and preliminary evaluation of the method. The presented results are not final results, further work is being carried out, which should be based on an increased database of recordings, a larger number of examined people in various health conditions and expand the experiment to include clinical groups, including patients with hypertension, to verify the method's effectiveness in medical practice. In addition, the use of other methods of parameterization and determination of features as well as optimization of the features taken into account for the analysis should be considered.

To improve the acquisition of sound signals, further research has begun to develop a mobile application that aims to allow the user to record heart sounds using the smartphone's built-in microphone. The application is developed using the Flutter development environment, which enables the creation of cross-

platform applications for Android and iOS using a single source codebase. The user interface is created using the Material Design 3 component library developed by Google, which enables the use of modern graphic elements, dynamic coloring and responsive layouts that adapt to the technical parameters of the device.

During the recording session, the user will be guided through the process of recording heart sounds using visual and text messages, operated within an interface adapted to typical touch interactions. The recorded signal will be stored locally in the device's memory as an audio file in the selected format, along with basic metadata such as timestamp and recording length. The data will be stored in a local database using the sqflite library, based on the SQLite relational database engine. The project places particular emphasis on issues related to data privacy and security. The app does not require Internet access or the creation of a user account – all data can only be stored locally on the end device. It is also planned to implement mechanisms to secure access to applications.

All the procedures in this study followed the ethical standards of the Declaration of Helsinki. Resolution No. 10/BNBO/2024 of the Bioethics Committee at the Lower Silesian Medical Chamber of November 13, 2024, obtained a positive opinion on the research project "Mobile phone as a tool for recording and analyzing phonocardiographic signal".

Glossary of Acronyms: HSMM – Hierarchical Segmental Hidden Markov Model, DCT – Discrete Cosine Transform, FFT – Fast Fourier Transform, S1 – First heart sound, S2 – Second heart sound, SBP – Systolic Blood Pressure, DBP – Diastolic Blood Pressure, BPM – Beats Per Minute.

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Additional information

The authors declare: no competing financial interests and that all material taken from other sources (including their own published works) is clearly cited and that appropriate permits are obtained.

References

1. F. Bolechowski; Podstawy ogólnej diagnostyki klinicznej (Basics of general clinical diagnostics); Warsaw, PZWL, 1982, 230-231
2. Y. Mohamadou et al.; Design and development of a phonocardiograph for telemedicine applications; Health Technol., 2022, 12, 453–463; DOI: 10.1007/s12553-022-00646-x
3. M. A. A. Hamid, M. Abdullah, N. A. Khan, & Y. M. A. AL-Zoom; Biotechnical System for Recording Phonocardiography; International Journal of Advanced Computer Science and Applications, 2019, 10(8), 493-497
4. L. J. Thoms, G. Colicchia, R. Girwidz; Phonocardiography with a smartphone; Physics Education, 2017, 52(2), 023004; DOI: 1361-6552/aa51ec
5. N. Mamorita, N. Arisaka, R. Isonaka, T. Kawakami, A. Takeuchi; Development of a Smartphone App for Visualizing Heart Sounds and Murmurs; Cardiology, 2017, 137(3), 193-200; DOI: 10.1159/000466683
6. D. Das et al.; Noise detection in smartphone phonocardiogram; 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP); New Orleans, LA, USA, 2017, 6584-6585, DOI: 10.1109/ICASSP.2017.8005305
7. H. Luo, et. al.; Smartphone as an electronic stethoscope: factors influencing heart sound quality; European Heart Journal - Digital Health, 2022, 3(3), 473–480; DOI: 10.1093/ehjdh/ztac044
8. S. Kang, et al.; Cardiac Auscultation Using Smartphones: Pilot Study; JMIR Mhealth Uhealth, 2018, 6(2), e49; DOI: 10.2196/mhealth.8946
9. M. Łuczyński; Preliminary study: mobile phone as a phonocardiographic signal recorder; International Journal of Electronics and Telecommunications, 2024, 70(3), 621-626; DOI: 10.24425/ijet.2024.149588
10. D. B. Springer et al.; Signal quality classification of mobile phone-recorded phonocardiogram signals; 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Florence, Italy, 2014, 1335-1339; DOI: 10.1109/ICASSP.2014.6853814

