Master's Thesis

Medical Informatics Master

Universität Heidelberg / Hochschule Heilbronn

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Predicting Blood Pressure from Photoplethysmogram Waveform Data: A Signal Processing and Machine Learning Approach

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Affidavit

I hereby declare under oath that I have independently prepared the present work without using sources other than those indicated; any thoughts taken directly or indirectly from external sources (including electronic sources) are identified as such.

The work has not been submitted to any examination authority, either domestic or foreign, in the same or similar form, and has not been published.

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1 Abstract

2 Introduction

2.1 Subject and Motivation

Cardiovascular diseases (CVDs) are the leading cause of death worldwide, according to WHO publishing statistics [47]. One of the main factors contributing to CVDs is Hypertension. It is the leading risk factor for mortality, and is ranked third as a cause of disability-adjusted life-years [21]. Currently, there is a significant need for continuous blood pressure (BP) monitoring due to various factors. Primarily, while hypertension is a manageable condition, the availability of accurate high BP detection remains scarce, especially in low-resource environments [9]. Additionally, blood pressure (BP) is subject to rapid fluctuations influenced by various factors, including stress, emotions, dietary intake, physical activity, and medication usage [50]. Continuous monitoring of blood pressure, rather than relying on isolated measurements, plays a vital role in the early detection and treatment of hypertension [18].

The current accurate methods for measuring BP continuously are either invasive or involving a cuff-mechanism. Catheterization is internationally recognized as the "gold standard" for obtaining the most accurate measurement of continuous blood pressure [56]. However, due to its invasive nature and limited applicability to hospital settings, this method requires medical intervention, which renders it inconvenient for everyday use.

While cuff-based devices are commonly utilized for this objective, it is worth noting that around 30% of home blood pressure monitors are found to be inaccurate, rendering continuous measurement unfeasible [35, 55]. Moreover, this approach relies on the individual consciously and intentionally engaging in manual blood pressure monitoring, which poses limitations and might be often overlooked.

An ideal technology for measuring blood pressure should have the following attributes: non-invasiveness, cuffless operation, optical functionality, wearable design, and cost-effectiveness [18]. One approach satisfying these requirements is the estimation of BP from a single measurement PPG sensor. This approach, using two modes, reflectance and transmission, has gained an increasing amount of attention in the literature due its simplicity, and ability to provide continuous and cuffless measurement [18]. Typically, the photoplethysmography (PPG) technique has been traditionally employed in healthcare settings to measure heart rate [51] and blood oxygen saturation using a pulse oximeter [67].

Nevertheless, establishing a straightforward, distinct, and continuous relationship between these characteristics and blood pressure (BP) has proven to be challenging. To address this, the approach heavily depends on signal pre-processing techniques, extracting PPG features, and utilizing machine learning algorithms to estimate BP based on these features [18]. A recent scoping review by Knight et al. concluded that PPG can be successfully used to continuously measure BP, by evaluating latest publications and finding over 80% accuracy in detecting hypertension [30].

This study examines the current methods and aims to develop efficient approaches for the continuous and accurate measurement of blood pressure using PPG and addresses the following research questions:

1. **What is the relationship between PPG data and blood pressure among ICU patients?**
2. **Can PPG-based data be used to estimate blood pressure accurately?**

2.2 Tasks and Objectives

The tasks of the thesis are as follows:

1. Signal Processing: to find an optimal data fetching and filtering approach from available MIMIC Databases.
2. Likewise, to create a consistent algorithm for key feature extraction.
3. Machine Learning: to develop a model based on the resulting features from Signal Processing, to reliably predict BP from PPG.

2.3 Structure of the Thesis

This thesis is organized as follows:

In Chapter 3, the foundations of the used terms and prerequisites for the methods are explained. For example, in 3.1, the terms "Blood Pressure" (3.1.1) and "Photoplethysmography" (3.1.2) are discussed. Furthermore, the general structure of MIMIC databases is explained (3.1.3). In addition, the essential information about the Computing part of this research is provided (3.2).

In Chapter 4, the methodology is explained.

Chapter 5 presents the results.

The focus of Chapters 6 and 7 is on summarizing the work. Here, both the future prospects for this research field and the next steps in relation to broader scope projects are presented.

3 Theoretical Background

3.1 Medical Background

3.1.1 Blood Pressure

Blood pressure (BP) is a physiological measure of the force exerted by circulating blood against the walls of the arteries [3]. It is highly dependent on blood flow, which refers to the movement of blood through a vessel, tissue, or organ. Blood circulation begins with the contraction of the heart's ventricles. This action generates a type of hydrostatic pressure, which is the force exerted by a fluid due to gravitational pull, typically against the walls of the container that confines it.

BP is a type of hydrostatic pressure, representing the force exerted by blood on the walls of blood vessels or the heart's chambers. While it can be assessed in various body regions, the term "blood pressure" without specific qualifiers commonly refers to systemic arterial BP. This denotes the pressure of blood within the arteries of the systemic circulation. In clinical settings, this pressure is measured in millimeters of mercury (mmHg) and is typically acquired using the brachial artery in the arm [7].

Measuring BP is crucial for assessing cardiovascular health and identifying potential risks. It allows for the early detection of conditions like hypertension and hypotension, enabling timely interventions to prevent serious cardiovascular events [46]. BP serves as a key indicator of the risk for heart attacks, strokes, and heart failure, guiding preventive measures and treatment strategies [20].

Various Types of Measurement

One of the most common BP measurement methods is one using a sphygmomanometer (see manual 1 and automatic 2 devices), also known as non-invasive blood pressure (NIBP), is typically recorded as numeric values at specific time intervals. The process involves inflating the cuff to temporarily stop blood flow and then gradually releasing the pressure to detect the sounds associated with the flow of blood through the brachial artery. Manually, the measurement entails one individual conducting the procedure on another, typically involving a healthcare professional administering the assessment to a patient. Conversely, automatic measurement allows the patient to independently measure their blood pressure without external assistance. Both approaches yield comparable measurements of the same nature. The two primary values obtained are systolic pressure (maximum pressure during heartbeats) and diastolic pressure (minimum pressure between heartbeats). During the process of cuff inflation and deflation, each heartbeat generates characteristic sounds (Korotkoff sounds) that are detected by a stethoscope placed over the brachial artery. Systolic pressure is recorded when the first tapping sounds are heard, and diastolic pressure is recorded when the sounds disappear or change character. This beat-to-beat approach provides information about individual fluctuations in blood pressure [7].

Figure 1: Standard Sphygmanometer [2]

Figure 2: Automatic Digital Sphygmanometer [1]

Although measuring blood pressure with a cuff using a sphygmomanometer is widely adopted as a common and convenient method, it is not without its constraints. Studies, such as those by Leung et al. and Sebo et al. , have highlighted the inability of home blood pressure monitoring devices to consistently and accurately detect hypertension [35, 55]. Furthermore, a significant limitation lies in its inability to provide continuous and consistent monitoring, necessitating patients to actively remember and engage in the effort to measure their blood pressure. This intermittent approach using a cuff provides valuable insights into systolic and diastolic pressures at specific time intervals, but it may not capture the nuanced changes that occur between measurements. To address the need for continuous monitoring, other methods, such as arterial catheterization, are employed.

Arterial catheterization (illustrated in Figure 3) is commonly employed in critical patient care, serving dual purposes: continuous blood pressure monitoring and obtaining frequent blood gas measurements. Typically conducted at bedside, the procedure utilizes percutaneous methods like the Seldinger technique to cannulate arteries [14]. The resulting arterial blood pressure (ABP) is a dynamic parameter that can change with each heartbeat, and it is typically represented as a waveform rather than a single numeric value. The ABP waveform consists of two main components: systolic pressure and diastolic pressure. Such continuous monitoring of ABP is usually done in clinical settings, using an arterial line connected to a pressure transducer. The resulting waveform is displayed on a monitor in real-time. However, for ease of interpretation and documentation, numeric values are commonly extracted from the waveform at specific time intervals [24].

