TASK Quarterly 29 (2) 2025

Comparative analysis of methods for calculating HRV values on heart rate monitoring devices

Bartosz Kołakowski *, **Piotr Noga, Paweł Mańczak, Mateusz Nowak**

Faculty of Electronics, Telecommunications and Informatics, Gdańsk University of Technology, Narutowicza 11/12, Gdańsk, 80-233, Poland

*s188701@student.pg.edu.pl

https://doi.org/10.34808/tq2025/29.2/c

Abstract

The aim of the study is to conduct a comparative analysis of HRV calculation methods and how they affect its measures (SDNN, SDNN Index, SDANN, RSA Index, Mean RR, RMSSD, pNN50) and their quality. Modern medical devices offer many possibilities, including heart rate and ECG measurement. An important issue in assessing heart function is HRV and its measures, which allow us to determine how the heart responds to different conditions, but the question of how to measure HRV and how its calculation works in different conditions remains open. The paper will show how HRV changes depending on frequency during rest, activity (walking), and sleep. HRV will be calculated using both an analytical method (using the Pan-Tompkins and U-Net algorithms) and a convolutional neural network.

Keywords:

HRV, Pan-Tompkins, U-Net

1. Introduction

Currently, we can see a growing availability of wearable devices on the market, such as smartwatches and smart rings, which are capable of measuring ECG signals and heart rate. This has led to an increased demand for HRV measurement. Thanks to HRV, we are able to determine the body's susceptibility to various heart diseases as well as how it reacts to stressful situations. The question arises as to how to obtain HRV values on heart monitoring devices as most of them do not have such functions. For this reason, we decided to examine the relevant methods of obtaining HRV measurements to determine which ones are the most accurate and in which situations.

In this paper, we present an experiment in which we compare three methods commonly used in scientific research to obtain HRV measurements, namely the Pan-Tompkins algorithm, a Convolutional Neural Network (CNN), and a U-Net deep neural network architecture. For this purpose, we use a dataset prepared by us, which we obtained using a measuring device - the Aidmed One chest band - during measurements in four different states with varying degrees of activity in which one tested person was involved.

This paper is divided into the following sections: **Section 2** defines the terms used in the paper, **Section 3** reviews the literature from which we drew the knowledge needed to conduct our study, and in **Section 4** we propose our experiment, in which we compare the performance of existing algorithms on a dataset that we created which consists of electrocardiographic measurements from the device. In **Section 5** we present the measurements taken during our experiment and in **Section 6** we discuss the results obtained from the experiment.

2. Explanation of concepts

Supervised learning is characterized by the presence of information indicating whether the model's prediction is correct or not. This enables the algorithm to learn the relationships between features and classes, based on which it makes categorization decisions. This method requires data for which classes are labeled, which often involves costly human involvement.

Measurement frequency – the number of data measurements performed in a specified period of time. The number of measurements per second is most commonly specified, and is determined by the following formula:

$$f = \frac{n}{t} \quad [\mathrm{Hz} = \mathrm{s}^{-1}] \tag{1}$$

- f is the frequency of measurements, expressed in hertz (Hz),
- n is the number of measurements taken,
- t is the duration of the measurement, expressed in seconds (s).

There are no standards that strictly define how often devices should collect the data needed to calculate HRV. According to research conducted in [1] [2] [3], too low a measurement frequency (around 25 Hz) can lead to inaccurate HRV results, with an error rate of at least 5% (for 25 Hz) if only raw data is used.

Heart rate – the number of heartbeats per unit of time. This is a physiological symptom of the heart's work and reflects how often the heart pumps blood through the body. The number of heartbeats per minute is most commonly determined and is defined by the formula:

$$\text{Heart rate} = \frac{\text{number of heartbeats}}{\text{time}} \tag{2}$$

According to [4], the heart rate level affects the predicted HRV value in two areas, physiological and mathematical, but in neither of them is this relationship linear.

ECG (electrocardiogram) – a test of the electrical activity of the heart. It records the electrical impulses that occur with each heartbeat and displays them in the form of a graph, usually as waves on a timeline. It records the differences in electrical potential between electrodes placed on the skin [5]. An important element of the ECG recording is the QRS complex (ventricular depolarization), which consists of three parts: Q – the first negative wave, R – a large positive wave (this is the peak on the graph), S – the decline after the peak (described in **Figure 1**). This is important because it allows the heart rate to be calculated from the ECG using the following formula:

$$f = \frac{60}{RR} \tag{3}$$

- f is the heart rate in beats per minute,
- RR is the time interval between successive QRS complexes in seconds [s].

HRV (Heart Rate Variability) – the variability of the intervals between successive heartbeats. It measures how much these intervals (RR intervals) differ from each other. The greater the variability, the better; higher variability means that the nervous system is flexible and responds well to stress, rest, and changes in the environment. Low HRV variability increases the risk of mortality from heart diseases such as ischemic heart disease, heart failure, hypertension, and diabetes [7]. There are several measures that can be used to determine HRV, such as SDNN, SDNN Index, SDANN, RSA Index, Mean RR,

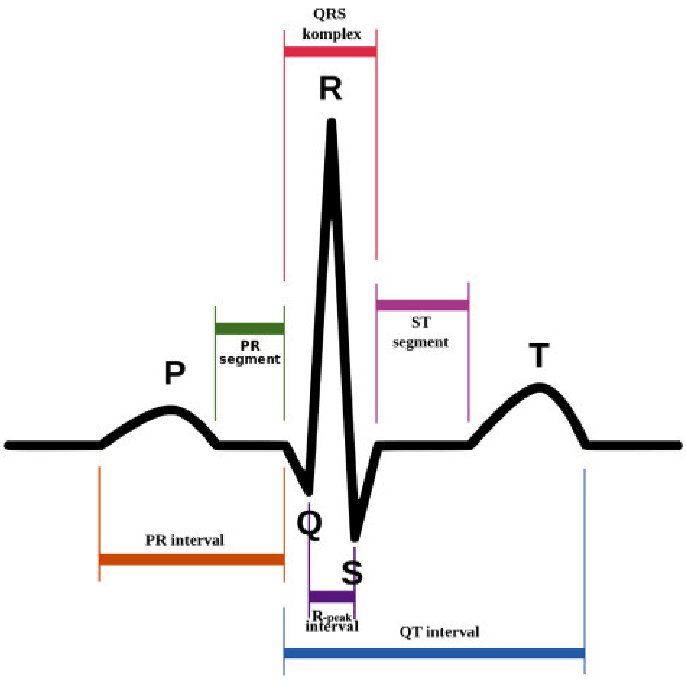

Figure 1: Q wave, R wave, S wave. The second one is very important in ECG. [6]

RMSSD, and pNN50. All of these measures will be explained below.

PRV (Pulse Rate Variability) – heart rate variability measured based on the intervals between successive heartbeats, most often using a PPG (photoplethysmography) signal, which is often used by devices such as smartwatches and smartbands [8]. It is analogous to the aforementioned HRV (Heart Rate Variability), but instead of a direct ECG recording, it is based on the heart rate signal, which allows it to be measured in a non-contact manner, e.g., through an appropriate camera system [2].

SDNN (Standard Deviation of NN intervals) – one of the basic measures of heart rate variability (HRV), classified as a *time domain measure*. It represents the standard deviation of all consecutive NN intervals (i.e., the time between heartbeats) in a given time interval. NN (or RR) intervals are measured based on the ECG signal. SDNN is determined by the formula:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - \overline{RR})^2} \tag{4}$$

- RR_i – the i-th interval between successive heartbeats,
- $\overline{RR}$ – the average value of all RR intervals,
- N – the number of RR intervals in the analyzed period.

SDNN Index (Standard Deviation of NN intervals Index) – one of the measures of heart rate variability (HRV) belonging to the category of time domain measures. It is the average standard deviation of NN intervals (RR) calculated in successive short segments of the ECG recording, usually one minute long. The SDNN Index allows for the assessment of short-term heart rate variability in different parts of the measurement and complements the SDNN measure, which covers the entire measurement period. There is no single universal formula for the SDNN Index, but it can be described as the arithmetic mean of SDNN calculated in M consecutive time segments:

$$SDNN_{Index} = \frac{1}{M}\sum_{j=1}^{M} SDNN_j \tag{5}$$

$$SDNN_{Index} = \frac{1}{M}\sum_{j=1}^{M}\sqrt{\frac{1}{N_j-1}\sum_{i=1}^{N_j}(RR_{i,j} - \overline{RR}_j)^2} \tag{6}$$

- M – number of segments (e.g., one-minute segments),
- N_j – number of RR intervals in segment j,
- $RR_{i,j}$ – i-th RR interval in segment j,
- $\overline{RR}_j$ – mean RR interval in segment j,
- $SDNN_j$ – standard deviation of RR intervals in segment j.

