Department of Electrical and Computer Engineering

Part IV Research Project

Literature Review and

Statement of Research Intent

Project Number: 97

Automated smartphone emergency callouts for heart disease sufferers

Author: Marcus Wong

Project Supervisor: Avinash Malik

Secondary Supervisor: Kevin Wang

24 August 2018

Declaration of Originality

This report is my own unaided work and was not copied from nor written in collaboration with any other person.

Marcus Wong

ABSTRACT: Sufferers of heart disease are often at risk of potentially life-threatening arrhythmia events, and existing solutions rely on human judgement to call for medical attention. Our research intent is to explore the feasibility of an automated heart alert system, suitable to be worn comfortably outside of clinical contexts. The system will alert for medical attention when anomalies in heart activity are detected. This literature review explores current research surrounding real-time heart monitoring, and machine learning for heart condition classification. Our findings supported a heart rate variability based (HRV) approach to heart monitoring, using the commercially available and ECG-accurate Polar H7 belt for data acquisition. Subsequent research proved that frequency-domain based HRV metrics were useful in training artificial neural networks to classify undesirable heart conditions, with one study obtaining a three-way classification accuracy of 95.4%. Thus, our project aims to combine these two fields of research in a smartphone/wearable based system. This is achieved through using a Polar H7 wearable to send R-R interval data to a smartphone app, which will be processed into a live calculation of HRV. A neural network will be trained to classify heart condition from HRV metrics, using datasets from Physionet. The resulting classifier will be used to issue an emergency callout if needed, ultimately assisting in the non-invasive monitoring of arrhythmia sufferers in their day-to-day lives.

1. Problem Statement & Research Intent

In New Zealand alone, one in twenty people currently suffer from heart disease [1]. A side effect of this condition includes disruptions and irregularities to heart rhythm, known medically as heart arrhythmia. Despite arrhythmia being a prolific and potentially life-threatening issue, it is often difficult for at-risk individuals to be constantly monitored in a clinical context. This is due to costs, healthcare system constraints and the fact that many at-risk people continue to function normally in their day-to-day lives.

This presents a growing need for an easily accessible and low cost solution for providing swift medical attention when anomalies in heart activity are detected. The solution must be designed to be able to monitor at-risk patients in their day-to-day lives, and thus must be simplistic in setup and everyday use. It should optimally also need as little user input as possible. It is well researched that sufferers often do not perceive they are in a life-threatening event, due to exaggerations of what heart problems look like in media [2]. Users often make misjudgments in the criticality of their condition, and cause unnecessary delays before calling appropriate emergency services.

The most elementary solution to this problem is the use of an medical alert button [3] placed in homes, or on the wrist to trigger medical services [4]. However, this approach often fails at its purpose. Utilizing these alerts are not necessarily top-of-mind when a user is suffering from an intense, life-threatening event; conversely, the user may underestimate the event that is occurring. This is made worse if the user needs to exhibit physical or mental effort, like running to an alert button's location in their home. There is also strong evidence to suggest that many at-risk patients may also suffer from other debilitating diseases that limit their ability to physically activate their alert [5].

With advancements in real-time heart monitoring and machine learning techniques, our research aims to improve upon these solutions.

2. Literature Review

2.1 Real-time Heart Monitoring

Real-time monitoring and emergency callouts for health related events have been explored in research quite extensively with the advent of sensor technology. For our particular use case, a highly cited paper by Aniker et. al [6] showcases AMON, a wearable multi-parameter medical monitoring and alert system. The first of its kind in 2004, the AMON standalone bracelet utilizes a multitude of biometric sensors to collect patient information, including an ECG sensor for heart condition data. However, as a standalone device, the AMON prototype soon found that a physical amplifier was required during readings to both amplify and filter out noise from the signal. The device itself also only supported a single-lead ECG reading, due to its compact size – which led to inaccuracies in readings. Ultimately, AMON proved the feasibility of lightweight wearables being used for medical monitoring and alerts – but more work was required to design a wearable suitable for everyday ambulatory use.

Other approaches inspired by the AMON device improved ease of use and accuracy, [8] by using mobile phone connectivity to allow visual prompts on how to manage and place ECG electrodes. This ensured that users were able to get as accurate a reading as possible – however the difficulty of acquiring an ECG reading on the go remained. A user-initiated heart-attack 'self-test' was used to ask a series of questions aimed to detect erratic heart behaviour based on symptoms. This data, combined with information from a 2-lead ECG reading, aimed to produce a more accurate output with less false positives. The issue with this approach, however, is that users are still required to initiate the test themselves – leading to possible human misjudgment and underestimation of the event's seriousness [3].