11. V. Chandrasekaran et al.; Cuffless differential blood pressure estimation using smart phones; IEEE Transactions on Biomedical Engineering, 2012, 60(4), 1080-1089; DOI: 10.1109/TBME.2012.2211078
12. R.-C. Peng et al.; Cuffless and Continuous Blood Pressure Estimation from the Heart Sound Signals; Sensors 2015, 15, 23653-23666; DOI: 10.3390/s150923653
13. R.-C. Peng, W.-R. Yan, X.-L. Zhou; Estimating Blood Pressure with a Smartphone; International Conference on Biomedical and Health Informatics: ICBHI 2015, Haikou, China; Springer Singapore, 2019
14. R. Gonzalez-Landaeta, B. Ramirez, J. Mejia; Estimation of systolic blood pressure by random forest using heart sounds and a ballistocardiogram; Sci. Rep., 2022, 12, 17196; DOI: 10.1038/s41598-022-22205-0
15. X.-F. Cheng, S.-C. Dai, P.-J. Zhao; Blood pressure estimation based on heart sound signals; Acta Physica Sinica, 2020, 69.14; DOI: 10.7498/aps.69.20200254
16. A. Nemcova et al.; Monitoring of heart rate, blood oxygen saturation, and blood pressure using a smartphone; Biomedical Signal Processing and Control, 2020, 59, 101928; DOI: 10.1016/j.bspc.2020.101928
17. Z. Zhao et al.; HearBP: Hear Your Blood Pressure via In-ear Acoustic Sensing Based on Heart Sounds; IEEE INFOCOM 2024 - IEEE Conference on Computer Communications, Vancouver, BC, Canada, 2024, 991-1000; DOI: 10.1109/INFOCOM52122.2024.10621249
18. E. Bondareva, et al.; Heart Sounds for High Blood Pressure Prediction; ICASSP 2025 - 2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Hyderabad, India, 2025; DOI: 10.1109/ICASSP49660.2025.10890434
19. K. Kokkhunthod, et al.; Phonocardiogram signal dataset paired with blood pressure measurements; Data in Brief, 2025, 59, 111433; DOI: 10.1016/j.dib.2025.111433
20. T. Grzywalski, A. Maciaszek, R. Belluzzo, K. Szarzyński, M. Piecuch, H. Hafke-Dys; Joint Heart Sounds Segmentation and Murmur Detection with Masked Loss Function; 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 2020, DOI: 10.1109/IJCNN48605.2020.9207315
21. H. Hafke-Dys, et al.; Artificial intelligence approach to the monitoring of respiratory sounds in asthmatic patients; Frontiers in physiology, 2021, 12, 745635; DOI: 10.3389/fphys.2021.745635
22. N. Damps, M. Kłaczyński; Usefulness of the matching pursuit method in phonocardiographic signal analysis. Vibrations in Physical Systems, 2021, 32(1), 2021102; DOI: 10.21008/j.0860-6897.2021.1.02
23. D. Springer; Logistic Regression-HSMM-based Heart Sound Segmentation (version 1.0); PhysioNet. 2019, RID:SCR_007345; DOI: 10.13026/vnt9-kf93
24. D. B. Springer, L. Tarassenko, G. D. Clifford; Logistic Regression-HSMM-Based Heart Sound Segmentation; IEEE Transactions on Biomedical Engineering, 2016, 63(4), 822-832; DOI: 10.1109/TBME.2015.2475278
25. F. Orhan, M.N. Kurutkan; Predicting total healthcare demand using machine learning: separate and combined analysis of predisposing, enabling, and need factors; BMC Health Serv. Res., 2025, 25, 366; DOI: 10.1186/s12913-025-12502-5
26. J. Klink, M. Łuczyński, S. Brachmański; Video Quality Modelling–Comparison of the Classical and Machine Learning Technique; Appl. Sci., 2024, 14, 7029; DOI: 10.3390/app14167029