SDANN (Standard Deviation of the Averages of NN intervals) – a measure of heart rate variability belonging to the group of *time domain measures*. SDANN measures the standard deviation of the *averages* of NN intervals (i.e., RR) calculated in successive, usually 5-minute, segments of the entire ECG recording. This means that we first divide the ECG signal into equal intervals (e.g., one minute), calculate the average time between heartbeats in each of these intervals, and then determine the standard deviation of these average values. It is defined by the formula:

$$SDANN = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}(\overline{RR}_j - \overline{RR}_{\text{total}})^2} \tag{7}$$

- M – number of time segments (e.g., 5-minute segments),
- $\overline{RR}_j$ – average value of RR intervals in segment j,
- $\overline{RR}_{\text{total}}$ – average of all $\overline{RR}_j$, i.e., average RR interval throughout the entire measurement period.

Its lower value is independently associated with the assessment of polygenic anxiety risk (Anxiety PRS) and with the use of certain antidepressants (venlafaxine and bupropion) [9], so people with lower SDANN values may be prone to depression.

RSA Index (Respiratory Sinus Arrhythmia Index) – a measure of heart rate variability (HRV) that reflects the influence of breathing on heart rate. During inhalation, the heart rate usually accelerates, and during exhalation, it slows down. This phenomenon is called respiratory sinus arrhythmia (RSA), and the RSA Index quantifies this effect. The RSA Index is an indicator of parasympathetic nervous system activity and is often used in breathing training and psychophysiology. Although there is no single, universal mathematical formula for the RSA Index, it is often calculated as the difference between the maximum and minimum RR (or heart rate) intervals in a breathing cycle:

$$RSA_{Index} = \max(RR_{\text{exhalation}}) - \min(RR_{\text{inhalation}}) \tag{8}$$

or in logarithmic form:

$$RSA_{Index}^{\log} = \log\left(\frac{\max(RR_{\text{exhale}})}{\min(RR_{\text{inhale}})}\right) \tag{9}$$

- $RR_{\text{inhalation}}$ – RR intervals during inhalation (heart rate accelerates),
- $RR_{\text{exhalation}}$ – RR intervals during exhalation (heart rate slows down),
- max, min – the largest and smallest RR intervals within the respiratory cycle.

Mean RR (Mean of RR intervals) – a basic time measure in heart rate variability (HRV) analysis, determining the *average duration of RR intervals* (i.e., the intervals between successive heartbeats). The RR interval is measured from the ECG signal as the time between two consecutive R waves in the electrocardiogram. The formula for Mean RR is:

$$\text{Mean } RR = \frac{1}{N}\sum_{i=1}^{N} RR_i \tag{10}$$

- RR_i – the i-th RR interval (time between successive heartbeats),
- N – the number of all RR intervals in the analyzed period.

RMSSD (Root Mean Square of Successive Differences) – one of the basic measures of heart rate variability (HRV). RMSSD measures the *root mean square of successive RR (NN) intervals*. It is sensitive to rapid, short-term activity of the parasympathetic nervous system, i.e., the actions of the vagus nerve affecting the heart rhythm. It is used as an indicator of the parasympathetic nervous system's response to stress, while deviations from its normative value may indicate sudden death in cases of epilepsy, atrial fibrillation, and other cardiovascular complications, such as congenital heart defects or sinus arrhythmia [10]. The formula for RMSSD is:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \tag{11}$$

- RR_i – the i-th RR interval (the time between successive heartbeats),
- N – the number of all RR intervals in the analyzed period.

pNN50 (percentage of NN intervals that differ by more than 50 ms from the previous one) – a time-domain measure of heart rate variability (HRV) that represents the *percentage of NN intervals (RR) whose difference from the next interval exceeds 50 ms.* It is sensitive to rapid changes in heart rate and strongly reflects the influence of the parasympathetic nervous system (vagus nerve) [11]. The formula for pNN50 is:

$$pNN50 = \frac{1}{N-1}\sum_{i=1}^{N-1}\delta_i \cdot 100\%, \text{ where} \tag{12}$$

$$\delta_i = \begin{cases} 1, & \text{if } |RR_{i+1} - RR_i| > 50\,\text{ms} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

- RR_i – the i-th interval between successive heartbeats (known as NN or RR),
- N – the number of all RR intervals in the analyzed period,
- δ_i – a logical indicator of whether the difference exceeds 50 ms.

3. Literature review

We reviewed various available scientific publications in order to gain a deeper understanding of the issues under study, as well as to learn about previous research on similar topics.

We started with *An overview of heart rate variability metrics and norms* [12], which provides an overview of HRV measurement methods, their physiological significance and limitations. As a result of this work, norms for many HRV measures were established, but no recommended sampling ranges were provided. Next was *Heart rate variability in practical terms — appreciated or forgotten parameter of Holter ECG monitoring?* [13], where the concept of Heart Rate Variability (HRV) and related parameters such as SDNN, SDANN, rMSSD, NN50, pNN50 are explained in Polish. The links between specific diseases and the predicted values of these parameters are also listed there. Considering that Polish is the native language of the authors of this publication, the article proved useful in terms of using concepts consistent with Polish medical terminology. Subsequently, we looked at *The pNNx files: re-examining a widely used heart rate variability measure* [11], where the effectiveness of pNN50 was evaluated in relation to other threshold values in the variable pNNx, where x denotes the minimum time between successive heartbeats under consideration. The probability distributions for the pNNx family of statistics were compared, where x ranged from 4 ms to 100 ms, in various configurations, for example, what pNNx values are found among a group of young people and what values are found among older people. A systematic review of the literature on HRV analysis was presented in *Uncertainties in the Analysis of Heart Rate Variability: A Systematic Review* [14]. This made it easier for us to find the information we needed, for example on HRV measures.

Let us move on to literature that no longer describes basic issues. The publication entitled *Assessing the accuracy of popular commercial technologies that measure resting heart rate and heart rate variability* [10] examines the accuracy of commercial solutions for measuring heart rate variability (HRV) due to the negligible number of independent tests conducted on them. This article explains the significance and impact of one of the HRV metrics – rMSSD. The publication *RR interval signal quality of a heart rate monitor and an ECG Holter at rest and during exercise* [15] examines the signal quality of RR intervals from medical devices monitoring electrocardiography (ECG) using the Holter method, while the subjects perform various physical activities or are at rest. The article provides an in-depth description of how measurements from this type of medical device should be processed in order to correctly analyze RR interval signals.

The authors of *Heart rate variability and pulse rate variability: do anatomical location and sampling rate matter?* [1] compared HRV (from ECG) and PRV (from PPG), taking into account sensor location and sampling frequency, showing that low sampling (25 Hz - 50 Hz) leads to significant differences in HRV. The publication*Sampling rate impact on heart rate variability* [16] also examines the impact of sampling at different frequencies (in this case from 100 Hz to 500 Hz) on HRV. Researchers indicated that there are significant differences between even 100 Hz and 200 Hz, but in this particular study the data was not tested under real conditions (it was not noisy). Yet another study related to HRV examined the direct impact of different sampling frequencies (125 Hz – 2000 Hz) on its accuracy. The authors conducting the study in *Insufficient sampling frequencies skew heart rate variability estimates* [17] showed that the recommended minimum is 250 Hz for accurate detection of R peaks. They also concluded that low values (e.g. 125 Hz) significantly reduce the accuracy of RMSSD and SDNN parameters. Research in *An extensive quantitative analysis of the effects of errors in beat-to-beat intervals on all commonly used HRV parameters* [18] analyzed the impact of various types of detection errors on over 60 HRV measures. It was established that the sensitivity of HRV measures to errors varies — RMSSD is particularly vulnerable, while SDNN is more stable. However, the impact of sampling on the occurrence of these errors was not analyzed. The influence of sampling frequency (100–1000 Hz) on the accuracy of HRV spectral analysis was investigated in *Sampling frequency of the RR interval time series for spectral analysis of heart rate variability* [19]. It was established that a frequency greater than or equal to 250 Hz ensures spectral stability, but the study did not take into account modern interpolation methods. We also found an article showing how the accuracy of R peak location affects heart rate complexity metrics. It was determined in *Uncertainty in heart rate complexity metrics caused by R-peak perturbations* [20] that all analyzed measures are sensitive to even very slight disturbances in R peak detection. Errors in HRV analysis may result from inaccuracies in determining photoplethysmographic (PPG) features, which can be caused, for example, by lower sampling rates, as studied in *Impact of sampling rate and interpolation on photoplethysmography and electrodermal activity signals' waveform morphology and feature extraction* [21]. Another scientific publication we reviewed,

Photoplethysmography sampling frequency: pilot assessment of how low can we go to analyse pulse rate variability with reliability? [22], also confirms the thesis that too low a PPG sampling frequency leads to a reduction in the quality of the data used for HRV calculations. According to the researchers, a minimum sampling frequency of at least 64 Hz is recommended. If it is not possible to sample at the minimum recommended sampling frequency, there are ways to improve such a signal. Researchers in the article *Quantifying errors in spectral estimates of HRV due to beat replacement and resampling* [23] tried various techniques to correct the signal through interpolation, resampling, or beat replacement. This work showed that even single errors in the positioning of R peaks significantly alter the bandwidth. A study was also conducted to examine the impact of missing data and strategies for filling in the gaps (interpolation, imputation) on HRV values. It has been shown that even 3–5% of missing data can distort HRV, particularly RMSSD and pNN50, which are more sensitive than SDNN. This research was included in the publication *Effects of missing data on heart rate variability metrics* [24]. The publication *A careful look at ECG sampling frequency and R-peak interpolation on short-term measures of heart rate variability* [25] examined the impact of interpolation on the accuracy of determining R peaks and demonstrated that interpolation can effectively compensate for lower sampling of certain measures – RMSSD and SDNN. However, the study was conducted only on clean (noise-free) data. A publication very similar to the previous one, *Sampling frequency of the electrocardiogram for spectral analysis of the heart rate variability* [26], also suggests that low ECG signal sampling frequency may introduce measurement errors in RR intervals, which in turn distorts the measurement of Heart Rate Variability (HRV). Another publication, *Everything Hertz: methodological issues in short-term frequency-domain HRV* [27], criticized HRV spectral analysis on inappropriate time segments, showing that inappropriate time windows lead to erroneous conclusions. Too short a measurement time leads to HRV instability, which was also proven in *Reliability and accuracy of heart rate variability metrics versus ECG segment duration* [28], where the relationship between ECG recording length and the stability and repeatability of selected HRV measures was investigated. It should be noted that these studies did not take into account different frequencies.