It was also mentioned that further signal processing work in software would be required to improve the range of conditions the system detected. In a subsequent study by Jin et. al [8], software capability was expanded to detect "normal, premature ventricular contraction, sinus bradycardia, ventricular flutter, and left bundle branch block beats." This research hints that the computational capabilities of a mobile phone would be adequate for the classification of various disease states; fitting well with our own system's desired outcome.

A pattern in research started to form; a lot of highly cited real-time heart monitoring research focused on ECG-based solutions. However, the difficulty of placing electrodes, noisy signals, and wrestling with ECG leads meant that these solutions did not fit well with our proposed system's plan of being worn constantly, in order to catch any heart anomalies as they come. Thus, exploration into research that tackled these challenges were necessary – this led to the discovery of research using wireless electrodes [9] [10]. These electrodes would be placed and maintained on the body with minimal upkeep and reduced wires, using communication protocols like Bluetooth to transmit data to a base unit. Studies concluded that the feasibility of these devices were uncertain. The accuracy of ECG readings was questioned, especially while wearing thick pieces of clothing. Most importantly, wireless electrode solutions remained expensive to produce and widely unseen in a commercial context, with cheapest solutions costing upwards of 500 US dollars [11]. This is simply not feasible given the budget of our research, thus ending endeavours in pursuing wireless electrode-based heart monitoring.

In an effort to find a heart monitoring system that would be both user-friendly and cost-effective, research moved towards evaluating solutions that potentially did not use the ECG signal to derive heart condition data. A widely cited and helpful paper by Pantelopoulos and Bourbakis analysed a variety of wearable sensor-based systems for health monitoring and prognosis [12]. The paper explored systems utilizing other metrics such as the photoplethysmogram (PPG) to capture heart condition data by analyzing changes in blood absorption. This is done through a pulse oximeter, which illuminates the skin surface. However, it was observed that the process of measurement is still awkward to use - the pulse oximeter is a large device surrounding an index finger, which is difficult to keep on at all times without inhibiting limb use. Additionally, the captured reading of SpO2 (peripheral oxygen saturation), is not always identical to the more desired SaO2 (arterial oxygen saturation) – the metric used to derive heart condition data – leading to reduced accuracy compared to ECG-based methods [13]. Ultimately, it was concluded that SpO2-based heart data would be a component of our system only if no other alternatives were found. SpO2 solutions were more portable and less 'messy' compared to ECG, but still felt strange to use in a day to day context.

2.2 HRV: Advantages and Methods of Derivation

The above study also mentioned the growing popularity of deriving heart condition data using heart rate variability metrics, or HRV. Heart rate variability is defined as the measure of overall variation between heart beats over a period of time. The time between two successive heart beats is academically referred to as R-R intervals. It is intuitively similar to the more well-known metric of BPM, or beats per minute. Conversion from BPM to an R-R interval is as shown below in Figure 1:

$$RR(ms) = 60seconds * \frac{1000}{BPM}$$

Figure 1: Conversion from BPM to R-R interval

By providing R-R intervals over a specified time window, variation between inter-beat durations can be quantified as HRV.

Compelling evidence has accumulated that correlate HRV parameters to performance mechanisms in the body involved in cardiac-related sudden death, such as the autonomic nervous system [14]. Research into commercially available solutions to help capture HRV data led to the discovery of the Polar line of heart rate monitoring products – aimed to capture ECG-accurate heart rate data. The Polar H7 Belt in particular was the subject of further medical studies which aimed to compare accuracies of commercially available heart rate monitoring solutions to ECG readings. Results of two popular studies showed that heart beats recorded using the Polar H7 belt highly correlated with the successive peaks of two QRS complexes (i.e. R-R intervals) in an ECG reading, with correlation reaching 99.6% in one study [15] and 80.0 - 98.8% in one confidence interval in another study [16].

Polar H7 belts are easy to wear. Currently, they are used in fitness contexts and require a slight wetting of the belt to activate the lining of electrodes. A hardware processing unit is attached to the belt, with the complete system being non-invasive and comfortable.

This ease of use was a key factor in finalizing our decision to use the Polar H7 belt in our research. Ultimately, this meant that the direction of our research aimed to further explore using heart rate variability for arrhythmia detection.

