# Heart Sounds for High Blood Pressure Prediction

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***Abstract*—Hypertension, a major risk factor for cardiovascular diseases, often goes undetected due to its asymptomatic nature. This study explores a novel approach to detecting elevated blood pressure using heart sounds, aiming to provide a non-invasive, potentially continuous monitoring solution. We evaluated our approach on a new dataset of 260 participants, employing patient-independent cross-validation to ensure generalisability. Our methodology utilises a convolutional neural network-based Hidden Semi-Markov Model for heart sound segmentation, followed by extraction of hand-crafted amplitude, duration, and frequency features. A random forest model was implemented for the binary classification of hypertension, achieving a promising 70% accuracy with 72% sensitivity. We conducted comprehensive analyses, including auscultation location and feature importance evaluation, and the investigation of the heart rate – blood pressure relationship. Our findings demonstrate the feasibility of this approach, providing a robust foundation for further research and development in this domain.**

***Index Terms*—blood pressure, hypertension, heart sounds, machine learning, signal processing.**

## I. Introduction

Cardiovascular diseases pose a significant global health challenge, with hypertension (chronically high blood pressure) being one of the most widespread conditions. A comprehensive study in 2019 revealed an alarming increase in global hypertension prevalence, from 650 million to 1.28 billion over the past 30 years, with 580 million unaware of their condition, likely due to its asymptomatic nature, and 720 million not receiving necessary treatment [1].

Blood pressure (BP), a vital sign crucial for assessing cardiovascular health, measures the force exerted by blood on vessel walls. It is expressed as systolic and diastolic pressure in millimetres of mercury (mmHg). Historically, BP measurements have been confined to clinical settings, relying on devices such as mercury sphygmomanometers, aneroid, and, over the past five decades, digital monitors [2]. However, the landscape of BP measurement is evolving, with digital BP monitors now readily available for home use, enabling more frequent and convenient assessments. Despite this availability, studies show that only about half of diagnosed hypertensive patients engage in home BP monitoring [3], indicating that home BP device usage remains limited.

While the shift towards home BP tracking represents significant progress, there is an obvious need to increase the accessibility and frequency of BP measurements further. Relying solely on clinical or home observations can lead to irregular checks and potentially inaccurate readings due to phenomena such as white coat syndrome [4].

Researchers have explored alternative approaches to BP monitoring using common sensing technologies such as electrocardiography (ECG) and photoplethysmography (PPG). Various methods have been developed, ranging from deep learning architectures [5,6] to traditional machine learning [7,8] and multimodal fusion techniques [9-12]. Most of these approaches incorporate heart rate or heart rate variability as key features, despite known heart rate and blood pressure correlations [13,14], potentially confounding their results.

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Among potential sensing modalities for BP monitoring, audio signals remain underexplored, despite being both ubiquitous and non-intrusive. By leveraging heart sound analysis, we aim to develop a method that could potentially offer continuous, non-invasive BP estimation. This approach could complement existing methods, enhancing the portability and accessibility of BP monitoring to potentially enable earlier detection and improve hypertension care.

BP is known to influence heart sounds, as elevated BP can lead to changes in cardiac structure and function. These alterations may manifest as increased intensity of heart sounds, particularly the second heart sound (S2), which can become more pronounced or split due to heightened pressure in the circulatory system [15].

The estimation of arterial BP from heart sounds has evolved from early Fourier coefficient analyses to sophisticated machine learning approaches. Early studies explored the relationship between BP and heart sounds [15], while theoretical models provided insights into valve vibration at different pressures [16]. These works demonstrated that heart sounds indeed contain information about BP, opening the possibility for more advanced techniques.

Recognising the potential of heart sounds as a non-invasive BP indicator, researchers have begun to leverage machine learning to extract and interpret this information. Castro et al. [17] employed features from the S2 for BP prediction in paediatric patients, achieving a promising mean absolute error of 6.08 mmHg, although the narrow BP range captured in the dataset could limit the generalisability of the approach. Peng et al. [18] applied support vector machines to data from 32 young, healthy adults undergoing cold-pressor tests, reporting mean errors below 5 mmHg. However, their approach lacked patient independence in data splitting, with data from the same patient explicitly appearing in both train and test sets. Kapur et al. [19] used neural networks on data from critically ill children, demonstrating correlation with intra-arterial measurements. Their method involved discarding predictions that disagreed with cuff measurements, which they termed "regularisation". This approach, whilst potentially improving apparent accuracy, may affect independent model performance. More recently, Landaeta et al. [20] used not just heart sounds but also ballistocardiogram data from 21 healthy adults in their early 20s for BP prediction using random forests, achieving a mean error of 3.3 mmHg for systolic BP. Also, they induced elevated BP in participants by asking them to perform physical activity for two minutes, but they did not analyse potential heart rate confounding.