The following publications that we would like to present show correlations between HRV and various relationships. The first such relationship is the non-linear relationship between heart rate and Heart Rate Variability (HRV), which is described in *Interaction between Heart Rate and Heart Rate Variability* [4]. According to this article, heart rate is important in two aspects of HRV, physiological as well as mathematical. The author specifies in which cases not taking heart rate into account improves the accuracy of HRV, and in which cases it actually worsens it. Another relationship tries to distinguish 'chaotic' heart rate variability from healthy fluctuations regulated by the autonomic nervous system. The authors of *Impact of heart rate fragmentation on the assessment of heart rate variability* [29] describe a new measure called Heart Rate Fragmentation (HRF) which shows that RMSSD and pNN50 may be overestimated if HRF is not taken into account. The problem of not separating HRV from average heart rate or cardiac period when analyzing data is pointed out in *Should heart rate variability be "corrected" for heart rate? Biological, quantitative, and interpretive considerations* [7]. The author of this study indicates that low HRV variability increases the risk of death in certain heart conditions. Another correlation we found in publications is the correlation between sleep quality and the parasympathetic nervous system. This can be found described in *The relationship between sleep quality and cardiac autonomic modulation according to physical activity levels in adults: a cross-sectional study* [30]. This correlation was measured using HRV indicators such as RMSSD and SDNN. It is also one example of research where these indicators are used in practice. The relationship between poor ADHF (Acute Decompensated Heart Failure) outcomes and Heart Rate Variability (HRV) was presented in *The correlation between heart rate variability index and vulnerability prognosis in patients with acute decompensated heart failure* [31]. Worse ADHF means that the patient may have shortness of breath or potentially chest pain. The last relationship we used our knowledge about was on how anxiety and antidepressant use are related to Heart Rate Variability (HRV), a study about which can be found in *Integrating Genome-wide information and Wearable Device Data to Explore the Link of Anxiety and Antidepressants with Heart Rate Variability* [9]. For this purpose, the research team conducted a series of measurements related to various types of antidepressants, taking into account external factors such as the age of the participants, their BMI and gender, and how these factors affect the HRV-SDANN metric.

We did not rely solely on HRV measurement which is obtained from ECG, as we also used PRV (Pulse Rate Variability) which is obtained from photoplethysmography (PPG). *Pulse rate variability in cardiovascular health: a review on its applications and relationship with heart rate variability* [8] presents Pulse Rate Variability (PRV) in terms of its advantages, when it can be used, and in which situations it can be compared to HRV. Measurement frequency is also crucial in PRV as is seen in *Impact of the PPG Sampling Rate in the Pulse Rate Variability Indices Evaluating Several Fiducial Points in Different Pulse Waveforms* [3]. This article presents a study of the impact of measurement frequency on PRV. This same topic was examined in another publication, *Noncontact imaging photoplethysmography to effectively access pulse rate variability* [2], which demonstrates the effectiveness of PRV measurement, provided that a high sampling frequency (200 fps) is used or appropriate signal interpolation is applied in the case of low-budget cameras performing the measurement.

We also reviewed the literature in search of descriptions of the algorithms used in our work. *A Real-Time QRS Detection Algorithm* [32] is a publication in which Jiapu Pan and Willis J. Tompkins demonstrated the operation of their algorithm, named after them, the Pan-Tompkins algorithm. Another algorithm we examind was U-Net, presented originally here [33]. It can be used in various fields, so we wanted to find scientific publications on its use in HRV measurement. For example *Ventricular Fibrillation Detection Based on Modified U-Net Feature Extraction Model* [34] shows an attempt to detect ventricular fibrillation by extracting HRV data from an ECG signal processed by a U-Net network that was successfully undertaken. The accuracy of ventricular fibrillation detection using this method was determined to be 99.56%. Another publication, *Validation of electrocardiogram-based photoplethysmogram generated using U-Net-based generative adversarial networks* [35], presents the use of U-Net to calculate one of the HRV metrics – SDNN – based on a video showing the face of the test subject. The recorded material is used to create a multidimensional map image, from which the relevant data is extracted to the U-Net layer, which then generates a PPG signal. This signal is used to calculate SDNN.

4. Experiment proposal

Three methods were used to calculate HRV measures: the Pan-Tompkins algorithm, the U-Net network, and a neural network. Below is an explanation of these concepts and related terms, along with a description of the measuring device.

The Pan-Tompkins algorithm is a classic and very popular method for detecting R waves in ECG signals, developed by Jiapu Pan and Willis J. Tompkins in 1985 [32]. It operates in real time and uses signal processing to highlight significant ECG features and eliminate noise. The algorithm consists of several stages of signal processing:

1. Bandpass Filter – removes low-frequency noise (e.g., baseline drift) and high-frequency noise (e.g., muscle interference).
2. Derivative – emphasizes the steep slopes characteristic of the R wave.
3. Squaring – amplifies the signal and emphasizes larger values (regardless of sign).
4. Moving Window Integration – smooths the signal and allows for better identification of potential R-wave regions.
5. Adaptive Thresholding – detects maxima in the processed signal as potential R-waves, with dynamic adjustment of the detection threshold.

The properties of the algorithm are:

- High detection efficiency even in the presence of noise,
- Low computational complexity – suitable for real-time applications (e.g., in ECG monitors, portable devices),
- Based on nonlinear processing – does not require frequency domain transformation.

U-Net – an *encoder–decoder* deep neural network architecture, originally designed for image segmentation [33], and now also successfully used in the analysis of biological signals such as ECG [34] and PPG [35]. When applied to R-wave detection, U-Net takes a fragment of an ECG signal as input and returns a probability mask indicating the locations of R-waves. Thanks to skip connections between the encoding and decoding layers, the network is able to precisely locate sharp transitions in the signal (such as QRS). Advantages of using U-Net:

- high resistance to noise and interference,
- ability to detect R-peaks with atypical QRS morphology,
- ability to operate without manual signal processing.

The U-Net architecture can be trained on data with labeled R waves and then used for real-time or offline detection.

CNN – Convolutional Neural Networks – a class of deep neural networks designed for automatic analysis of grid-structured data (e.g., images, time signals, sequences). CNNs use a *convolution* operation, which replaces traditional fully connected layers with preprocessing of local features. This allows the network to effectively detect spatial and temporal patterns. The main elements of CNN architecture:

- Convolutional layer – applies multiple filters (kernels) to extract local features from the input data,
- Activation function – usually ReLU, adds non-linearity to the model,
- Pooling layer (subsampling) – reduces the dimensionality of the data, e.g., by *max pooling*,
- Fully connected layers – at the end of the network, usually for classification.

The advantages of CNNs are:

- Automatic feature detection from raw data,
- High resistance to interference and noise,
- Generalization to different types of spatial and temporal data.

Methods implementation – In our experiment we used an implementation of each method mentioned above from a repository related to an engineering thesis available here: [36]

Neural network model – The presented solution for automatic analysis of heart rate variability (HRV) uses a deep neural network designed to process raw ECG signals and calculate HRV measures. This architecture consists of several modules that perform successive stages of signal processing. The whole system operates in *end-to-end* mode, i.e., from the input signal to the final HRV values without the need for manual segmentation. The first stage is feature extraction using 1D convolutional layers (CNN), which automatically learn to represent local patterns in the ECG signal, such as QRS complexes. These layers use convolution operations, ReLU activation functions, and pooling layers, which allow for generalization and compression of information. The processed data is then passed to a segmentation module based on the U-Net architecture. The U-Net network enables precise localization of R waves through the use of a symmetric encoder-decoder structure and skip connections that transfer information from high-resolution layers to the appropriate decoding layers. The result of the U-Net operation is a binary mask indicating the positions of R waves in the signal. Based on the detected positions of R waves, RR intervals are calculated, i.e., the time differences between successive R waves. The sequence of RR intervals forms the basis for calculating selected HRV measures. In the final stage, fully connected layers are used to transform the input data into final HRV measures, such as SDNN, RMSSD, pNN50, or to classify the heart rhythm. This model combines high R-wave detection efficiency with the possibility of fully automating the HRV analysis process, making it a useful tool for both clinical diagnostics and mobile applications. The neural network diagram is shown in **Figure 2**.