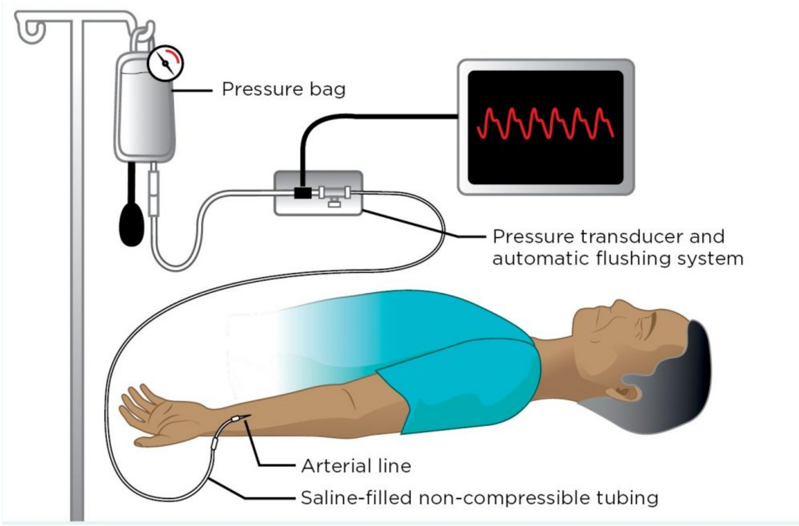

Figure 3: Arterial Catheterization and Stationary BP Monitoring [15]

In situations where high temporal resolution is crucial, ABP can be recorded beat-to-beat, providing a value for each heartbeat. This is particularly important in situations where rapid changes in blood pressure need to be closely monitored, such as during certain medical procedures or in critically ill patients [34].

For routine monitoring and documentation, numeric values are often averaged over a specific time interval, such as every 1, 5, or 15 minutes. This averaged value may be reported as the mean arterial pressure (MAP), which is a weighted average of the systolic and diastolic pressures over a cardiac cycle [16] Some monitoring systems may also provide systolic and diastolic blood pressure readings at regular intervals.

Alternative approaches for measuring BP have emerged over the past years. Volume clamping [29] and tonometry [25] are some of the other methods. These non-invasive techniques offer continuous monitoring of blood pressure values. Volume clamping, which involves the use of a small finger cuff and a PPG sensor, is one method for continuous blood pressure measurement. Tonometry, on the other hand, is a cuffless approach that utilizes a manometer-tipped probe pressed directly on an artery. The volume clamping approach allows for instantaneous and prolonged blood pressure measurement. However, it is associated with high costs and still necessitates the use of a cuff, which can be inconvenient and uncomfortable. Conversely, the tonometry method is sensitive to movement of the arm and probe, making it challenging to maintain accuracy in practical applications. Additionally, constant calibration with a cuff blood pressure device is required [48].

In conclusion, blood pressure serves as a critical physiological measure, representing the force exerted by blood on the walls of blood vessels. The conventional method of measuring blood pressure with a cuff and sphygmomanometer provides valuable insights into systolic and diastolic pressures but is limited by its intermittent nature. To address the need for continuous monitoring, arterial catheterization is commonly employed in critical care, offering real-time data through a dynamic waveform. Alternative non-invasive approaches like volume clamping and tonometry aim to provide continuous blood pressure monitoring, but they come with their own challenges and considerations. As technology advances, these methods contribute to a comprehensive understanding of blood pressure dynamics, facilitating improved patient care and risk assessment.

3.1.2 Photoplethysmography

Photoplethysmography (PPG) is an optical measurement technique designed to identify changes in blood volume within the microvascular bed of tissue [11]. Its clinical application is extensive, as the technology is integrated into commercially available medical devices, including pulse oximeters, vascular diagnostics, and digital beat-to-beat blood pressure measurement systems. The fundamental structure of PPG technology is straightforward, requiring only a few opto-electronic components: a light source for tissue illumination, usually a light-emitting diode (LED) and a photodiode (PD) to gauge slight variations in light intensity correlated with changes in perfusion in the catchment volume.

History

One of the first mentioned instances on the use of PPG were recorded in 1936 by Molitor and Kniazuk [41]. They outlined comparable devices employed for tracking alterations in blood volume in the rabbit ear under conditions of venous occlusion and the administration of vasoactive drugs. A pioneer who helped establish the PPG technique was Alrick Hertzman [23]. In his 1937 paper, Hertzman coined the term "Photoelectric Plethysmograph" etymologically meaning: photo - "light", plethora - "exess of body fluid, blood", graph - "something written". He detailed the application of a reflection mode system to assess alterations in blood volume within the fingers, particularly during the Valsalva maneuver [57], exercise, and exposure to cold. This contribution not only demonstrated the versatility of the technique but also underscored its potential clinical relevance.

Hertzman and Spealman [23] outlined two crucial features of the PPG pulse waveform. They categorized the pulse appearance into two phases: the anacrotic phase representing the ascending edge of the pulse, and the catacrotic phase representing the descending edge of the pulse. The initial phase primarily corresponds to systole, while the subsequent phase relates to diastole and wave reflections from the periphery. In individuals with healthy compliant arteries, a dicrotic notch is commonly observed during the catacrotic phase.

In the late 1970s, there arose a renewed interest in the PPG technology, driven by the demand for compact, dependable, cost-effective, and user-friendly noninvasive cardiovascular assessment techniques [68]. The progress in opto-electronics and clinical instrumentation has played a significant role in advancing PPG technology. Semiconductor advancements, particularly in LEDs, photodiodes, and phototransistors, have brought about substantial improvements in the size, sensitivity, reliability, and reproducibility of PPG probe design. A significant leap in the clinical application of PPG-based technology occurred with the introduction of the pulse oximeter [6]. This device revolutionized non-invasive monitoring of patients' arterial oxygen saturation, marking a major advancement in the field.

Other emerging technologies encompass PPG imaging technology, telemedicine, and remote monitoring. In 2005, Wieringa et al. detailed a contactless multiple-wavelength

PPG imaging system designed primarily for remotely imaging the distribution of arterial oxygen saturation (SpO2) within tissue [65]. The system captures movies of two-dimensional matrix spatially resolved PPG signals at different wavelengths during respiratory changes. PPG was found to have substantial potential in telemedicine, particularly for remote/home health monitoring of patients. Miniaturization, user-friendliness, and robustness stand as pivotal design criteria for such systems. This is exemplified by finger ring-based PPG sensors for monitoring beat-to-beat pulsations ([52], [70]).

Most PPG devices these days either use the transmissive or reflective operating modes (illustrated in Figure 4). Currently, the prevalent method is the transmissive mode, chosen for its notable accuracy and stability [33]. However, there is a growing interest in reflective-mode PPG due to its elimination of the need for a thin measurement site. This method proves versatile, applicable to various sites such as the feet, forehead, chest, and wrists. Especially when the wrist serves as the designated measurement site, PPG sensors can be conveniently employed in the form of a band or watch.

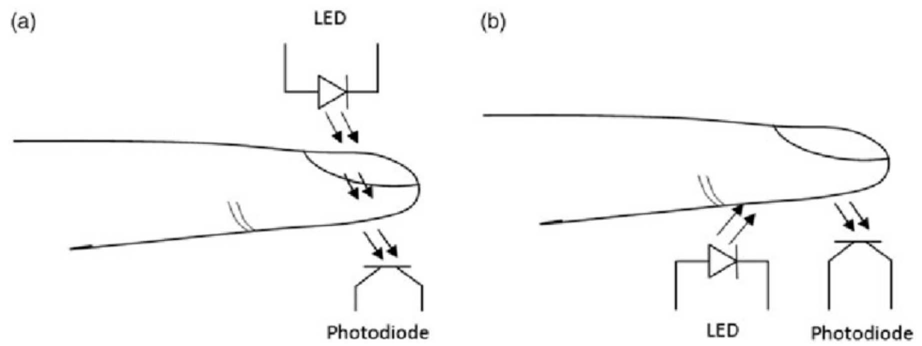

Figure 4: PPG Transmission (a) and Reflection (b) operating modes [40]

Working Principle

The PPG signal consists of pulsate (AC) and superimposed (DC) components (see Figure 5). The AC component originates from variations in blood volume associated with heartbeats, while the DC component is influenced by factors such as respiration, sympathetic nervous system activity, and temperature regulation [4]. The AC component specifically illustrates changes in blood volume during phasic cardiac activity, representing both the systolic and diastolic phases. The systolic phase, also known as the "rise time" initiates with a valley and concludes at the pulse wave systolic peak. The pulse wave concludes with another valley at the end of the diastolic phase [64]. In most PPG waveform analyses including this one, the AC component in the form of a waveform signal is used.