There is a large amount of research surrounding the derivation of HRV metrics from ECG readings, as well as real-time smartphone-based implementations using Polar H7 heart rate data for calculating HRV [17] [18] [19]. This gave us confidence in the feasibility of our proposed system – ECG-based datasets or raw R-R intervals could be processed into HRV metrics, and these metrics would be used as inputs to train a neural network capable of classifying different heart states. On the smartphone, heart rate data from the Polar H7 belt could be processed into the same HRV metrics, and fed through our algorithm to give a resultant decision of current heart condition.

With most heart rate data being ECG-based, it was suspected that understanding how to convert an ECG signal into R-R intervals would be a necessary preceding step before conversion into HRV. The data preparation steps shown in the study by Timothy et. al [17, Tab. 4] highlights the steps required to turn any ECG signal into HRV metrics, by first using a what is known as the Pan-Tompkins algorithm [20]. This algorithm calculates R-R intervals from ECG readings through identifying 'peaks' of a QRS complex (i.e. the visual 'spike' on an ECG graph) and then filtering the signal through use of a band pass filter to clean out noise, differentiator to accentuate rate-of-change movements, and moving window integration to produce a digital pulse stream. This stream indicates an R-R interval by observing the time between two high 'pulses'.

After producing R-R intervals, quantifying its variability can be approached in three ways: metrics in the time domain, the frequency domain and through non-linear analysis. To decide what approach to use, more research would be required to see which methods have been used successfully in the context of machine learning.

2.3 Machine Learning

The first paper exploring the use of machine learning to classify HRV metrics into disease states used metrics gathered from non-linear analysis [21]. The choice to use non-linear analysis is justified in the study, explaining that the beating of the heart encompasses lots of relationships between interconnected physiological systems. Factors such as the nervous system, respiration, thermoregulation and blood pressure all contribute to a heartbeat. This means the behaviour of the cardiovascular system can be better modelled using a non-linear complex system to observe overall patient health, instead of the function of its individual parts. This paper in particular used Parallel Cascade Identification (PCI) for feature extraction, a technique involving the gradual building of a complex non-linear system aimed to model heart behaviour, given output and input information. Each successive component is added iteratively to the model, and is 'best fit' in order to reduce residual error between desired output and the sum of the outputs of previously added cascade models. Statistical tests are also applied to the potential cascade models to decide whether certain models are relevant data or just noise artefacts. Results of this paper were lukewarm, with a 56.5% sensitivity rate and 60.8% specificity rate when attempting four-way classification between three undesired heart states and a normal sinus rhythm. Overall, these results seemed poor and may not be accurate enough to use in our proposed system.

Subsequent research attempting to build on non-linear HRV analysis have moved into using Poincare plots [22] to achieve much higher success with classification (with a 97.31% accuracy). A Poincare plot is a recurrence plot often used to quantify self-similarity, and thus helps distinguish chaos from randomness in data. In the context of HRV, the Poincare plot is constructed by plotting an R-R interval on the x-axis, versus the succeeding R-R interval on the y-axis. Various non-linear metrics are derived from this plot, with the paper using K-nearest neighbour classifier to achieve strong classification rates.

Non-linear analysis is not the only method of HRV classification. Another popular method involves frequency domain analysis via first order spectra and higher order spectra, first seen in a study by Obayya and Abou-Chadi [23]. Interestingly, despite non-linear analysis-focused HRV research touting frequency domain metrics as inferior in accuracy, this paper contradicts this notion by achieving classification rates greater than the previous paper.

Frequency-domain based HRV metricss utilize the fact that power spectral analysis of HRV quantifies the sensitivity of the heart to modulation. This fact has been scientifically proven in medical journals, with particular spectrum bands correlating to sympathetic and parasympathetic activity [24], thus allowing the behaviour of the autonomic nervous system to be inferred. Three specific frequency domain HRV parameters were calculated from ECG datasets during first order spectra analysis:

- normalised low frequency power in the band 0.04-0.15 Hz, 'LF'. This reading correlates to

sympathetic activity, which infers increasing heart rate among other uses
- normalised high frequency power in the band 0.18-0.4 Hz, 'HF'. This reading correlates to parasympathetic activity, which infers decreasing heart rate among other uses
- the ratio between low frequency and high frequency LF/HF, correlating to sympathovagal balance, or the comparison of 'nerve traffic' in the autonomic nervous system.