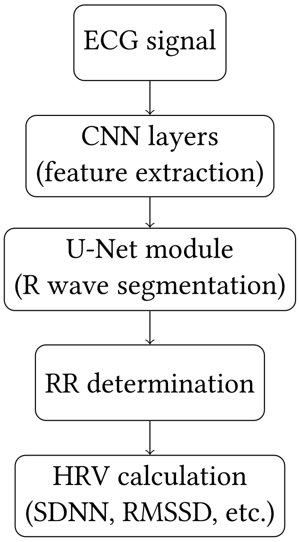

Figure 2: Block diagram of the neural network architecture for calculating HRV measures.

Heart Rate Fragmentation (HRF) – a class of indicators used to analyze heart rate dynamics, focusing on short-term, often chaotic changes in successive RR intervals. Unlike classic measures of heart rate variability (HRV), which describe overall temporal variability, HRF assesses irregularity and fragmentation of the rhythm — particularly important in the context of assessing autonomic aging and the risk of cardiovascular death. HRF focuses on short-term oscillations in the RR sequence that are not caused by physiological rhythms (e.g., breathing), but rather by dysregulation of heart rate control mechanisms. HRF is considered an independent prognostic marker — high levels of heart rhythm fragmentation are associated with a poorer prognosis and even an increased risk of death. HRF measures are particularly useful in older patients, where traditional HRV measures may not fully reflect the state of the autonomic nervous system.

PPG signal (photoplethysmographic) – a non-invasive biological signal recorded using photoplethysmography, an optical method for measuring changes in blood volume in microcirculation. This technology is widely used in medical and consumer devices (e.g., smartwatches, fitness bands) to monitor heart rate, blood oxygen saturation (SpO_2), and derived parameters such as heart rate variability (HRV). Photoplethysmography is based on the emission of light (usually in the red or infrared range) by an LED toward the skin. This light is partially absorbed and reflected by the tissues and then recorded by a photodetector. Since the degree of light absorption varies with blood flow in the vessels (related to the cardiac cycle), the PPG signal reflects pulsatile changes in blood volume. The PPG signal is wave-like and consists of:

- A constant component (DC) – dependent on tissue structure and average perfusion level,
- A variable component (AC) – corresponding to pulsatile changes in blood volume.

A typical PPG waveform contains an ascending systolic wave (associated with heart contraction) and a secondary (reflected) wave, from which characteristic points such as *peak*, *foot*, and *dicrotic notch* can be distinguished.

EDA Electrodermal Activity signals – bioelectrical signals reflecting changes in skin conductivity resulting from the activity of sweat glands controlled by the Sympathetic Nervous System. EDA measurement allows for the assessment of emotional arousal, stress, anxiety, concentration, and other psychophysiological states in humans. Electrodermal activity is usually recorded as changes in skin conductance (SC) measured between two electrodes placed on the skin surface, most often on the hand or foot. Changes in sweat gland activity, even in the absence of visible sweat, cause changes in the amount of ions on the skin surface, which affects its electrical conductivity. The EDA signal consists of two main components:

- Tonic component (SCL – Skin Conductance Level) – a slowly changing signal background reflecting the overall level of autonomic arousal,
- Phasic component (SCR – Skin Conductance Response) – rapid, transient changes in conductivity associated with responses to stimuli (e.g., sounds, emotions, stress).

EDA signals are non-invasive, relatively simple to acquire, and very sensitive to changes in sympathetic activity. However, their interpretation can be hampered by external factors (e.g., temperature, humidity) and individual variability.

Aidmed One – a medical wristband for testing apnea and arrhythmia. It has features such as ECG recording (1 channel, 250Hz, Holter ECG function), sound intensity measurement (cough and snoring detection), chest movement measurement, nasal airflow measurement (nasal cannula), blood oxygen saturation level (compatible finger pulse oximeter), skin temperature measurement, movement and position testing.

HRV examination – HRV analysis was performed on one-minute samples. Based on the ECG values, HRV measures were calculated in three ways: analytically, i.e., using mathematical formulas with the times of successive R peaks determined using the Pan-Tompkins or U-Net algorithm, and using convolutional neural networks (CNN).

Creating own dataset – This was done by using Aidmed One, which can collect ECG signal values 250 times per second. For this purpose one person wore this device while doing various types of activity, i.e. rest, walking (called "activity"), sleep and excercizing alternately with resting (called "mixed activity"). For every state, we measured for at least several dozen minutes.

Usage of prepared dataset – To use our own dataset, we had to trim it to 10 minutes frame for each state. One frame contains 150,000 samples. This is because Aidmed One takes measurement 250 times per second and multiplying this by 600 second (10 minutes) gives us 150,000 values in a given frame.

5. Results

The code and data used from our dataset are available here: [37]. For data obtained during rest, ten one-minute measurements were taken, using different methods of calculating HRV:

Table 1: HRV values for resting measurements using the Pan-Tompkins algorithm

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	10.54	39.25	19.33	827.06	48.15	36.66	15.49
2	3.63	32.47	16.07	846.23	43.71	27.85	8.7
3	57.69	44.83	23.47	850.26	71.23	32.89	**10.29**
4	0.97	**43.45**	14.15	913.23	42.95	35.89	20.31
5	11.32	49.16	23.97	**858.96**	58.88	32.21	8.82
6	31.15	51.54	25.23	852.87	59.25	**30.53**	10.29
7	22.75	40.47	24.02	901.15	**56.29**	32.0	7.69
8	**16.27**	35.21	15.76	887.28	41.12	25.9	9.09
9	10.03	34.95	**21.19**	838.4	45.15	28.46	5.8
10	26.51	57.66	28.17	821.17	60.96	26.3	1.41
Average	19.09	42.9	21.14	859.66	52.77	30.87	9.79
Std Dev	16.65	8.07	4.65	31.03	9.96	3.75	5.13

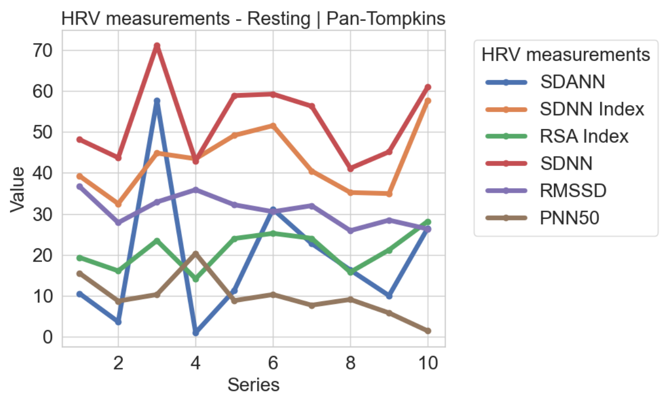

Figure 3: Chart of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements at rest using the Pan-Tompkins algorithm

Table 2: HRV measure values for resting measurements using the U-Net network

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	31.29	122.8	50.25	851.41	159.23	213.43	19.12
2	6.55	178.25	47.85	884.16	183.31	261.4	13.64
3	21.54	109.91	48.28	862.75	**115.1**	137.14	13.43
4	9.48	40.18	12.53	915.1	40.56	35.36	19.05
5	12.75	89.29	45.72	871.65	92.28	131.19	13.43
6	**18.67**	**99.68**	54.35	862.36	109.2	**144.26**	11.76
7	4.22	50.43	24.03	902.95	54.84	32.25	6.25
8	14.01	101.97	**41.56**	900.72	113.45	154.64	10.77
9	43.35	154.2	59.46	**877.15**	217.51	312.18	**12.31**
10	34.25	47.95	28.37	821.18	61.07	26.68	1.41
Average	19.61	99.47	41.24	874.94	114.66	144.85	12.12
Std Dev	12.94	45.39	14.85	27.72	57.49	97.33	5.31

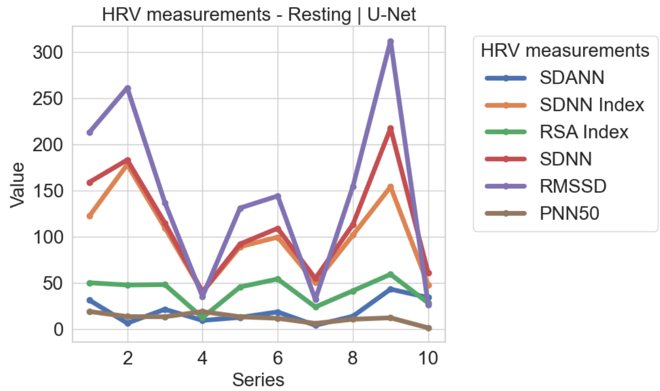

Figure 4: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements at rest using the U-Net network