Whilst these studies have made significant contributions, opportunities remain for expanding data diversity to populations that would benefit the most from BP monitoring, ensuring patient-independent validation, and investigating the relationship between BP and heart rate. Therefore, the contributions of this paper are as follows:

- We present a novel heart sound dataset which contains blood pressure (BP) measurements;
- We propose segmentation-based hand-crafted features with a random forest to predict high BP using heart sounds in previously unseen patients, achieving 70% accuracy and 72% sensitivity on our high BP detection binary task;

- We conduct a comprehensive feature importance analysis and evaluate prediction accuracy at various auscultation locations;
- We identify the apex as the best auscultation site for audio-based high BP detection, potentially simplifying future screening;
- We study the relationship between BP and heart rate in our dataset, with our analysis corroborating the model's specificity to BP, distinguishing our work from previous studies that may not have accounted for the influence of heart rate on BP.

## II. Methodology

### A. Dataset description

Given that most existing heart sound datasets focus on murmur detection, a new dataset was collected for this work to explore the relationship between heart sounds and blood pressure.

The data were collected at the Digital Biomarkers Laboratory in Leszek Giec Upper-Silesian Medical Centre of the Medical University of Silesia in Katowice. The heart sounds were recorded using an EKO stethoscope, following standard cardiac auscultation practice by collecting sounds from four distinct locations on the chest, corresponding to four heart valves: right upper sternal border in the second intercostal space (aortic valve, RUSB), left upper sternal border in the second intercostal space (pulmonary valve, LUSB), left sternal border in the fourth intercostal space (tricuspid valve, LLSB), and left midclavicular line in the fifth intercostal space (mitral valve, APEX). These recordings were then exported to WAV format with a 4000 Hz sampling rate. BP was collected using a Philips IntelliVue MX450 patient monitor with a built-in BP monitor with a cuff.

The data collection effort was approved by the Bioethics Committee of the Medical University of Silesia and reviewed by the University of Cambridge School of Computer Science and Technology Ethics Committee to approve the secondary use of data.

This dataset comprises heart sounds from 264 participants (169 male, 95 female; age 67.8 $\pm$ 13.2 years, range 20–95 years), of whom 226 have a heart murmur. From these 264 participants, 260 with recorded BP were divided into classes based on their systolic blood pressure (sBP): 64 participants with sBP equal to or below 120 mmHg formed the normotensive class, 61 with sBP equal to or above 140 mmHg were classified as high BP, and 135 with sBP between 120 and 140 mmHg formed the pre-hypertensive class. These values were chosen based on guidelines for healthy and hypertensive BP ranges from The European Society of Cardiology and European Society of Hypertension [21].

### B. Preprocessing

Our approach to BP detection from heart sounds utilises a segmentation-based method. We opted for the convolutional neural network (CNN)-based Hidden Semi-Markov Model (HSMM) approach developed by Renna, Oliveira, and Coimbra [22]. This method uses a 1-dimensional CNN, applied to four different envelograms extracted from the audio signal, then combined with an HSMM to enforce a natural sequence of heart sounds to split them into the main components (S1, systole, S2, diastole). Following segmentation, we extracted three classes of features, guided by the following intuition:

- **Amplitude-based features** capture the strength and relative intensity of different parts of the heart cycle, including peak amplitudes of S1 and S2 and their ratio. We expect to see an effect on the amplitude of S2 in patients due to increased pressure in the arteries.
- **Duration-based features** measure the timing of different parts of the cardiac cycle, including durations of S1, S2, systole, diastole, and various ratios between these components. We believe that increased blood pressure might lead to longer systole as the heart works harder to pump blood against higher resistance.
- **Frequency-based features** analyse the frequency characteristics of heart sounds, including mean and standard deviation of frequencies for S1 and S2. We hypothesise that increased tension in the aortic valve caused by high blood pressure might lead to higher frequency components in S2.

For each audio recording, we computed these parameters over the entire duration. We then calculated ten statistical measures for each parameter over the entire recording duration: mean, standard deviation, median, interquartile range, minimum, maximum, skewness, kurtosis, range (peak-to-peak amplitude), and coefficient of variation. This resulted in a one-dimensional feature vector with 130 elements for each recording.