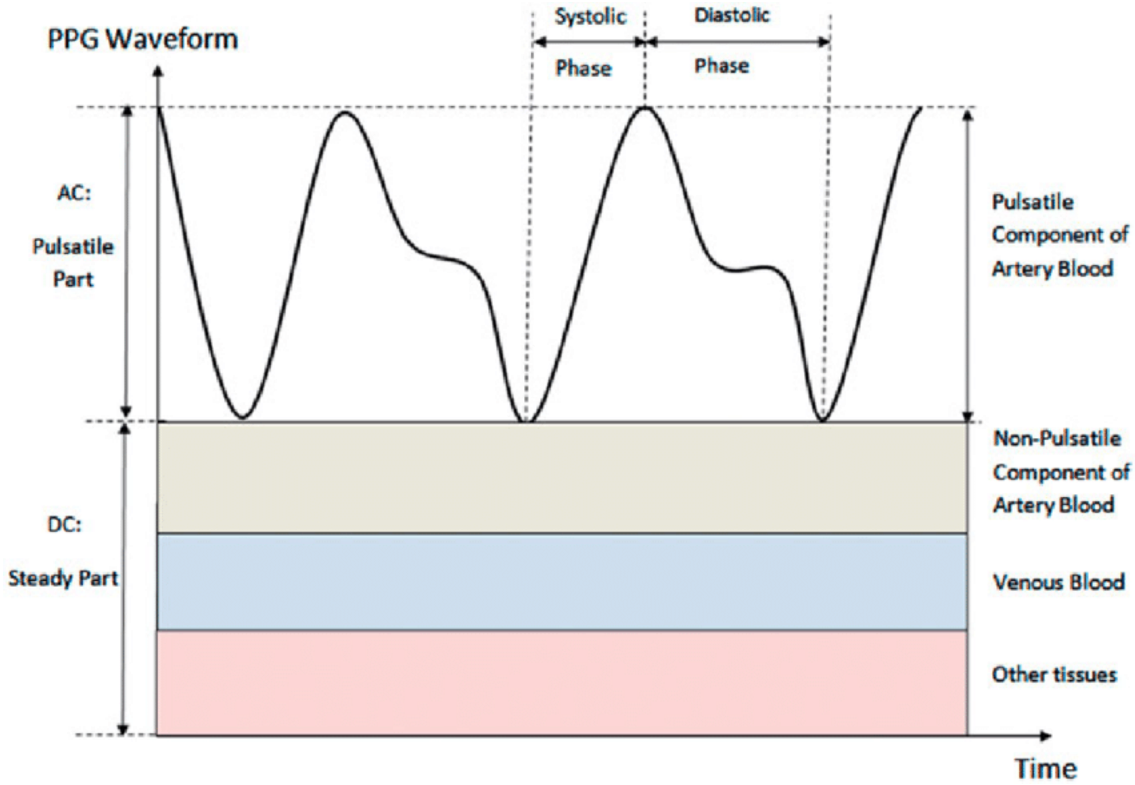

Figure 5: AC and DC components of the PPG signal [40]

Use Cases

PPG finds diverse applications in clinical settings, covering physiological monitoring (such as blood oxygen saturation and heart rate), vascular assessment (including arterial disease, aging and tissue viability), and autonomic function evaluations (such as thermoregulation, heart rate and other assessments of cardiovascular variability) [4]. Furthermore, the popularity of PPG technology as an alternative for monitoring heart rate has risen recently, primarily attributed to its ease of use, user-friendly wearing comfort, and cost-effectiveness [60]. Nowadays, almost every wearable devices uses the PPG technology to track the user's heart rate and other extractable vital parameters [10]. PPG sensors in mobile and wearable devices typically feature red, green, or both light-emitting diodes. Most devices incorporate a green-light PPG sensor for continuous heart rate monitoring during daily activities. Some devices also include red-light PPG sensors, which are effective for measuring heart rate when a person is stationary, providing insights into hydration, muscle saturation, and total hemoglobin. While red-light PPG can penetrate tissue layers more deeply using near-infrared spectroscopy, it is susceptible to disturbance from ambient light. In contrast, green light, being less absorbed by the skin, minimizes the impact of ambient light noise on the heart rate signal. As a result, wearable devices commonly utilize green light rather than red-light PPG [49]. Different types of devices implement the PPG technology. It can be found in pulse oximeters, smartphones, smartwatches and other wearable devices (examples in Figure 6).

Figure 6: AC and DC components of the PPG signal [69]

In conclusion, the PPG is an optical sensor, consisting of an LED paired with a PD, hence it is simple, inexpensive and can be easily build into a wearable device. The PPG waveform can be obtained using two modes, reflectance and transmission. This waveform corresponds to the blood volume in blood vessels. Traditionally employed in healthcare for heart rate and blood oxygen saturation measurements, particularly with pulse oximeters, the PPG plays a pivotal role [4].

Additionally, peripheral volumetric changes exhibit correlation with BP [32]. Utilizing characteristic PPG features, machine learning functions can estimate Systolic BP (SBP) and Diastolic BP (DBP). However, establishing a simple, clear, and continuous relationship between these features and BP remains elusive. This method heavily relies on signal pre-processing, feature extraction, and the application of machine learning algorithms for BP estimation based on these features.

3.1.3 MIMIC Databases

Patient records and documentation are crucial for maintaining a comprehensive overview of medical history, aiding in accurate diagnosis, treatment planning, and ensuring continuity of care. They also serve as legal documents, providing evidence of the care provided and facilitating communication among healthcare professionals. Collecting digital data during routine clinical practice has become widespread across hospitals. Over time, a pattern has emerged in the collection and storage of patient data for subsequent utilization in future research endeavors.

Origin

In 1996, two researchers at the Massachusetts Institute of Technology, George B. Moody and Roger G. Mark, introduced the MIMIC (Multiparameter Intelligent Monitoring in Intensive Care) Database. The database was derived from patient monitors in the medical, surgical, and cardiac intensive care units of Boston's Beth Israel Hospital [44]. The first instance of the database included 100 patient records, each typically containing between 24 and 48 hours of continuous recorded data. The second version of the database (MIMIC-II) was introduced in 2011 boasting a notably larger sample size and a wider scope of information sourced entirely from diverse digital information systems [54]. MIMIC-III [27] was finalized in 2016, marking a significant expansion from MIMIC-II, with data available from over 40,000 patients. The fourth and latest MIMIC Database was publicly released in 2023 spanning a decade of admissions from 2008 to 2019. MIMIC-IV was announced to enhance the realm of publicly accessible critical care datasets, by integrating precise digital sources like the electronic medicine administration record and featuring a modular structure enabling seamless integration with external departments and diverse data modalities [26].

Structure

Both the MIMIC-III and MIMIC-IV Databases are cited and employed in this investigation, exhibiting comparable structures (depicted in Figure 7), encompassing diverse data categories. However, the primary emphasis of this inquiry lies in the Waveform Section of the Database (highlighted by a red rectangle in Figure 7).

The Waveform data from both the MIMIC-III and MIMIC-IV Databases is publicly available on the Physionet internet website [43, 42]. In both databases recorded waveforms typically encompass one or more electrocardiogram(ECG) signals, often feature continuous ABP waveforms and fingertip PPG signals. Numeric data typically includes