Table 3: HRV values for resting measurements using convolutional neural networks

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	4.17	99.99	46.68	839.25	102.69	140.89	18.84
2	**22.2**	115.67	44.7	**871.16**	147.79	205.7	**13.43**
3	35.98	62.35	23.47	850.24	71.24	32.97	10.29
4	9.48	40.18	12.53	915.1	40.56	35.36	19.05
5	27.52	52.9	24.15	859.02	58.99	32.7	10.29
6	41.19	104.69	53.79	865.44	124.79	153.2	13.43
7	4.22	50.43	24.03	902.95	54.84	32.25	6.25
8	26.01	155.85	**42.4**	914.57	156.52	226.96	14.06
9	6.4	**98.51**	46.68	850.52	**100.37**	**135.3**	8.82
10	50.86	117.12	57.4	832.75	126.19	155.79	4.29
Average	22.8	89.77	37.58	870.1	98.4	115.11	11.88
Std Dev	16.57	36.98	15.22	30.46	40.61	75.76	4.87

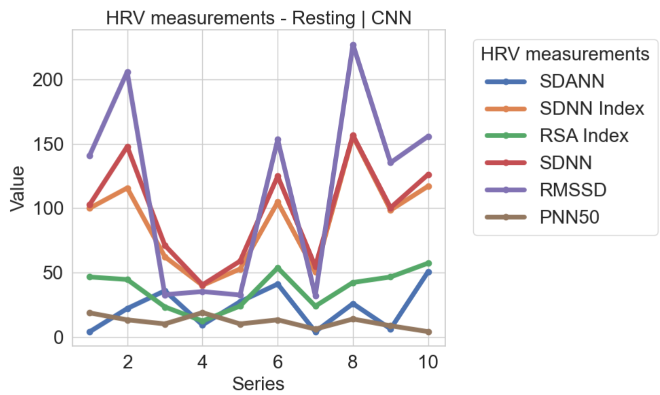

Figure 5: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements at rest using convolutional neural networks

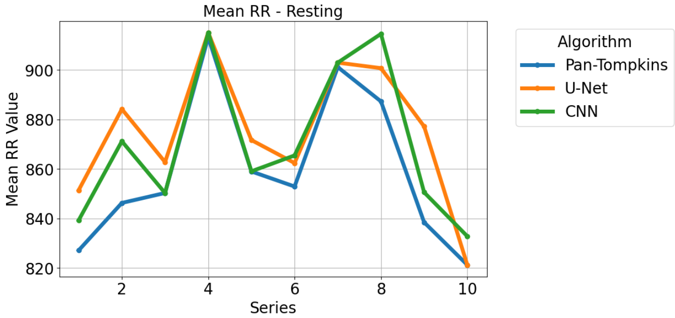

Figure 6: Mean RR graph for resting measurements

For data during activity (walking), ten one-minute measurements were taken using different methods of calculating HRV:

Table 4: HRV values for measurements during a walk using the Pan-Tompkins algorithm

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	0.51	9.49	14.94	512.9	10.98	10.81	**0.0**
2	1.25	7.84	12.66	**518.71**	10.93	12.81	0.0
3	11.0	9.25	**15.67**	492.56	15.12	8.88	0.0
4	11.03	**12.02**	16.8	490.61	**16.69**	10.68	0.0
5	**7.96**	9.37	12.46	518.71	13.04	14.23	0.0
6	2.14	10.99	9.46	505.05	10.25	12.71	0.0
7	0.19	7.77	10.01	511.83	8.76	14.28	0.0
8	3.9	8.43	11.84	517.46	10.84	10.24	0.0
9	25.78	37.58	29.35	580.24	43.28	10.55	0.0
10	11.24	25.83	26.09	562.49	37.94	**11.02**	0.0
Average	7.5	13.86	15.93	521.06	17.78	11.62	0.0
Std Dev	7.86	9.89	6.68	28.66	12.32	1.79	0.0

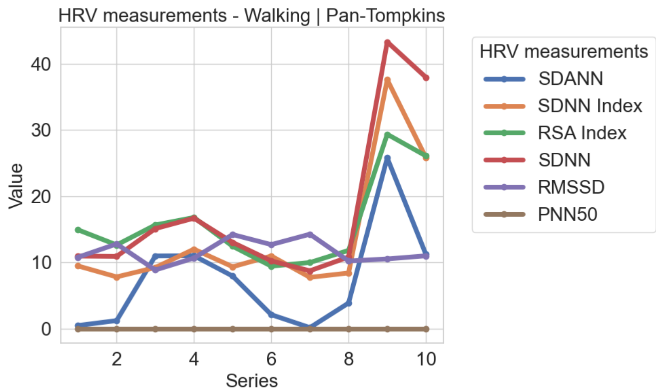

Figure 7: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements during walking using the Pan-Tompkins algorithm

Table 5: HRV measure values for measurements during walking using the U-Net network

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	3.81	43.49	66.07	517.42	49.54	68.9	1.77
2	5.6	6.83	10.47	**518.81**	9.01	4.42	0.0
3	5.28	78.93	70.66	505.11	77.72	111.42	5.13
4	17.08	44.04	71.1	494.7	50.36	**66.71**	**1.68**
5	**6.9**	8.93	10.91	518.62	11.25	5.31	0.0
6	0.28	34.73	64.63	509.38	47.07	66.72	1.72
7	6.83	40.92	61.94	516.26	48.72	68.95	1.75
8	0.15	9.09	10.81	517.39	9.53	4.27	0.0
9	28.0	**33.93**	**28.5**	580.23	43.33	10.39	0.0
10	25.95	23.78	26.12	562.58	**37.62**	7.1	0.0
Average	9.99	32.47	42.12	524.05	38.42	41.42	1.2
Std Dev	10.11	21.92	26.93	26.42	22.25	39.28	1.63

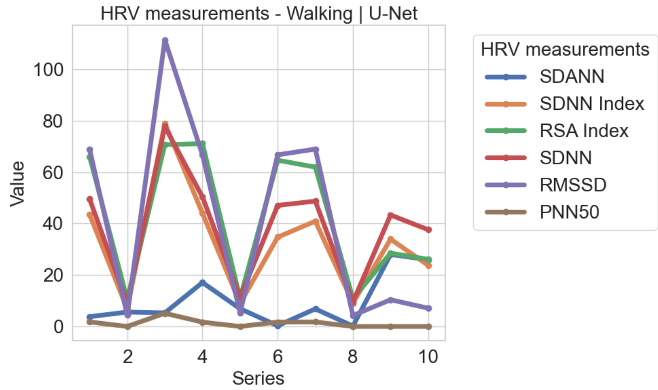

Figure 8: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements during walking using the U-Net network

Table 6: HRV values for measurements during walking using convolutional neural networks

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	**20.62**	232.04	101.57	584.69	258.95	366.04	**18.18**
2	30.87	198.06	63.83	609.74	196.07	275.75	28.12
3	4.58	183.55	88.65	562.29	**184.8**	280.87	26.67
4	27.88	152.21	89.52	530.03	152.18	220.96	14.41
5	15.54	130.64	65.32	552.24	128.52	188.84	13.08
6	7.57	185.65	83.38	**578.61**	190.44	249.22	21.57
7	7.29	134.94	80.37	544.67	142.56	201.81	10.19
8	30.41	**175.99**	80.52	589.83	189.43	262.51	23.23
9	40.58	207.95	83.11	636.99	206.39	297.38	14.29
10	45.06	158.52	**82.62**	609.9	178.64	**257.74**	14.74
Average	23.04	175.96	81.89	579.9	182.8	260.11	18.45
Std Dev	14.23	32.34	11.06	33.29	36.75	51.02	6.13

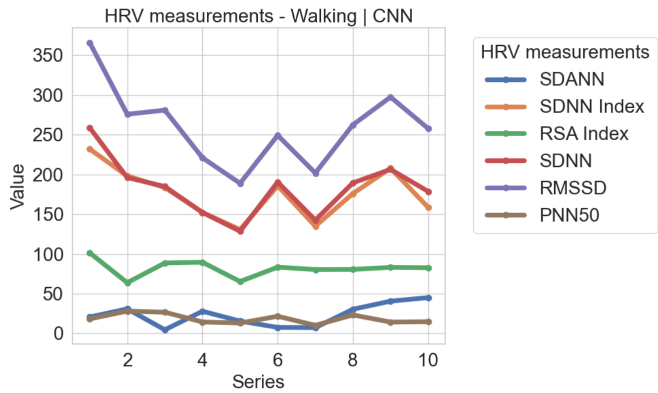

Figure 9: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements during walking using convolutional neural networks

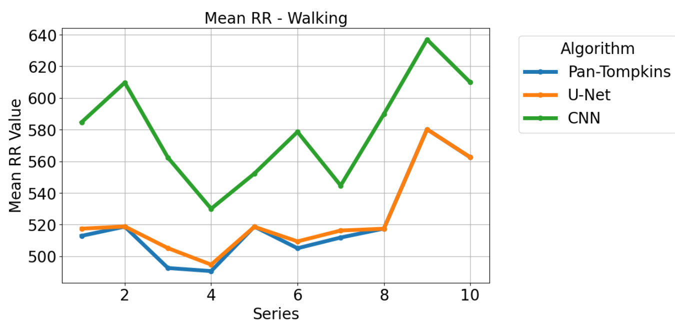

Figure 10: Mean RR graph for measurements during walking

Ten one-minute measurements were taken during sleep, using different methods of calculating HRV:

Table 7: HRV values for measurements during sleep using the Pan-Tompkins algorithm