### C. Experimental design

Detecting high blood pressure from heart sounds of previously unseen patients is a novel task in signal processing and machine learning. Therefore, we aimed to assess the feasibility of this idea by conducting the following experiments:

- **Exp 1: High blood pressure detection**
  We used normotensive patients and those with high BP for a binary classification task. We extracted heart sound segmentation-based hand-crafted features and evaluated the performance of traditional machine learning methods. We also analysed the effect of heart sound auscultatory location on the performance of the highest-scoring method.
- **Exp 2: Feature importance analysis**
  We identified the most influential features for high BP prediction.
- **Exp 3: Heart rate correlation study**
  We examined the correlation between heart rate and BP to ensure our model detected elevated BP rather than varying heart rates.

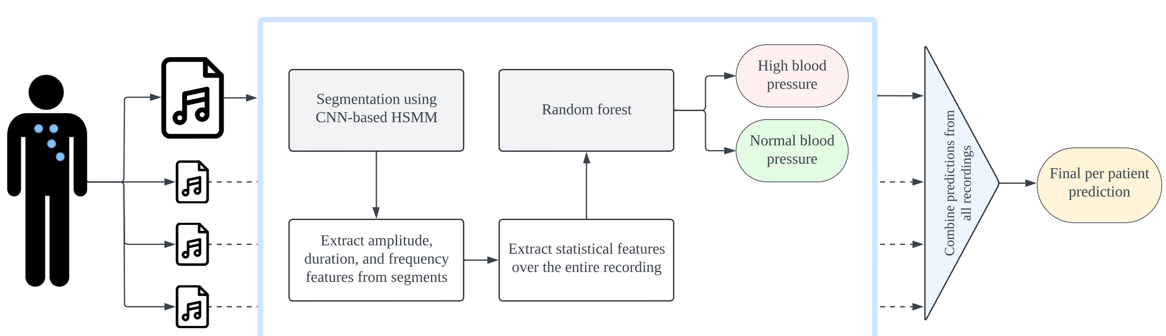


Fig. 1. Summary of the methodology used in this study for high systolic blood pressure prediction.

TABLE I
HIGH sBP DETECTION PER INDIVIDUAL RECORDING AND PREDICTIONS AGGREGATED PER PATIENT (MEAN ± STANDARD DEVIATION).

| Metric | Per recording | Per patient |
|---|---|---|
| Accuracy | 0.629 ± 0.069 | 0.701 ± 0.079 |
| Sensitivity | 0.565 ± 0.010 | 0.723 ± 0.102 |
| Specificity | 0.701 ± 0.117 | 0.696 ± 0.226 |

- **Exp 4: Borderline cases analysis**
  We assessed our algorithm's performance on pre-hypertensive class, who were not included in the normal or high BP classes.

The methodology summary is presented in Figure 1. All experiments were performed on a patient-independent train/test split, meaning that all data belonging to one patient appears exclusively in the training or testing sets but not in both. We used five-fold cross-validation, so most of the results are presented as mean and standard deviation across the five folds. Finally, accuracy, sensitivity, and specificity were used for evaluation.

## III. RESULTS AND DISCUSSION

### A. Exp 1: High blood pressure detection

We employed a segmentation-based approach using hand-crafted features based on evidence from existing research indicating that high blood pressure (BP) alters the second heart sound. Using these extracted features, we trained several traditional machine learning models: support vector machines with radial basis function (RBF) and linear kernels, a decision tree, a random forest, k-nearest-neighbours (k-NN), multilayer perceptron, and logistic regression.

For each patient, multiple predictions were obtained — one for each audio sample corresponding to the four chest locations from which sounds were collected. These predictions were then averaged to get the final prediction per patient.

The random forest model performed best in high systolic BP (sBP) detection. It was implemented using scikit-learn (v1.3.0), utilising 40 trees (n_estimators=40) and a fixed random state (random_state=3) for reproducibility. All other hyperparameters were kept at their default values. Table I presents the results before and after prediction aggregation per patient.

To assess the predictive capability of each auscultation location, we analysed the model's performance separately for each site, using predictions obtained from the five-fold cross-validation. It is worth noting that the model was trained on data from all locations, as training on individual locations would have reduced the size of the already limited dataset by 75%. The results of this location-specific analysis are presented in Table II.

Generally, we observed that aggregating the results from all four locations yielded the highest accuracy and specificity, as seen in Table I. However, for the individual locations, the apex (corresponding to the mitral valve area) yielded the highest accuracy and sensitivity. This may be attributed to the fact that the mitral valve is directly affected by left ventricular pressure changes, which is closely related to sBP. Moreover, sBP is associated with left ventricular mass and global radial strain [23], which might cause audible changes.