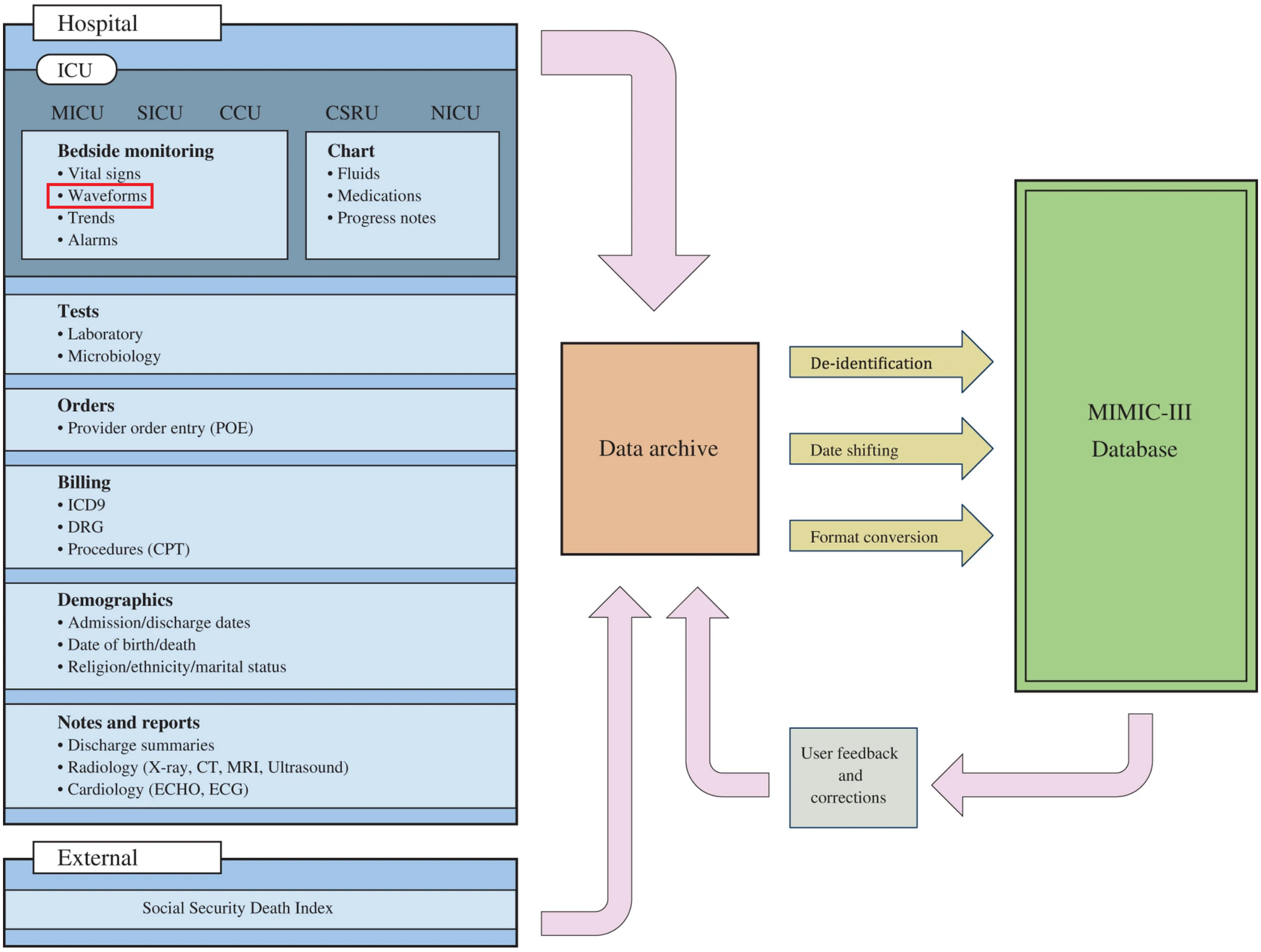

Figure 7: General Structure of the MIMIC-III Database [27]

heart and respiration rates, SpO2, and systolic, mean, and diastolic blood pressure, among other metrics when accessible. Recording durations also vary, with most lasting a few days, although some are shorter and other might even extend over several weeks. Both projects consist of two types of data: waveform data, comprising high-resolution, regularly sampled time series obtained directly from measuring devices, and numeric data, including digitally derived values or irregularly sampled data (like NIBP).

Differences and Similarities between MIMIC-III and MIMIC-IV

In MIMIC-III, waveforms were collected in a largely automated manner from selected adult and neonatal ICUs, resulting in a random sample of patients. The data archiving process was not continuous, and the recorded waveforms and numerics varied based on ICU staff choices. The individual patient consent waived due to de-identification. On the other hand, MIMIC-IV collected data from intensive care units where bedside monitors were linked to a local area network, allowing continuous monitoring and data transfer to a proprietary relational database. Data was stored for several weeks before being retrieved and archived daily. The de-identification process for MIMIC-IV followed the same method as MIMIC-III, removing or replacing protected health information with non-identifying information.

Both the MIMIC-III and MIMIC-IV databases encompass waveform and numeric datasets sourced from intensive care units. While both datasets feature detailed waveform records and numerical values, their storage and acquisition methods differ. MIMIC-III organizes its records within a directory structure with segmented waveform data, while MIMIC-IV adopts WFDB format for waveforms and compressed CSV files for numerics. However, MIMIC-IV incorporates enhancements like automated record partitioning and optimized storage formats to enhance data management efficiency.

Clinical Research Databases such as MIMIC play a pivotal role in facilitating global access to critical patient data, thereby supporting scientific endeavors across various medical domains. By ensuring the anonymity and de-identification of patient information, these databases uphold stringent standards of data privacy and ethics, thereby avoiding any infringement upon patient rights or privacy regulations. Such databases serve as invaluable resources for conducting comprehensive studies spanning diverse medical disciplines, including but not limited to the detection and treatment of various cancers, cardiovascular diseases, and even neonatal care in stationary settings. Their expansive datasets offer researchers an extensive pool of information to draw insights from, ultimately advancing the overall understanding and management of complex medical conditions.

3.2 Computing Background

3.2.1 Signal Processing

This section explores various techniques and methods employed in the analysis of PPG signals and their correlation to BP measurements. PPG-based BP estimation has emerged as a promising non-invasive approach, utilizing waveform observations from signals like PPG signals from different anatomical sites or their combination with ECG signals. This section delves into the diverse methodologies and algorithms utilized for processing PPG signals to derive meaningful insights into BP dynamics.

PPG Signal Processing Methods

Previous research has documented an inverse relationship BP and pulse transit time (PTT) [45]. Extensive investigation over past decades has focused on the PTT-based approach, revealing growing support for its potential in offering non-invasive BP measurements without the need for cuffs. PTT refers to the delay in time for the pressure waveform to traverse between two arterial locations (see Figure 8). It can be calculated as the time difference between proximal and distal waveforms indicative of the arterial pulse.

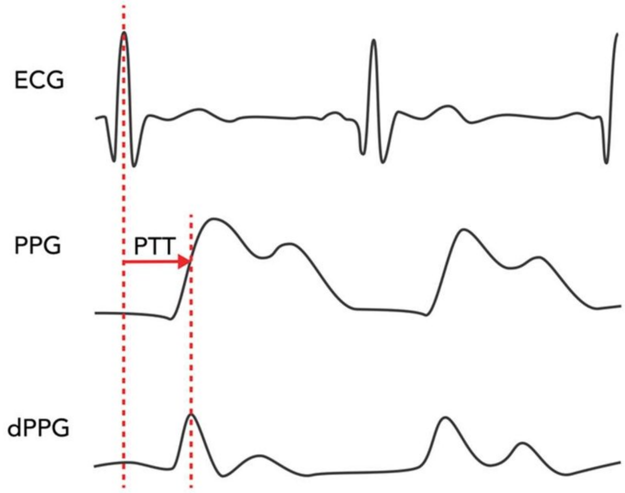

Figure 8: Calculation of PTT from ECG, PPG and first PPG derivative waveforms [38]

Pulse arrival time (PAT) represents another widely employed technique [56]. It is defined as the time that takes the pulse wave to travel from the heart to a peripheral site e.g. finger, toe, etc. It denotes the temporal discrepancy between the R-peak of the ECG signal and the peak of the PPG signal, measured within the same cardiac cycle (see Figure 9). Both PTT and PAT require simultaneous measurement at two different sites on the body, hence two measurement sensors (ECG and PPG) are needed for recording the signals in order to estimate these parameters.

Pulse wave velocity (PWV) is another alternative method for estimating BP [39]. PWV determines the speed of the pulse wave by utilizing two PPG sensors positioned along the same arterial branch, separated by a known distance (see Figure 10), portrayed by the following formula $PWW = \frac{D}{PTT}$ where D is the distance between two known body parts.

Estimating BP through PTT, PAT, or PWV parameters involves mathematical models, but implementing these models faces challenges, and none of these techniques has become a reliable clinical tool for BP measurement. Challenges include the need for

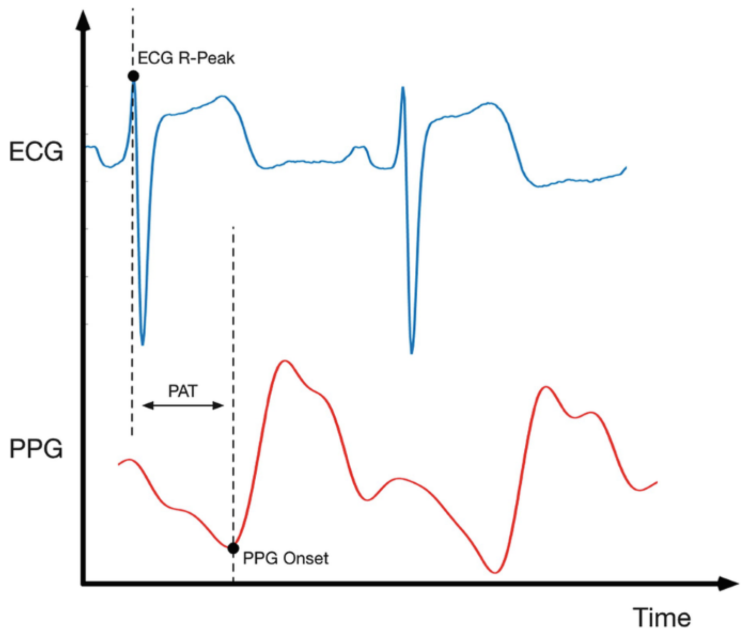

Figure 9: Calculation of PAT from ECG and PPG waveforms [17]

synchronized sensors, varying sampling rates, and reliance on complex arterial wave propagation models, making continuous BP measurement inconvenient and requiring constant calibration. Despite per-person calibration, these models offer only short-term BP estimation and remain unreliable for beat-to-beat BP measurement.