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	**12.11**	48.0	10.49	999.93	41.44	33.84	12.07
2	22.79	33.91	**13.81**	1004.41	**48.63**	38.69	15.52
3	7.33	31.06	7.75	981.8	32.0	28.32	6.78
4	33.08	65.57	22.37	983.8	54.41	39.43	**18.64**
5	4.61	51.76	23.04	1011.53	63.63	51.22	25.86
6	1.93	**39.11**	9.25	**988.34**	39.35	35.79	20.69
7	4.25	52.68	21.79	981.13	70.42	40.84	25.42
8	9.18	36.69	8.68	1009.63	37.61	**36.38**	18.97
9	4.44	34.01	10.07	983.2	37.46	32.18	15.25
10	9.42	31.89	11.08	975.33	38.89	34.35	11.86
Average	10.91	42.47	13.83	991.91	46.38	37.1	17.11
Std Dev	9.77	11.48	6.13	13.2	12.64	6.17	6.05

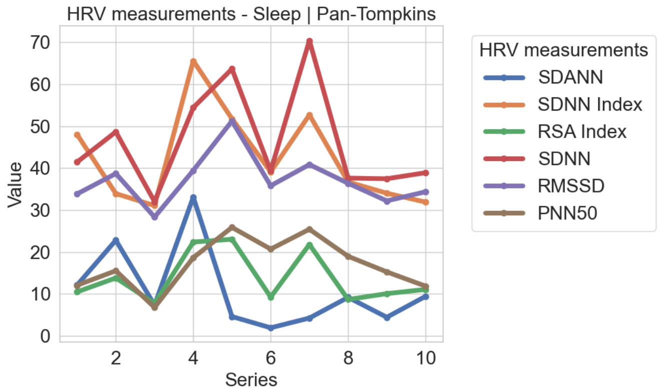

Figure 11: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements during sleep using the Pan-Tompkins algorithm

Table 8: HRV measure values for measurements during sleep using the U-Net network

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	8.31	40.54	10.56	999.91	41.41	33.77	12.07
2	14.32	**42.94**	**13.92**	1004.38	**48.61**	**38.49**	**17.24**
3	5.03	31.2	7.81	981.81	32.06	28.29	6.78
4	6.87	53.33	22.46	983.8	54.53	39.63	20.34
5	**7.64**	58.12	23.15	1011.53	63.8	51.4	24.14
6	10.43	38.47	9.44	**988.32**	39.26	35.63	20.69
7	3.8	65.79	21.78	978.73	72.27	44.02	30.0
8	9.81	36.23	8.8	1009.65	37.52	35.91	17.24
9	10.38	36.55	10.01	983.15	37.38	31.98	13.56
10	1.08	37.24	11.19	975.32	39.08	34.66	11.86
Average	7.77	44.04	13.91	991.66	46.59	37.38	17.39
Std Dev	3.8	11.21	6.12	13.44	13.07	6.54	6.75

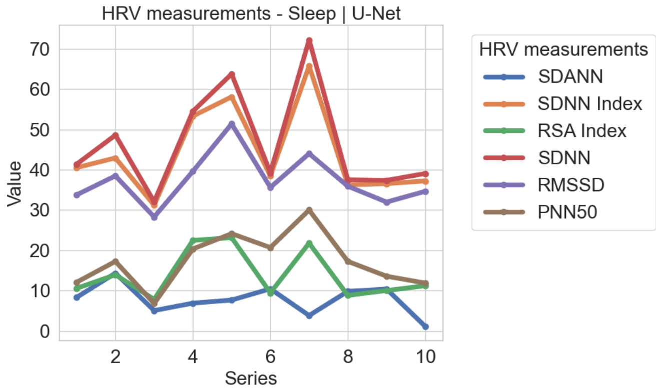

Figure 12: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measures for measurements during sleep using the U-Net network

Table 9: HRV values for measurements during sleep using convolutional neural networks

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	**8.31**	40.54	10.56	999.91	41.41	33.77	12.07
2	14.32	**42.94**	**13.92**	1004.38	**48.61**	38.49	**17.24**
3	5.03	31.2	7.81	981.81	32.06	28.29	6.78
4	6.87	53.33	22.46	983.8	54.53	39.63	20.34
5	7.64	58.12	23.15	1011.53	63.8	51.4	24.14
6	10.43	38.47	9.44	**988.32**	39.26	35.63	20.69
7	6.87	60.51	21.78	981.11	70.47	41.01	28.81
8	9.81	36.23	8.8	1009.65	37.52	**35.91**	17.24
9	10.38	36.55	10.01	983.15	37.38	31.98	13.56
10	1.08	37.24	11.19	975.32	39.08	34.66	11.86
Average	8.07	43.51	13.91	991.9	46.41	37.08	17.27
Std Dev	3.56	10.14	6.12	13.2	12.69	6.26	6.51

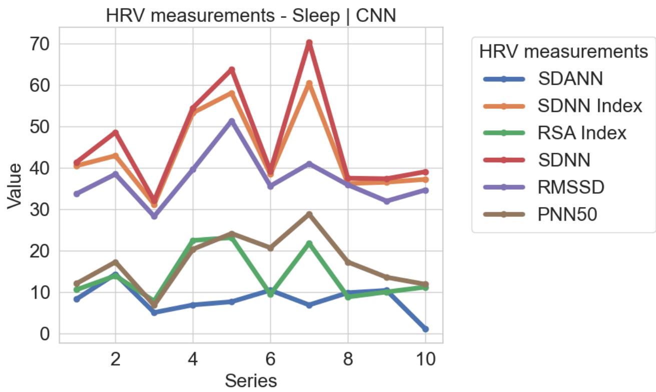

Figure 13: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements during sleep using convolutional neural networks

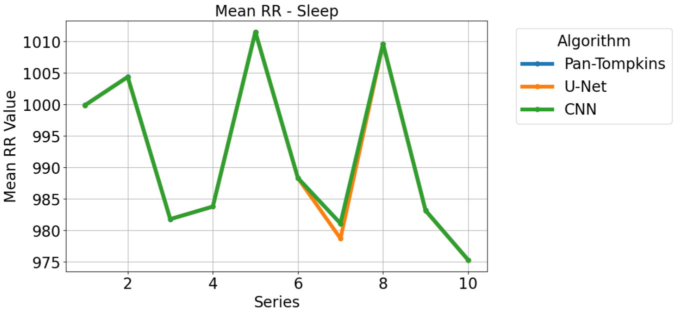

Figure 14: Mean RR graph for measurements during sleep

For data during mixed activity (one-minute activity interspersed with one-minute rest), ten one-minute measurements were taken using different methods of calculating HRV:

Table 10: HRV values for measurements during mixed activity using the Pan-Tompkins algorithm

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	35.66	39.02	55.42	538.65	**68.52**	**19.12**	4.59
2	80.58	70.64	56.49	582.04	87.32	18.37	2.97
3	29.84	34.23	186.02	507.25	60.94	41.09	2.59
4	**48.59**	**42.78**	47.42	519.51	48.68	10.48	0.88
5	16.17	35.82	**61.11**	522.51	62.58	19.91	3.57
6	62.17	47.02	50.33	592.24	76.53	15.98	**2.02**
7	24.27	43.49	175.7	544.73	76.8	40.03	3.67
8	51.25	38.85	37.29	**550.65**	60.13	8.85	0.0
9	18.41	25.26	36.11	551.7	45.41	11.47	0.0
10	63.75	35.43	34.78	581.53	70.37	7.81	0.0
Average	43.07	41.25	74.07	549.08	65.73	19.31	2.03
Std Dev	21.63	11.94	57.06	28.81	12.92	12.01	1.72

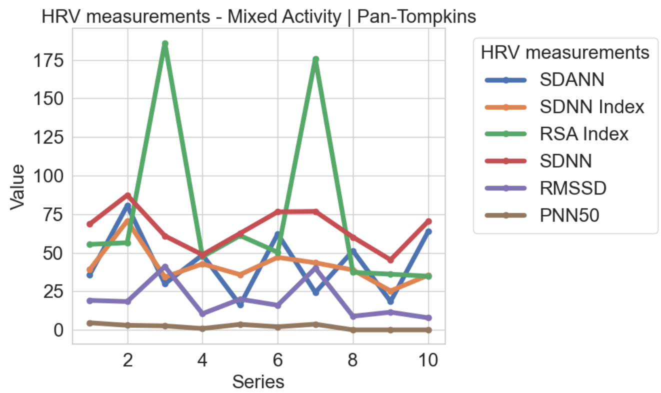

Figure 15: Chart of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measurements during mixed activity using the Pan-Tompkins algorithm

Table 11: HRV measure values for measurements during mixed activity using the U-Net network

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	48.8	127.84	**89.65**	564.31	143.2	188.41	12.5
2	70.74	**120.34**	83.97	605.81	**137.98**	**161.33**	11.34
3	13.57	207.54	102.95	565.19	204.67	274.03	14.42
4	28.89	80.08	78.75	528.74	83.0	97.76	4.46
5	33.52	211.97	102.13	**574.05**	235.99	329.64	13.86
6	49.04	90.01	157.17	592.05	104.55	105.17	**8.0**
7	31.26	152.08	148.25	580.12	159.95	220.22	12.87
8	**43.07**	62.92	64.91	566.53	92.38	117.65	5.83
9	13.17	96.42	61.14	566.61	95.86	129.14	5.83
10	59.75	51.57	60.0	587.29	81.71	71.34	2.0
Average	39.18	120.08	94.89	573.07	133.93	169.47	9.11
Std Dev	18.73	55.98	34.17	20.75	53.29	83.54	4.43