Resulting metrics were fed into a back propagation neural network. The network was configured to train datasets until the sum of the square of absolute error < 0.01, or 2000 epochs was reached. The chosen architecture of the neural network contained 3 inputs, one hidden layer with 15 neurons and 3 outputs. The paper does not go into detail on the choice of using 15 neurons, or why a back propagation network is necessary with only one hidden layer; however using the sum of the square of absolute error as the loss function is a typical practice and the choice of input and output values are self-explanatory.

Results of three-way classification between congestive heart failure, myocardial infarction and normal sinus rhythm in this study proved surprisingly accurate using first order spectra, achieving an accuracy rate of 95.4% [23, Tab. 1].

The paper also explores the more complicated higher order spectra technique for classification. This involved the calculation of three key parameters – the estimated bisprectrum, bicoherence index and bispectral entropy. These three parameters are essentially calculated from a combination of fourier transforms, averaging of power spectrum analysis, and normalized logarithmic equations. These, fed into a neural network, produced results that were slightly more accurate than first order spectra, with an accuracy rate of 98.8%. However, for our purposes, there were concerns regarding the ability for higher order spectra parameters to be calculated on a smartphone in a timely manner. First order spectra remained promising as a good starting point due to ease of computation.

In summary, from reviewing literature we have identified gaps in research. Our project aims to combine the two research fields of smartphone-based real-time heart monitoring via HRV, with machine learning research on classifying heart activity. This effectively replaces the issues presented in ambulatory monitoring of ECG signals in a low cost fashion. Our solution also builds upon a commercially available product, the Polar H7 belt, thereby keeping our implementation practical and easy to use for a patient.

3. Proposed Methodology

From the literature reviewed, the implementation of our system will be organized as below.

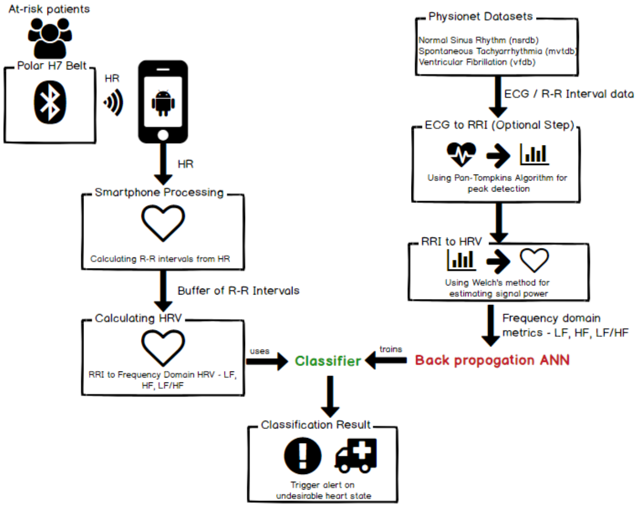

Figure 2: High-level system diagram

We plan to start our implementation by downloading the relevant datasets for different heart states, for the purposes of machine learning. Publicly identifiable datasets were found on Physionet, pertaining to undesirable states such as ventricular fibrillation and supraventricular arrhythmia, which are serious conditions that often lead to cardiac arrest.

Interestingly enough, there is a database on Physionet capturing R-R interval data prior to ventricular tachyarrhythmia. Known as the Spontaneous Ventricular Tachyarrhythmia Database [25], data was captured via an implantable cardioverter-defibrillator (ICD), a medical device used for defibrillation and pacing of the heart. Upon the detection of a heart event, a snapshot of the ICD R-R interval buffer in memory was made, storing the 1024 R-R intervals preceding the event. Of all the data, this particular dataset remains the most promising to use for the timely detection of abnormal heart events – it even provides the added benefit of not needing ECG to R-R interval conversion.

In terms of power spectrum analysis, initial exploration using Python's scipy library [26] brought attention to the fact that it is ill-advised to use computationally cheap methods, such as the Fast Fourier Transform for ECG analysis. This is due to the method having little consideration for the noise naturally present in a stochastic process such as an ECG recording. However, the alternative "Welch" method accounts for noise by splitting samples into further pieces and performing the average of those samples to smooth outliers out. Fortunately, this method was found to have many open source, GPL-licensed implementations [27]. From this information, we opt to use Welch to calculate the three frequency domain metrics identified in research (LF, HF and LF/HF).