Pulse wave analysis (PWA) offers a multifaceted solution to the previously mentioned issues. It serves as an umbrella term encompassing signal processing and feature extraction of certain PPG waveform characteristics. PWA offers a novel method for cuffless, continuous, and calibration-free BP measurement by extracting temporal features from the PPG waveform, which demonstrate a strong correlation with individual BP levels [19]. Utilizing only one PPG sensor, PWA presents several advantages over previous methods, including simplicity, affordability, straightforward signal acquisition, and a resemblance between BP pulse waveform and PPG blood volume pulse (example in Figure 11). This data-driven approach to BP estimation provides optical BP measurement with promising potential for practical applications. Advancements in computational technology and data analysis software have simplified the preprocessing and analysis of physiological signals. Techniques such as filtering and feature extraction are commonly utilized in the analysis of PPG pulse waves, often integrated into machine learning and deep neural network models for blood pressure estimation.

Signal Pre-Processing

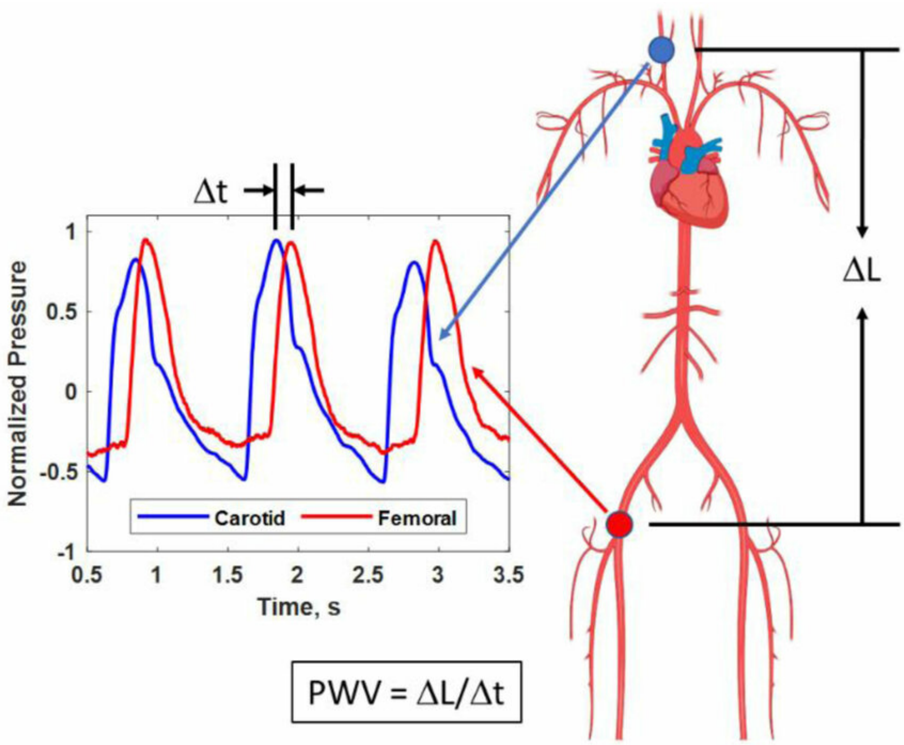

Figure 10: Calculation of PWW from two PPG signals at different body parts [63]

The preprocessing of physiological signals, crucial for accurate BP estimation, involves a variety of signal filtering techniques. Techniques like Chebyshev, Butterworth, and Savitzky-Golay filtering, along with methods such as second derivative analysis, play pivotal roles in enhancing signal quality. These preprocessing steps, facilitated by advancements in computational technology, pave the way for more refined analysis and interpretation of PPG pulse waves.

An investigation into various signal pre-processing techniques necessitates an examination of different types of filters. One prominent representative is the Butterworth filter, characterized by its flat frequency response within the passband. Belonging to the Infinite Impulse Response (IIR) category, Butterworth filters offer efficiency in processing low-frequency signals and exhibit rapid computational capabilities, as demonstrated by Chatterjee et al. in their PPG-based heart rate analysis [13]. The filter order directly correlates with the number of energy storage components present in the analogous analog circuit, such as inductors and capacitors.

Another noteworthy filter type is the Savitzky-Golay filter, introduced by Savitzky and Golay [22]. Falling under the Finite Impulse Response (FIR) category, this filter effectively smooths data while removing unwanted frequencies. Its inherent stability

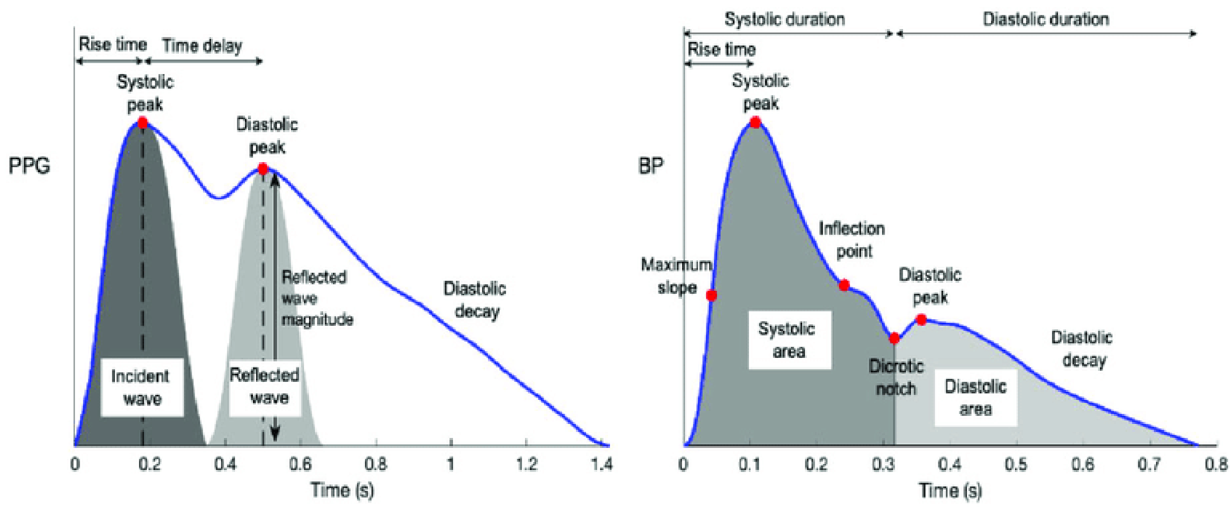

Figure 11: Example of a PWA used to extract features from the PPG waveform [8]

ensures a finite output for any finite input. Additionally, the linear phase property guarantees the absence of frequency-dependent time shifts.

Furthermore, the Chebyshev filter offers a steeper roll-off compared to other filters, leading to sharper distinctions between desired and unwanted frequencies. While this advantage comes at the cost of controlled passband ripples, these filters remain valuable tools for applications requiring precise frequency separation. Beyond digital signal improvement, they find applications in audio crossovers, image noise reduction, and data communication, as discussed by Antoniou [5].

In their 2018 study, Liang et al. investigated nine different digital signal filters to identify the optimal approach for short PPG signals (2.1s) [36]. Their performance-based ranking revealed the Chebyshev II filter as the most effective in enhancing PPG signal quality, with the optimal order at 4th.

Second derivative & Age analysis [61]

Hemodynamics and vascular age [12]

3.2.2 Machine Learning

1. What are the methods of machine learning for estimating BP from PPG?

Approaches for estimating BP from PPG:

BP estimation using ML techniques is data driven, unlike the traditional PTT/PAT only models. Several studies attempted to fit regression models, such as **multilinear**

regression, support vector machine and random forest, for estimating BP using PTT/PAT based approach with some degree of success, but the results did not always satisfy the international standards.

Teng and Zhang [62] tried to fit a **linear regression** model to study the relationship between four PPG features and BP. It was reported that the diastolic time has higher correlation with SBP and DBP than the other features.

Suzuki and Oguri [59] used **AdaBoost** classifier for the estimation of BP. In this technique, SBP values were classified according to a threshold and afterward the nonlinear machine learning model was employed for estimating SBP.

Ruiz-Rodriguez et al. [53] employed a probabilistic generative model, **Deep Belief Network Restricted Boltzmann Machine**, for predicting SBP, DBP and mean arterial pressure simultaneously. The results of this study were highly variable, and therefore was not reliable.

Kurylyak et al. [31] extracted 21 characteristic features from the PPG waveform. These features were used for estimating SBP and DBP using a **feed forward neural network**. The results were promising towards an accurate cuffless BP monitoring.