Notably, the sensitivity of high sBP prediction from the apex alone surpassed that of aggregating predictions from all four locations. This finding suggests that for potential audio-based BP screening tools, the apex may be the optimal, and perhaps sufficient, auscultation site.

TABLE II
HIGH SYSTOLIC BLOOD PRESSURE DETECTION PERFORMANCE ON EACH DISTINCT AUSCULTATION LOCATION.

| Location | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| APEX | 0.661 | 0.724 | 0.600 |
| LLSB | 0.642 | 0.603 | 0.677 |
| LUSB | 0.626 | 0.500 | 0.746 |
| RUSB | 0.587 | 0.414 | 0.746 |

TABLE III
ABLATION STUDY RESULTS FOR DIFFERENT FEATURE GROUPS.

| Feature Set | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| Amplitude | 0.581 ± 0.101 | 0.643 ± 0.182 | 0.539 ± 0.110 |
| Duration | 0.548 ± 0.072 | 0.526 ± 0.143 | 0.584 ± 0.112 |
| Frequency | 0.491 ± 0.091 | 0.541 ± 0.192 | 0.456 ± 0.071 |
| Amp + Dur | 0.573 ± 0.112 | 0.622 ± 0.112 | 0.546 ± 0.243 |
| Amp + Freq | 0.589 ± 0.089 | 0.613 ± 0.197 | 0.582 ± 0.097 |
| Dur + Freq | 0.540 ± 0.060 | 0.523 ± 0.095 | 0.575 ± 0.210 |

### B. Exp 2: Feature importance analysis

Given the novelty of sound-based high BP detection, understanding the factors influencing the model's classification decision is crucial. Therefore, we conducted two feature importance analyses: a per-feature-group ablation study and a mean decrease in impurity analysis for individual feature importance evaluation.

Table III presents the results of the per-feature-group ablation study. Among individual feature groups, amplitude features independently achieved the best accuracy and sensitivity of 58% and 64%, respectively. For unique pairs of feature groups, amplitude and frequency features achieved the best accuracy of 59%, while amplitude and duration yielded the best sensitivity of 62%.

We also identified the most critical individual features using the mean decrease in impurity method, a feature importance measure intrinsic to the random forest.The results of this analysis are presented in Table IV, with the most significant individual features being mean and median systolic duration, and median S1 amplitude peak.

The ablation study showed that amplitude features alone yield the highest performance among individual feature groups. However, the mean decrease in impurity analysis revealed that duration features, particularly systole and diastole duration statistics, are among the most important individual features. This apparent discrepancy highlights the complex interplay between feature groups. Interestingly, while the combination of amplitude and frequency features achieved the best accuracy in the ablation study, frequency-based features did not appear in the top 10 most important features according to the mean decrease in impurity method. These results suggest that the model's performance relies on the collective contribution of many features rather than any single feature or feature group.

TABLE IV
TEN MOST IMPORTANT FEATURES FOR HIGH BP PREDICTION ACCORDING TO THE MEAN DECREASE IN IMPURITY METHOD.

| Feature description | Importance |
|---|---|
| **Mean systolic duration** | **0.0378** |
| **Median systolic duration** | **0.0302** |
| **Median S1 amplitude peak** | **0.0204** |
| Mean S1 amplitude peak | 0.0167 |
| Skewness of S2 amplitude peaks | 0.0159 |
| Mean diastolic duration | 0.0153 |
| Skewness of systolic durations | 0.0148 |
| Skewness of diastolic durations | 0.0145 |
| Median ratio of systole to diastole | 0.0140 |
| Median S2 amplitude peak | 0.0140 |

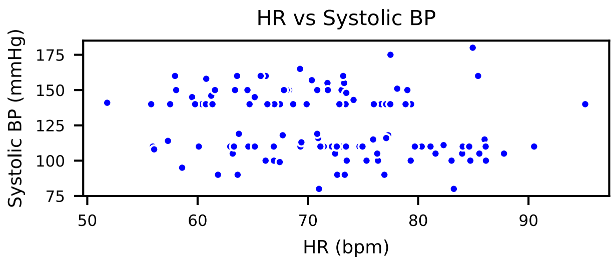


Fig. 2. Correlation of average heart rate and systolic blood pressure, where each point represents a patient.

### C. Exp 3: Heart rate correlation study

Heart rate (HR) and BP are known to have a complex and context-dependent correlation. HR and BP can be chronically elevated in a stressed (i.e., unhealthy) cardiovascular system. However, when observing the same individual, especially if they are healthy, an elevated HR (for example, during physical activity) can be associated with decreased BP [24]. This important dynamic highlights a challenge in adaptive BP prediction models that rely on historical data, as these models may incorrectly interpret changes in HR as changes in BP, potentially leading to false predictions.