From these metrics, an artificial neural network is to be designed to test the presence or absence of a heart condition (binary classification), following the methodology found in Obbaya and Abou-Chadi's paper [24]. Development will be done via Keras, a high-level Python library that wraps Tensorflow implementation. This library was chosen due to its consistent and simple APIs, allowing for different network layers to be designed on a conceptual level [28]. Neural networks designed through Keras are also compatible with exporting to Android, which is a necessity for our implementation.

A heatmap will be used in testing the back propagation neural network under different hidden layer and neuron configurations, starting with one hidden layer and fifteen neurons, as per our research. From this starting point, we aim to use the heatmap to optimise the network for increased accuracy towards our own use case. Sensitivity, specificity and overall accuracy rates of our algorithm in the form of a confusion matrix would be required to understand the overall validity of the model. This can be output using well known Python libraries such as scikit-learn. To follow best practice, k-fold cross validation will be conducted to ensure that the model is adequately trained.

Android as a smartphone app platform was chosen given our familiarity with Java compared to iOS's Swift. As shown in Figure 2, a successful Bluetooth Low Energy connection will need to be made between belt and device – transferring heart rate data. According to the datasheet for the Polar H7 [29, p. 7], the services and characteristics to facilitate communication is done via the Bluetooth Heart Rate Service specification (HRS), a Bluetooth SIG defined communication profile [30]. After establishing a successful app-to-belt connection, processing will be required on the smartphone to develop HRV metrics that is fed into the classifier, in order for the system to reach a result. This may require a custom library to be written and implemented on the phone. Once a complete classification can be completed on an app, timing logs should be conducted to better understand response time of our system. Time periods of interest would include the time taken from acquiring the data from the Polar H7 to calculating HRV metrics, time taken for the classifier to return a result, and time taken for the overall process. Timeliness is a critical component in medical scenarios.

Lastly, as a time constraint, it will not be possible to test the system on real patients. In order to assess our real-time classification rigorously, it will be mandatory to create a custom device to simulate a distressed heart. This can be done by holding out ventricular tachyarrhythmia R-R interval datasets, and using an external embedded device that can simulate the Polar H7. Luckily, as the Polar H7 follows the Bluetooth SIG defined Heart Rate Service mentioned earlier, we can use a Bluetooth Low Energy enabled embedded development kit to setup an identical connection to the app over HRS. The device will then send custom R-R interval data from the ventricular tachyarrhythmia dataset, and analysis will be done to check the classifier's real-time accuracy.

4. Conclusion

From reviewing literature in real-time heart monitoring, heart rate variability and machine learning techniques, we have established feasibility on engineering a system that incorporates research outcomes from all three fields. A user-friendly, cost-effective system for automated emergency callouts will be developed, triggering on the detection of a potentially life threatening event. To achieve this, the system will use machine learning to train datasets related to different heart states, based on heart rate variability metrics. An Android app interfacing with a heart-rate monitoring wearable will then be used to gather real-time heart rate variability data and process it as input into our machine learning classifier. The resulting classification will ultimately help assist in the non-invasive monitoring of arrhythmia sufferers in their day-to-day lives.

5. References

[1] "Heart disease statistics - Heart Foundation," *Heart Foundation NZ.* [Online]. Available: https://www.heartfoundation.org.nz/statistics. [Accessed: 05-Apr-2018].

[2] J. R. Finnegan *et al.*, "Patient Delay in Seeking Care for Heart Attack Symptoms: Findings from Focus Groups Conducted in Five U.S. Regions," *Prev. Med.*, vol. 31, no. 3, pp. 205–213, Sep. 2000.

[3] "How the St John Medical Alarm service works." [Online]. Available: https://www.stjohn.org.nz/Medical-Alarms/Medical-Alarm-Services/. [Accessed: 05-Apr-2018].

[4] K. M. Lerro, "Medical alert bracelet," US4078660A, 14-Mar-1978.

[5] C. Turesson, A. Jarenros, and L. Jacobsson, "Increased incidence of cardiovascular disease in patients with rheumatoid arthritis: results from a community based study," *Ann. Rheum. Dis.*, vol. 63, no. 8, pp. 952–955, Aug. 2004.