Xing and Sun [66] applied **Fast Fourier Transformation** for selecting frequency domain features from the PPG waveform followed by a **feed forward neural** network for BP estimation. However, the authors suggested that these features are not sufficient for effective BP estimation.

Liu et al. [37], added 14 features extracted from the PPG's second derivative, in addition to the 21 features used in Kurylyak et al. A **support vector machine (SVM)** was then applied for estimating SBP and DBP. The authors reported that these 14 features further improved the estimation.

The connection between blood pressure (BP) and photoplethysmography (PPG) characteristics doesn't consistently follow a linear pattern. Consequently, linear models are unsuitable and frequently unable to accurately depict the correlation between BP and PPG when evaluated using extensive data gathered from various demographics. Alternative traditional machine learning models like Support Vector Machines (SVM) and Random Forest tend to yield higher levels of accuracy. Estimation using these models requires establishing one model per objective, hence, SBP and DBP are estimated separately. However, DBP strongly correlates with SBP and improve its estimation [49], thus should be modelled simultaneously using one model architecture. This can be achieved using neural networks. Neural network models have the capability to utilize vast amounts of data more swiftly and with greater precision when contrasted with traditional machine learning models.

El-Hajj and Kyriacou proposed using **Bidirectional Long Short-term memory (Bi-LSTM) and Bidirectional Gated Recurrent Units (Bi-GRU) with attention mechanisms** [18].

In Su et al. [58], a four layers **LSTM** with bidirectional structure and residual connections has been employed for BP estimation using the PTT approach. The findings surpass those of other BP regression models based on PTT.

Joung et al. [28] conducted a study to assess a learning-driven cuffless BP estimation system under challenging conditions, incorporating calibration. A one dimensional CNN-based network was designed, that could efficiently extract BP from PPG signals using a comparative paired 1D-CNN structure with calibration.

To precisely design a learning-based BP estimation model such that its estimation accuracy obtained during the test is sustained after being built upon a practical cuffless BP monitoring system, the following delicate yet realistic experimental principles are applicable: i) the number of subjects should be sufficiently large, ii) subject independent training and test datasets are required, and iii) the intrasubject BP variation should be carefully scrutinized in the model design [28].

4 Methods

1. Data fetching and reading using WFDB and NumPy libraries.

    Get all available data from MIMIC-IV DB.

    This data is used as the validation dataset, since it is the one that's most up-to-date, most modern, and supposedly most reliable

    There are 198 subjects and 200 total studies in the DB (two subjects have two separate studies)

    The studies contain records with various signals (ECG, ABP, Pleth etc.) and are of different lengths

    A single record can contain various segments also of different lengths and signals

    Segments contain continuous values, that are used in this research

Only segments with at least 10 minutes of length are considered

These segments must also not contain "faulty" values

Faulty values: NaN, inf, negative values, for ABP values not below 30 and not above 250, for PPG only between 0 and 1

If a 10-minute part of the segment matches these criteria, it is saved to the ./validation directory, as 2 separate and synchronous ABP and PPG files

If a segment is longer than 10 minutes, then more 10 minute segments may be extracted (marked by a _ and a number representing the sequence)

Example of the files: `abp_80057524_0005_0`, `ppg_80057524_0020_18`

For MIMIC-IV data fetching, no limits on the total records and single study records are given. For MIMIC-III - 4 times the records of MIMIC-IV are fetched and a maximum of 100 segments per study is set, to avoid over-representation of single person or study data in the ML part of the research.

2. Digital signal filtering using Savitzky-Golay and Butterworth Lowpass filters.

3. Beat detection algorithms from MIMIC WFDB Tutorial used for primary estimation. Beat detection improved with manual implementation of SciPy library.

4. Fiducial Point calculation based on the algorithm provided in the MIMIC WFDB Tutorial.

5. Feature extraction with personally created code to extract time domain features, and NumPy library to extract frequency domain features (FFT). Median value calculation using NumPy library.

6. Machine Learning Model creation using PyTorch and Scikit-Learn libraries.

5 Results

5.1 Data Fetching

Data for Validation from MIMIC4: 5508 records each containing 37795 values corresponding to 605 seconds (fs=64.4725);

Data for Training/Testing from MIMIC3 (1st Iteration): 22083 (4*MIMIC4) records each containing 75625 values corresponding to 605 seconds (fs=125);

5.2 Data Processing

Same Signaling processing approaches were included (see 4.2) for both the MIMIC4 and MIMIC3 data.

5.3 Feature Extraction

CAVE: out of the 34 features, 2 (delta T and resistive index) depend on the accurate detection of the dicrotic notch. Significantly more values can be extracted if finding the dicrotic notch would not be necessary

FE from MIMIC4 for Validation: - For target reference Systolic, Diastolic and MAP values were extracted from the waveform data. - For Machine Learning, 34 features were extracted from the PPG waveform A total of **1,309,265** values were extracted, resulting in a 34 x 1,309,265 matrix. Total of **183,140** median values were extracted.

FE from MIMIC3 for Training/Testing:

- For target reference ABP Systolic, Diastolic and MAP values were extracted from the waveform data. - For Machine Learning, 34 features were extracted from the PPG waveform A total of **13,659,375** values were extracted, resulting in a 34 x 13659375 matrix. Total of **1,918,623** median values were extracted.

The summarized results are displayed in Figure 12.

5.4 Machine Learning

6 Discussion

Limitations: - not knowing what devices were used - how they were calibrated - how accurate they are - pulse oximeter and arterial catheter parameters - sampling rates are different for every device (even between MIMIC 3 and 4)

Possible Improvements: - integrate both the ECG and PPG graphs for a more precise prediction - use further signal processing approaches - manually filter waveform graphics (e.g. faulty PPG signal) - expand on machine learning algorithms - experiment with different median intervals

7 Conclusion

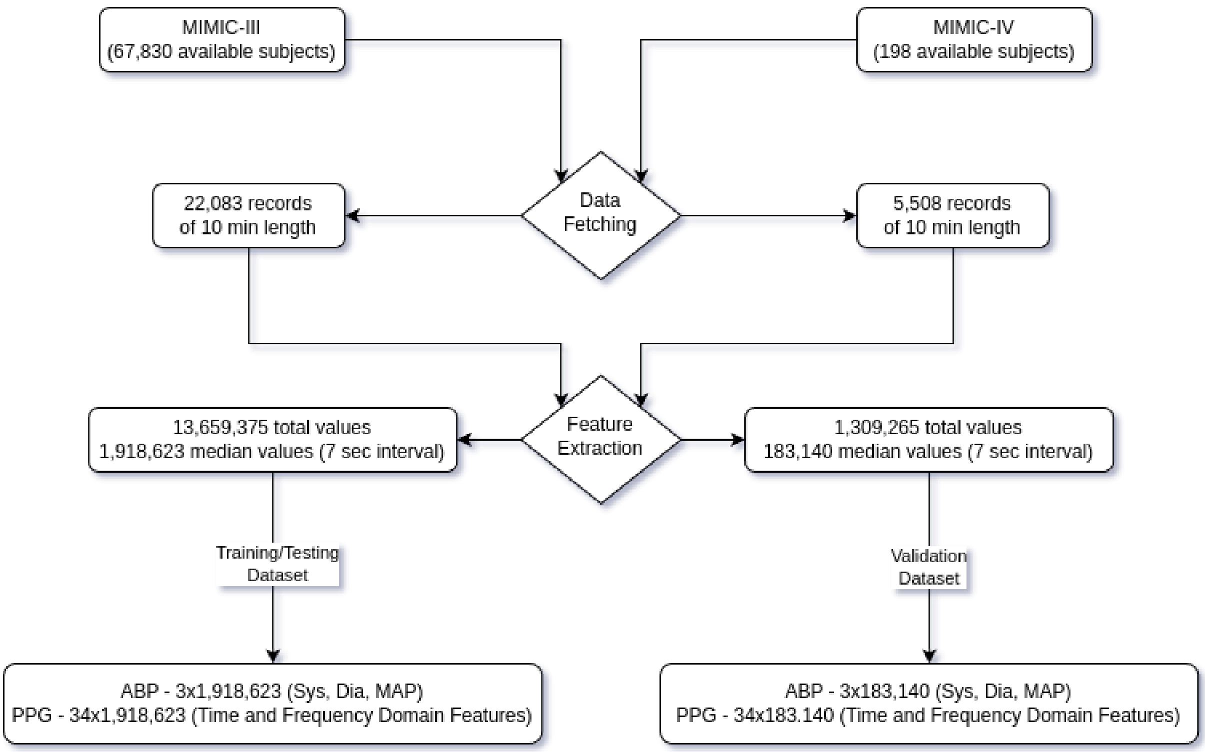

Figure 12: Flow Diagram presenting the Data Fetching and Processing

References

[1] Automatic Digital Blood Pressure Monitor.