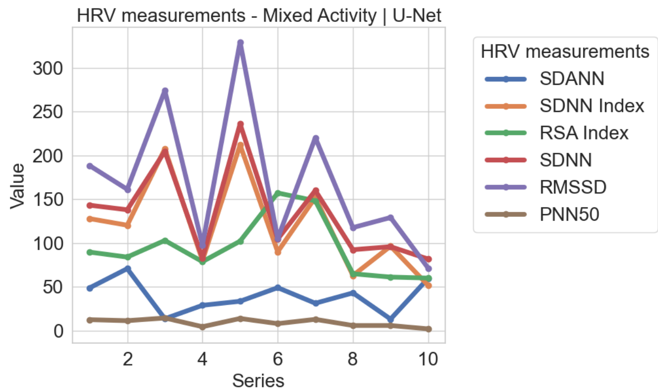

Figure 16: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measures for measurements during mixed activity using the U-Net network

Table 12: HRV values for measurements during mixed activity using convolutional neural networks

Series	SDANN	SDNN Index	RSA Index	Mean RR	SDNN	RMSSD	PNN50
1	32.3	133.01	79.46	569.74	135.88	178.62	16.5
2	57.05	154.24	**87.6**	624.94	172.58	233.86	**15.96**
3	24.53	**183.63**	92.78	565.19	**183.07**	**265.24**	17.31
4	46.5	157.04	81.53	563.65	158.31	218.45	17.14
5	61.93	288.92	108.61	602.47	343.51	496.79	20.62
6	**41.02**	188.46	113.6	623.42	279.65	382.15	6.38
7	24.99	253.95	85.09	643.18	253.75	325.54	23.08
8	25.81	101.62	85.21	589.19	144.23	173.51	9.09
9	45.22	145.79	79.58	589.28	174.38	226.57	10.1
10	64.98	106.49	75.17	**599.16**	120.41	142.94	6.12
Average	42.43	171.32	88.86	597.02	196.58	264.37	14.23
Std Dev	15.39	60.35	12.75	27.15	72.03	108.76	5.93

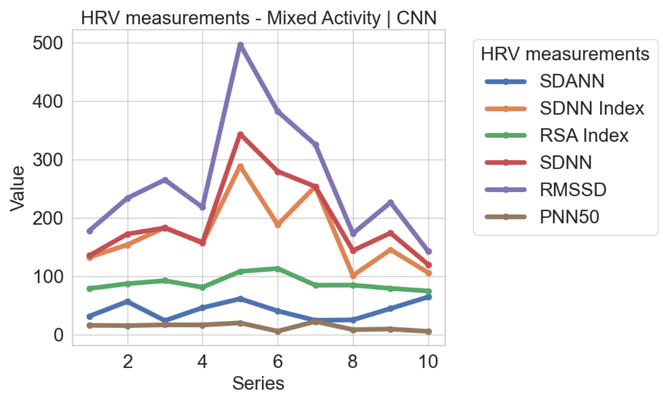

Figure 17: Graph of SDANN, SDNN Index, RSA Index, SDNN, RMSSD, pNN50 measures for measurements during mixed activity using convolutional neural networks

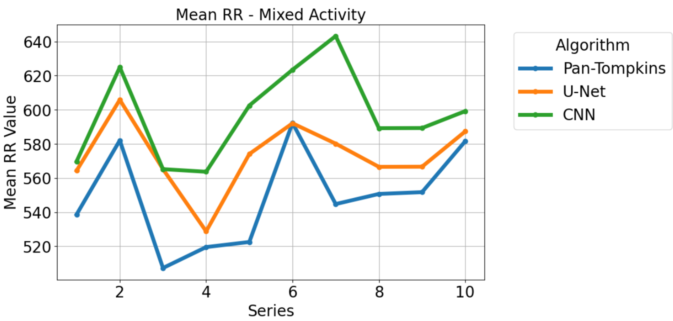

Figure 18: Mean RR graph for measurements during mixed activity

6. Conclusions

6.1. Resting

The resting state is characterized by stable heart function, i.e., RR intervals do not change significantly over time, which makes it possible to determine with high accuracy when successive heartbeats occur. Thanks to predictable periodicity, R wave detection should not pose any problems for algorithms. The Pan-Tompkins algorithm generally shows more favorable standard deviation results for HRV calculations compared to U-Net or convolutional neural networks. Only in two of the calculated measures, i.e. SDANN and Mean RR, were the results the worst, and in the case of pNN50, neural networks obtained a lower standard deviation value than this algorithm. This difference is most noticeable in RMSSD and SDNN, where in the case of the former, using the Pan-Tompkins algorithm, the standard deviation is 3.75, and in U-Net and convolutional neural networks, it is 97.33 and 75.76, respectively. Given that the average results are 30.87, 144.85, and 115.11, respectively, the standard deviation expressed as a percentage is 12.15%, 67.19%, and 65.82%. These results indicate that HRV measurement using the Pan-Tompkins algorithm in a person at rest is significantly more accurate than using the other HRV calculation methods discussed.

6.2. Walking

When walking, a person already exerts some effort, so their heart rate increases slightly compared to the previously discussed resting state. This can be seen in the lower HRV metrics we obtained, which only confirm that the intervals between successive heartbeats are shorter. Walking does not necessarily have to be done at a constant speed, e.g., due to stopping at a crosswalk. For this reason, the heart rate may also not be completely regular. This can be seen in the higher standard deviation values compared to the results obtained at rest. In the case of measurements taken during a walk, we can initially observe an interesting anomaly. In **Table 4**, i.e. using the Pan-Tompkins algorithm, the pNN50 value is 0 for each measurement, which can be interpreted in two ways; either there was a series of errors in calculating the pNN50 value for this algorithm, or the values were calculated correctly and, according to the research [11], the test subject may have had increased stress levels during the heart rate measurement. Regardless of this issue, when calculating almost every variable, the Pan-Tompkins algorithm mentioned before performed best, as apart from the standard deviation of the Mean RR variable, it obtained the lowest value in every other variable. The next algorithm that performed well was U-Net, which, apart from the RSA Index, was better at calculating the other variables compared to CNN.

6.3. Sleep

When considering the indicated types of activity, sleep is characterized by the most stable heart function. This is because people move the least during sleep, so their muscles relax, allowing the heart to pump less oxygen to them, which results in a stable, slower heartbeat. This is also confirmed by the results we obtained, as we achieved the highest HRV metrics for all types of activity during sleep. For this reason, the standard deviation results obtained for all variables are satisfactory when using each of the algorithms. Nevertheless, the best results were obtained using convolutional neural networks, but the difference compared to other methods of calculating HRV was minor. Due to the visible difference in the SDANN standard deviation, the Pan-Tompkins algorithm performed the worst, with a value of 9.77, while U-Net had 3.8 and CNN had 3.56.

6.4. Mixed activity

Of the four types of activity examined, i.e. rest, walking, sleeping and mixed activity, the algorithms performed worst at calculating the exact result for this one. This is due to a simple fact, namely the periodic change in activity, i.e. every minute, the test subject either performed physical exercise, which caused the heart to beat faster, or rested, which caused the heart to try to return to its normal rhythm. Such alternating changes in heart rate complicate the operation of each of these algorithms, as they are not adapted to continuous rapid changes with each subsequent measurement. None of the algorithms stood out significantly from the others in terms of standard deviation results. As in previous cases, the best results were obtained when using the Pan-Tompkins algorithm, but its advantage in this case was the smallest of all the types of activity compared. Pan-Tompkins obtained a significantly lower standard deviation value for RMSSD, i.e. 12.01, compared to 83.54 for U-Net and 108.76 for CNN. With regard to SDNN, the values were 12.92, 53.29 and 72.03, respectively, and in the case of SDNN Index, the standard deviation for the individual algorithms was as follows: 11.94, 55.98 and 60.35. The other algorithms, on the other hand, showed more promising results when calculating SDANN or RSA Index, as in the case of the former, the values were 21.63, 18.73 and 15.39, and in the case of the latter, they were 57.06, 34.17 and 12.75.

6.5. Overall summary

In most cases, when activity was more dynamic the most accurate method for calculating HRV values was the Pan-Tompkins algorithm. When data was gathered from periods when heart function was more stable, Convolutional Neural Network and U-Net network performed slightly better than the Pan-Tompkins algorithm. This means the Pan-Tompkins algorithm should be used for calculating HRV values in wristbands for runners and other devices used during sport activities. CNN or U-Net network may be used for devices that monitor heart functions during sleep, e.g. in field hospitals or at home.