Given the importance of understanding this relationship, we conducted a correlation analysis between heart rate and BP. Our dataset did not include HR ground truth, so we extracted the average HR by finding the midpoint of each S1 segment and using consecutive midpoints to calculate the instantaneous HR. The instantaneous heart rates from the entire recording were then averaged to obtain the average HR. Finally, we averaged heart rates from the four recordings belonging to each patient to pair with the BP measurement.

The correlation between the systolic and diastolic BP and HR for the patients included in this study can be seen in Figure 2. We conducted a Pearson correlation analysis, which revealed a weak negative correlation ($r = -0.163$) between HR and sBP, with a p-value of 0.07. This p-value, above the conventional significance threshold of 0.05, suggests that while there is a trend, it is not statistically significant. Therefore, this finding confirms the validity of our model in detecting BP rather than merely identifying HR variations.

### D. Exp 4: Borderline cases analysis

Our final experiment addressed a critical question regarding our binary classification approach: how does the model perform for patients with systolic blood pressure (sBP) between 120 and 140 mmHg, a range considered borderline or pre-hypertensive?

To investigate this, we used the previously created five folds for the cross-validation. While one of the folds was withheld as the testing set and the remaining four were used for training, we also obtained predictions for the mid-range patients. As a result, the audio recordings belonging to the mid-range patients each received five predictions. These predictions were first averaged for each recording, and then a final prediction per patient was obtained by averaging across the four recordings for each patient.

Figure 3 demonstrates the results of this experiment. Among participants with normal BP, 20 out of 64 were incorrectly labelled as hypertensive, and 17 out of 61 participants with high sBP were incorrectly labelled as normotensive. In the mid-range group, 42% were labelled as having normal BP, with the remaining participants labelled as hypertensive.

It can be seen in Figure 3 that patients with lower systolic and diastolic BPs were more likely to be labelled as normotensive compared to those with higher BP in this pre-hypertensive range. This shift in classification as BP increases could imply that the model captured meaningful patterns related to blood pressure changes, even within this borderline range.

## IV. Conclusions and Future Work

In this work, we explored and demonstrated the feasibility of detecting elevated blood pressure using a novel dataset of heart sound recordings. We propose an approach which relies on CNN-based HSMM segmentation for hand-crafted feature extraction, which are used by a random forest model to predict high blood pressure. On this binary task, the proposed method achieved promising results, yielding 70% accuracy and 72% sensitivity. We also demonstrated the absence of a statistically significant correlation between heart rate and blood pressure in our dataset.

Future work should explore regression models, which could provide more granular blood pressure estimates, which would be particularly beneficial for borderline cases in the pre-hypertensive range. Additionally, combining heart sounds with complementary modalities, such as ECG or PPG, could enhance high blood pressure detection by leveraging their unique advantages. Furthermore, expanding the dataset will enable balanced gender representation, strengthening the robustness of heart sound-based blood pressure detection.

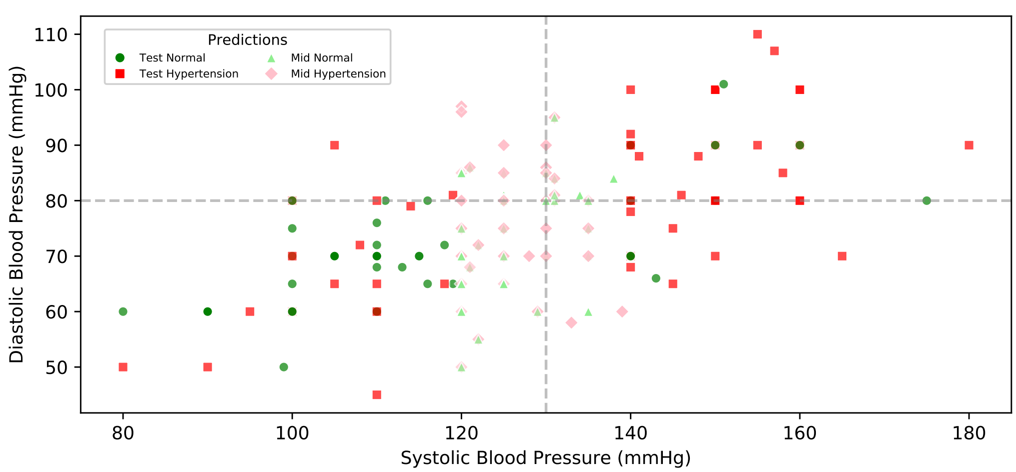


Fig. 3. High systolic blood pressure predictions on pre-hypertensive patients.

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