[2] Standard Sphygmomanometer.

[3] What is blood pressure and how is it measured? In *InformedHealth.Org [Internet]*. Institute for Quality and Efficiency in Health Care (IQWiG).

[4] John Allen. Photoplethysmography and its application in clinical physiological measurement. 28(3):R1.

[5] Andreas Antoniou. *Digital Filters: Analysis, Design, and Signal Processing Applications*. McGraw-Hill Education, 1st edition edition.

[6] Takuo Aoyagi and Katsuyuki Miyasaka. Pulse oximetry: Its invention, contribution to medicine, and future tasks. 94:S1–3.

[7] J. Gordon Betts, Kelly A. Young, James A. Wise, Eddie Johnson, Brandon Poe, Dean H. Kruse, Oksana Korol, Jody E. Johnson, Mark Womble, Peter DeSaix,

J. Gordon Betts, Kelly A. Young, James A. Wise, Eddie Johnson, Brandon Poe, Dean H. Kruse, Oksana Korol, Jody E. Johnson, Mark Womble, and Peter DeSaix. 20.2 Blood Flow, Blood Pressure, and Resistance - Anatomy and Physiology 2e — OpenStax.

[8] Vasiliki Bikia, Terence Fong, Rachel Climie, Rosa Bruno, Bernhard Hametner, Christopher Mayer, Dimitrios Terentes-Printzios, and Peter Charlton. Leveraging the potential of machine learning for assessing vascular ageing: State-of-the-art and future research. 2.

[9] V.L. Burt, P. Whelton, E.J. Roccella, C. Brown, J.A. Cutler, M. Higgins, M.J. Horan, and D. Labarthe. Prevalence of hypertension in the US adult population: Results from the third National Health and Nutrition Examination Survey, 1988-1991. 25(3):305–313.

[10] Denisse Castaneda, Aibhlin Esparza, Mohammad Ghamari, Cinna Soltanpur, and Homer Nazeran. A review on wearable photoplethysmography sensors and their potential future applications in health care. 4(4):195–202.

[11] A. V. J. Challoner and C. A. Ramsay. A photoelectric plethysmograph for the measurement of cutaneous blood flow. 19(3):317.

[12] Peter H. Charlton, Birutė Paliakaitė, Kristjan Pilt, Martin Bachler, Serena Zanelli, Dániel Kulin, John Allen, Magid Hallab, Elisabetta Bianchini, Christopher C. Mayer, Dimitrios Terentes-Printzios, Verena Dittrich, Bernhard Hametner, Dave Veerasingam, Dejan Žikić, and Vaidotas Marozas. Assessing hemodynamics from the photoplethysmogram to gain insights into vascular age: A review from VascAgeNet. 322(4):H493–H522.

[13] Ayan Chatterjee and Uttam Kumar Roy. PPG Based Heart Rate Algorithm Improvement with Butterworth IIR Filter and Savitzky-Golay FIR Filter. In *2018 2nd International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech)*, pages 1–6.

[14] V. L. Clark and J. A. Kruse. Arterial catheterization. 8(4):687–697.

[15] N. T. Contributor. Essential critical care skills 3: Arterial line care.

[16] Daniel DeMers and Daliah Wachs. Physiology, Mean Arterial Pressure. In *StatPearls*. StatPearls Publishing.

[17] Marshal S. Dhillon and Matthew J. Banet. Pulse Arrival Time Techniques. In Josep Solà and Ricard Delgado-Gonzalo, editors, *The Handbook of Cuffless Blood Pressure Monitoring: A Practical Guide for Clinicians, Researchers, and Engineers*, pages 43–59. Springer International Publishing.

[18] C El-Hajj and given-i=PA family=Kyriacou, given=PA. Deep learning models for cuffless blood pressure monitoring from PPG signals using attention mechanism. 65:102301.

[19] Mohamed Elgendi. On the Analysis of Fingertip Photoplethysmogram Signals. 8(1):14–25.

[20] Dena Ettehad, Connor A. Emdin, Amit Kiran, Simon G. Anderson, Thomas Callender, Jonathan Emberson, John Chalmers, Anthony Rodgers, and Kazem Rahimi. Blood pressure lowering for prevention of cardiovascular disease and death: A systematic review and meta-analysis. 387(10022):957–967.

[21] Majid Ezzati, Alan D Lopez, Anthony Rodgers, Stephen Vander Hoorn, and Christopher JL Murray. Selected major risk factors and global and regional burden of disease. 360(9343):1347–1360.

[22] given-i=Abraham family=Savitzky, given=Abraham. and M. J. E. Golay. Smoothing and Differentiation of Data by Simplified Least Squares Procedures. 36(8):1627–1639.

[23] Alrick B. Hertzman. Photoelectric Plethysmography of the Fingers and Toes in Man. 37(3):529–534.

[24] Brian L. Hill, Nadav Rakocz, Ákos Rudas, Jeffrey N. Chiang, Sidong Wang, Ira Hofer, Maxime Cannesson, and Eran Halperin. Imputation of the continuous arterial line blood pressure waveform from non-invasive measurements using deep learning. 11:15755.

[25] B.P.M. Imholz, W. Wieling, G.A. Van Montfrans, and K.H. Wesseling. Fifteen years experience with finger arterial pressure monitoring: Assessment of the technology. 38(3):605–616.

[26] Alistair E. W. Johnson, Lucas Bulgarelli, Lu Shen, Alvin Gayles, Ayad Shammout, Steven Horng, Tom J. Pollard, Sicheng Hao, Benjamin Moody, Brian Gow, Li-

wei H. Lehman, Leo A. Celi, and Roger G. Mark. MIMIC-IV, a freely accessible electronic health record dataset. 10(1):1.

[27] Alistair E. W. Johnson, Tom J. Pollard, Lu Shen, Li-wei H. Lehman, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi, and Roger G. Mark. MIMIC-III, a freely accessible critical care database. 3(1):160035.

[28] Jingon Joung, Chul-Woo Jung, Hyung-Chul Lee, Moon-Jung Chae, Hae-Sung Kim, Jonghun Park, Won-Yong Shin, Changhyun Kim, Minhyung Lee, and Changwoo Choi. Continuous cuffless blood pressure monitoring using photoplethysmography-based PPG2BP-net for high intrasubject blood pressure variations. 13:8605.

[29] Chang-Sei Kim, Andrew M. Carek, Omer T. Inan, Ramakrishna Mukkamala, and Jin-Oh Hahn. Ballistocardiogram-Based Approach to Cuffless Blood Pressure Monitoring: Proof of Concept and Potential Challenges. 65(11):2384–2391.

[30] Sheida Knight, Jessica Lipoth, Mina Namvari, Carol Gu, Mojtaba Hedayati Ch, Shabbir Syed-Abdul, and Raymond J. Spiteri. The Accuracy of Wearable Photoplethysmography Sensors for Telehealth Monitoring: A Scoping Review.

[31] Yuriy Kurylyak, Francesco Lamonaca, and Domenico Grimaldi. A Neural Network-based method for continuous blood pressure estimation from a PPG signal. In *2013 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, pages 280–283.

[32] G.J. Langewouters, A. Zwart, R. Busse, and K.H. Wesseling. Pressure-diameter relationships of segments of human finger arteries. 7(1):43–55.

[33] Hooseok Lee, Hoon Ko, and Jinseok Lee. Reflectance pulse oximetry: Practical issues and limitations. 2(4):195–198.

[34] Li-wei H. Lehman, Mohammed Saeed, Daniel Talmor, Roger Mark, and Atul Malhotra. Methods of Blood Pressure Measurement in the ICU. 41(1):34–40.

[35] Alexander A. Leung, Kara Nerenberg, Stella S. Daskalopoulou, Kerry McBrien, Kelly B. Zarnke, Kaberi Dasgupta, Lyne Cloutier, Mark Gelfer, Maxime Lamarre-Cliche, Alain Milot, Peter Bolli, Guy Tremblay, Donna McLean, Sheldon W. Tobe, Marcel Ruzicka, Kevin D. Burns, Michel Vallée, G. V. Ramesh Prasad, Marcel Lebel, Ross D. Feldman, Peter Selby, Andrew Pipe, Ernesto L. Schiffrin, Philip A.