6.6. Future work

Future work will focus on testing methods of calculating HRV on devices with different sampling rate than Aidmed One, e.g significantly higher such as 500 Hz and 1000 Hz or lower such as 100 Hz and 50 Hz, but the latter may be problematic because some HRV values require high enough sampling rates. This difficulty, however, may be overcome using interpolation. Future work will also focus on comparing new methods of HRV calculation, such as the Hamilton–Tompkins algorithm, Christov Algorithm or Engelse–Zeelenberg algorithm.

References

[1] J. Burma, J. Griffiths, A. Lapointe, I. Oni, and A. Soroush, "Heart rate variability and pulse rate variability: do anatomical location and sampling rate matter?," *Sensors*, vol. 24, no. 7, p. 2048, 2024.

[2] Y. Sun, S. Hu, V. Azorin-Peris, R. Kalawsky, and S. E. Greenwald, "Noncontact imaging photoplethysmography to effectively access pulse rate variability," *Journal of Biomedical Optics*, vol. 18, no. 6, p. 061205, 2012.

[3] M. D. Peláez-Coca, A. Hernando, J. Lázaro, and E. Gil, "Impact of the ppg sampling rate in the pulse rate variability indices evaluating several fiducial points in different pulse waveforms," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 2, pp. 539–549, 2022.

[4] J. Sacha, "Interaction between heart rate and heart rate variability," *Annals of noninvasive electrocardiology*, vol. 19, no. 3, pp. 207–216, 2014.

[5] K. S. Quigley, P. J. Gianaros, G. J. Norman, J. R. Jennings, G. G. Berntson, and E. J. de Geus, "Publication guidelines for human heart rate and heart rate variability studies in psychophysiology—part 1: Physiological underpinnings and foundations of measurement," *Psychophysiology*, vol. 61, no. 9, p. e14604, 2024.

[6] U. Zalabarria, E. Irigoyen, R. Martinez, and A. Lowe, "Online robust r-peaks detection in noisy electrocardiograms using a novel iterative smart processing algorithm," *Applied Mathematics and Computation*, vol. 369, p. 124839, 2020. Image from Figure 4 is taken from this article.

[7] E. J. C. de Geus, P. J. Gianaros, R. C. Brindle, J. R. Jennings, and G. G. Berntson, "Should heart rate variability be "corrected" for heart rate? biological, quantitative, and interpretive considerations," *Psychophysiology*, vol. 56, no. 2, p. e13287, 2019.

[8] E. Mejía-Mejía, J. M. May, R. Torres, and P. A. Kyriacou, "Pulse rate variability in cardiovascular health: a review on its applications and relationship with heart rate variability," *Physiological measurement*, vol. 41, no. 7, pp. 7–, 2020.

[9] E. Friligkou, D. Koller, G. A. Pathak, E. J. Miller, R. Lampert, M. B. Stein, and R. Polimanti, "Integrating genome-wide information and wearable device data to explore the link of anxiety and antidepressants with heart rate variability," *medRxiv*, 2023.

[10] J. D. Stone, H. K. Ulman, K. Tran, A. G. Thompson, M. D. Halter, J. H. Ramadan, M. Stephenson, V. S. Finomore Jr, S. M. Galster, A. R. Rezai, *et al.*, "Assessing the accuracy of popular commercial technologies that measure resting heart rate and heart rate variability," *Frontiers in Sports and Active Living*, vol. 3, p. 585870, 2021.

[11] J. E. Mietus, C.-K. Peng, I. Henry, R. L. Goldsmith, and A. L. Goldberger, "The pnnx files: re-examining a widely used heart rate variability measure," *Heart*, vol. 88, no. 4, pp. 378–380, 2002.

[12] F. Shaffer and J. Ginsberg, "An overview of heart rate variability metrics and norms," *Frontiers in Public Health*, vol. 5, p. 258, 2017.

[13] B. Przybysz-Zdunek and R. Główczyńska, "Zmienność rytmu serca w ujęciu praktycznym — doceniany czy zapomniany parametr oceny holterowskiej?," *Folia Cardiologica*, vol. 12, no. 6, pp. 617 – 624, 2017.

[14] L. Lu, T. Zhu, D. Morelli, A. Creagh, Z. Liu, J. Yang, F. Liu, Y.-T. Zhang, and D. A. Clifton, "Uncertainties in the analysis of heart rate variability: A systematic review," *IEEE Reviews in Biomedical Engineering*, vol. 17, pp. 180–196, 2024.

[15] R. Gilgen-Ammann, T. Schweizer, and T. Wyss, "Rr interval signal quality of a heart rate monitor and an ecg holter at rest and during exercise," *European Journal of Applied Physiology*, vol. 119, p. 1525–1532, Apr. 2019.

[16] M. Gusev and S. Tudjarski, "Sampling rate impact on heart rate variability," in *30th International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, 2022.

[17] J. Burma, A. Lapointe, A. Soroush, and I. Oni, "Insufficient sampling frequencies skew heart rate variability estimates," *Journal of Biomedical Informatics*, vol. 118, p. 103778, 2021.

[18] M. Rohr, M. Tarvainen, S. Miri, G. Güney, and A. Vehkaoja, "An extensive quantitative analysis of the effects of errors in beat-to-beat intervals on all commonly used hrv parameters," *Scientific Reports*, vol. 14, p. 2341, 2024.

[19] D. Singh, K. Vinod, and S. Saxena, "Sampling frequency of the rr interval time series for spectral analysis of heart rate variability," *Journal of Medical Engineering & Technology*, vol. 28, no. 6, pp. 263–272, 2004.

[20] N. Napoli, M. Demas, S. Mendu, and C. Stephens, "Uncertainty in heart rate complexity metrics caused by r-peak perturbations," *Computers in Biology and Medicine*, vol. 100, pp. 43–50, 2018.

[21] R. Silva, G. Salvador, P. Bota, and A. Fred, "Impact of sampling rate and interpolation on photoplethysmography and electrodermal activity signals' waveform morphology and feature extraction," *Neural Computing and Applications*, 2023.

[22] A. Choi and H. Shin, "Photoplethysmography sampling frequency: pilot assessment of how low can we go to analyze pulse rate variability with reliability?," *Physiological Measurement*, vol. 38, no. 9, p. 1655, 2017.

[23] G. Clifford and L. Tarassenko, "Quantifying errors in spectral estimates of hrv due to beat replacement and resampling," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 4, pp. 630–638, 2005.

[24] D. Cajal, D. Hernando, J. Lázaro, P. Laguna, and E. Gil, "Effects of missing data on heart rate variability metrics," *Sensors*, vol. 22, no. 15, p. 5774, 2022.

[25] R. Ellis, B. Zhu, J. Koenig, and J. Thayer, "A careful look at ecg sampling frequency and r-peak interpolation on short-term measures of heart rate variability," *Physiological Measurement*, vol. 36, no. 9, p. 1827, 2015.

[26] M. Merri, D. Farden, J. Mottley, and E. Titlebaum, "Sampling frequency of the electrocardiogram for spectral analysis of the heart rate variability," *IEEE Transactions on Biomedical Engineering*, vol. 37, no. 1, pp. 99–106, 1990.

[27] J. Heathers, "Everything hertz: methodological issues in short-term frequency-domain hrv," *Frontiers in Physiology*, vol. 5, p. 177, 2014.

[28] J. McNames and M. Aboy, "Reliability and accuracy of heart rate variability metrics versus ecg segment duration," *Medical and Biological Engineering and Computing*, vol. 44, no. 9, pp. 747–756, 2006.

[29] J. Hayano, M. Kisohara, N. Ueda, and E. Yuda, "Impact of heart rate fragmentation on the assessment of heart rate variability," *Applied Sciences*, vol. 10, no. 9, p. 3314, 2020.

[30] L. J. Onimaru, D. G. D. Christofaro, H. B. Valente, I. C. Leoci, M. L. Andersen, S. Tufik, G. Ferrari, L. C. M. Vanderlei, W. R. Tebar, and P. K. Morelhão, "The relationship between sleep quality and cardiac autonomic modulation according to physical activity levels in adults: a cross-sectional study," *Sleep breathing*, vol. 29, no. 4, pp. 216–, 2025.

[31] H. Liu, X. Wang, and X. Wang, "The correlation between heart rate variability index and vulnerability prognosis in patients with acute decompensated heart failure," *PeerJ*, vol. 11, p. e16377, 2023.

[32] J. Pan and W. J. Tompkins, "A real-time qrs detection algorithm," *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230–236, 1985.

[33] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," 2015.

[34] D. Sharma and N. Kohli, "Ventricular fibrillation detection based on modified u-net feature extraction model," in *International Conference on Mathematics and Logics in Computer Science*, pp. 1–13, Springer, 2024.

[35] J. Sohn, H. Shin, J. Lee, and H. C. Kim, "Validation of electrocardiogram based photoplethysmogram generated using u-net based generative adversarial networks," *Journal of Healthcare Informatics Research*, vol. 8, no. 1, pp. 140–157, 2024.

[36] J. W. Piotr Wesołowski, "Engeenering thesis repository," 2024. https://github.com/PiotrexOG/ECG , accesed on 5th of July 2025.

[37] B. Kołakowski, "Dataset used in this paper," 2025. https://github.com/bartekk3007/ComparativeAnalysisOfMethodsForCalcu accesed on 25th of September 2025.