McFarlane, Paul Oh, Robert A. Hegele, Milan Khara, Thomas W. Wilson, S. Brian Penner, Ellen Burgess, Robert J. Herman, Simon L. Bacon, Simon W. Rabkin, Richard E. Gilbert, Tavis S. Campbell, Steven Grover, George Honos, Patrice Lindsay, Michael D. Hill, Shelagh B. Coutts, Gord Gubitz, Norman R. C. Campbell, Gordon W. Moe, Jonathan G. Howlett, Jean-Martin Boulanger, Ally Prebtani, Pierre Larochelle, Lawrence A. Leiter, Charlotte Jones, Richard I. Ogilvie, Vincent Woo, Janusz Kaczorowski, Luc Trudeau, Robert J. Petrella, Swapnil Hiremath, Denis Drouin, Kim L. Lavoie, Pavel Hamet, George Fodor, Jean C. Grégoire, Richard Lewanczuk, George K. Dresser, Mukul Sharma, Debra Reid, Scott A. Lear, Gregory Moullec, Milan Gupta, Laura A. Magee, Alexander G. Logan, Kevin C. Harris, Janis Dionne, Anne Fournier, Geneviève Benoit, Janusz Feber, Luc Poirier, Raj S. Padwal, Doreen M. Rabi, and CHEP Guidelines Task Force. Hypertension Canada's 2016 Canadian Hypertension Education Program Guidelines for Blood Pressure Measurement, Diagnosis, Assessment of Risk, Prevention, and Treatment of Hypertension. 32(5):569–588.

[36] Yongbo Liang, Mohamed Elgendi, Zhencheng Chen, and Rabab Ward. An optimal filter for short photoplethysmogram signals. 5(1):180076.

[37] M. Liu, X. Zhan, J. Tu, B. Liu, and Z.H. Zhu. Integrated navigation for tethered nano-satellite system by modified input-delay neural networks and PROSAC. volume 2017-May, pages 202–210.

[38] Hin Wai Lui and King Chow. A Novel Calibration Procedure of Pulse Transit Time based Blood Pressure measurement with Heart Rate and Respiratory Rate. volume 2018.

[39] Devin B. McCombie, Andrew T. Reisner, and H. Harry Asada. Adaptive blood pressure estimation from wearable PPG sensors using peripheral artery pulse wave velocity measurements and multi-channel blind identification of local arterial dynamics. 2006:3521–3524.

[40] P Mohan, Nagarajan Velmurugan, and J Vignesh. Spot measurement of heart rate based on morphology of PhotoPlethysmoGraphic (PPG) signals. 41:1–10.

[41] Hans Molitor and Michael Kniazuk. A New Bloodless Method for Continuous Recording of Peripheral Circulatory Changes. 57(1):6–18.

[42] Benjamin Moody, Sicheng Hao, Brian Gow, Tom Pollard, Wei Zong, and Roger Mark. MIMIC-IV Waveform Database.

[43] Benjamin Moody, George Moody, Mauricio Villarroel, Gari Clifford, and Ikaro Silva. MIMIC-III Waveform Database.

[44] G.B. Moody and R.G. Mark. A database to support development and evaluation of intelligent intensive care monitoring. In *Computers in Cardiology 1996*, pages 657–660.

[45] Ramakrishna Mukkamala, Jin-Oh Hahn, Omer T. Inan, Lalit K. Mestha, Chang-Sei Kim, Hakan Töreyin, and Survi Kyal. Toward Ubiquitous Blood Pressure Monitoring via Pulse Transit Time: Theory and Practice. 62(8):1879–1901.

[46] Amanda J. Naylor, Daniel I. Sessler, Kamal Maheshwari, Ashish K. Khanna, Dongsheng Yang, Edward J. Mascha, Iman Suleiman, Eric M. Reville, Devan Cote, Matthew T. Hutcherson, Bianka M. Nguyen, Hesham Elsharkawy, and Andrea Kurz. Arterial Catheters for Early Detection and Treatment of Hypotension During Major Noncardiac Surgery: A Randomized Trial. 131(5):1540–1550.

[47] World Health Organization. *World Health Statistics 2023: Monitoring Health for the SDGs, Sustainable Development Goals*. World Health Organization.

[48] L. Peter, N. Noury, and M. Cerny. A review of methods for non-invasive and continuous blood pressure monitoring: Pulse transit time method is promising? 35(5):271–282.

[49] Aditya Ponnada. Technological considerations for sensor-assisted chronic pain assessment in natural environments.

[50] C.C.Y. Poon and Y.T. Zhang. Cuff-less and Noninvasive Measurements of Arterial Blood Pressure by Pulse Transit Time. In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, pages 5877–5880.

[51] Ivan Reyes, Homer Nazeran, Mario Franco, and Emily Haltiwanger. Wireless photoplethysmographic device for heart rate variability signal acquisition and analysis. In *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 2092–2095.

[52] Sokwoo Rhee, Boo-Ho Yang, and H.H. Asada. Artifact-resistant power-efficient design of finger-ring plethysmographic sensors. 48(7):795–805.

[53] Juan C. Ruiz-Rodríguez, Adolf Ruiz-Sanmartín, Vicent Ribas, and Jesús Caballero. Innovative continuous non-invasive cuffless blood pressure monitoring based on photoplethysmography technology. 39(9):1618–1625.

[54] Mohammed Saeed, Mauricio Villarroel, Andrew T. Reisner, Gari Clifford, Li-Wei Lehman, George Moody, Thomas Heldt, Tin H. Kyaw, Benjamin Moody, and Roger G. Mark. Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC-II): A public-access intensive care unit database. 39(5):952–960.

[55] Paul Sebo, Antoinette Pechère-Bertschi, François R. Herrmann, Dagmar M. Haller, and Patrick Bovier. Blood pressure measurements are unreliable to diagnose hypertension in primary care. 32(3):509–517.

[56] Manuja Sharma, Karinne Barbosa, Victor Ho, Devon Griggs, Tadesse Ghirmai, Sandeep K. Krishnan, Tzung K. Hsiai, Jung-Chih Chiao, and Hung Cao. Cuff-Less and Continuous Blood Pressure Monitoring: A Methodological Review. 5(2):21.

[57] Shival Srivastav, Radia T. Jamil, and Roman Zeltser. Valsalva Maneuver. In *StatPearls*. StatPearls Publishing.

[58] Peng Su, Xiao-Rong Ding, Yuan-Ting Zhang, Jing Liu, Fen Miao, and Ni Zhao. Long-term blood pressure prediction with deep recurrent neural networks. In *2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, pages 323–328.

[59] Satomi Suzuki and Koji Oguri. Cuffless blood pressure estimation by error-correcting output coding method based on an aggregation of AdaBoost with a photoplethysmograph sensor. In *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 6765–6768.

[60] Nina Sviridova and Kenshi Sakai. Human photoplethysmogram: New insight into chaotic characteristics. 77:53–63.

[61] K. Takazawa, N. Tanaka, M. Fujita, O. Matsuoka, T. Saiki, M. Aikawa, S. Tamura, and C. Ibukiyama. Assessment of vasoactive agents and vascular aging by the second derivative of photoplethysmogram waveform. 32(2):365–370.

[62] X.F. Teng and Y.T. Zhang. Continuous and noninvasive estimation of arterial blood pressure using a photoplethysmographic approach. In *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat. No.03CH37439)*, volume 4, pages 3153–3156 Vol.4.

[63] Matthew Urban. Understanding Arterial Biomechanics with Ultrasound and Waveguide Models. 19:46.

[64] A. M. Weissler, W. S. Harris, and C. D. Schoenfeld. Systolic time intervals in heart failure in man. 37(2):149–159.

[65] F. P. Wieringa, F. Mastik, and A. F. W. van der Steen. Contactless multiple wavelength photoplethysmographic imaging: A first step toward "SpO2 camera" technology. 33(8):1034–1041.

[66] X. Xing and M. Sun. Optical blood pressure estimation with photoplethysmography and fft-based neural networks. 7(8):3007–3020.

[67] Gilwon Yoon, Jong Youn Lee, Kye Jin Jeon, Kun-Kook Park, Hyung S. Yeo, Hyun Tae Hwang, Hong Sig Kim, and In-Duk Hwang. Multiple diagnosis based on photoplethysmography: Hematocrit, SpO2, pulse, and respiration. In *Optics in Health Care and Biomedical Optics: Diagnostics and Treatment*, volume 4916, pages 185–188. SPIE.

[68] I. Yoshiya, Y. Shimada, and K. Tanaka. Spectrophotometric monitoring of arterial oxygen saturation in the fingertip. 18(1):27–32.

[69] Serena Zanelli, Mounim El Yacoubi, Magid Hallab, and Mehdi Ammi. On the potential of AI based health assessment from photopletysmographic signals.

[70] D.C. Zheng and Y.T. Zhang. A ring-type device for the noninvasive measurement of arterial blood pressure. In *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat. No.03CH37439)*, volume 4, pages 3184–3187 Vol.4.