[6] U. Anliker *et al.*, "AMON: a wearable multiparameter medical monitoring and alert

system," *IEEE Trans. Inf. Technol. Biomed.*, vol. 8, no. 4, pp. 415–427, Dec. 2004.
[7] P. Leijdekkers and V. Gay, "A Self-Test to Detect a Heart Attack Using a Mobile Phone and Wearable Sensors," in *2008 21st IEEE International Symposium on Computer-Based Medical Systems*, 2008, pp. 93–98.
[8] Z. Jin, J. Oresko, S. Huang, and A. C. Cheng, "HeartToGo: A Personalized medicine technology for cardiovascular disease prevention and detection," in *2009 IEEE/NIH Life Science Systems and Applications Workshop*, 2009, pp. 80–83.
[9] M. A. Reyna, C. I. Lima, R. L. Avitia, and M. E. Bravo, "Wireless Electrodes for Electrocardiography," in *2015 Pan American Health Care Exchanges (PAHCE)*, 2015, pp. 1–1.
[10] Y. M. Chi and G. Cauwenberghs, "Wireless Non-contact EEG/ECG Electrodes for Body Sensor Networks," in *2010 International Conference on Body Sensor Networks*, 2010, pp. 297–301.
[11] "Wearable ECG Sensor | Wireless ECG sensor | Electrocardiogram." [Online]. Available: http://www.shimmersensing.com/products/shimmer3-ecg-sensor. [Accessed: 05-Apr-2018].
[12] A. Pantelopoulos and N. G. Bourbakis, "A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis," *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.*, vol. 40, no. 1, pp. 1–12, Jan. 2010.
[13] "Pulse Oximetry," 18-Mar-2015. [Online]. Available: https://web.archive.org/web/20150318054934/http://www.oximetry.org/pulseox/principles.htm. [Accessed: 29-Apr-2018].
[14] F. Lombardi and A. Mortara, "Heart rate variability and cardiac failure," *Heart*, vol. 80, no. 3, pp. 213–214, Sep. 1998.
[15] S. Gillinov *et al.*, "Variable Accuracy of Wearable Heart Rate Monitors during Aerobic Exercise," *Med. Sci. Sports Exerc.*, vol. 49, no. 8, pp. 1697–1703, Aug. 2017.
[16] S. W. Cheatham, M. J. Kolber, and M. P. Ernst, "Concurrent Validity of Resting Pulse-Rate Measurements: A Comparison of 2 Smartphone Applications, the Polar H7 Belt Monitor, and a Pulse Oximeter With Bluetooth," *J. Sport Rehabil.*, vol. 24, no. 2, pp. 171–178, May 2015.
[17] V. Timothy, A. S. Prihatmanto, and K. H. Rhee, "Data preparation step for automated diagnosis based on HRV analysis and machine learning," in *2016 6th International Conference on System Engineering and Technology (ICSET)*, 2016, pp. 142–148.
[18] "Elite HRV on the App Store," *App Store*. [Online]. Available: https://itunes.apple.com/us/app/elite-hrv/id868829970?mt=8. [Accessed: 29-Apr-2018].
[19] "HRV + on the App Store," *App Store*. [Online]. Available: https://itunes.apple.com/us/app/hrv/id711463963?mt=8. [Accessed: 29-Apr-2018].
[20] J. Pan and W. J. Tompkins, "A Real-Time QRS Detection Algorithm," *IEEE Trans. Biomed. Eng.*, vol. BME-32, no. 3, pp. 230–236, Mar. 1985.
[21] S. Nizami, J. R. Green, J. M. Eklund, and C. McGregor, "Heart disease classification through HRV analysis using Parallel Cascade Identification and Fast Orthogonal Search," in *2010 IEEE International Workshop on Medical Measurements and Applications*, 2010, pp. 134–139.
[22] S. Rezaei, S. Moharreri, M. Abdollahpur, and S. Parvaneh, "Heart arrhythmia classification using extracted features in poincare plot of RR intervals," in *2017 Computing in Cardiology (CinC)*, 2017, pp. 1–4.
[23] M. I. Obayya and F. E. Z. Abou-Chadi, "Classification of heart rate variability signals using higher order spectra and neural networks," in *2009 International Conference on Networking and Media Convergence*, 2009, pp. 137–140.
[24] Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology, "Heart rate variability: Standards of measurement, physiological interpretation, and clinical use," *Eur Heart J*, vol. 17, p. 28, 1996.
[25] A. M. Pearson and W. H. Olson, "Spontaneous Ventricular Tachyarrythmia Database." physionet.org, 1997.
[26] "scipy.signal.welch — SciPy v0.14.0 Reference Guide." [Online]. Available: https://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.signal.welch.html. [Accessed: 30-Apr-2018].
[27] A. A. Rosenberg, *mhrv: Matlab toolbox for calculating Heart-Rate Variability metrics on ECG signals*. 2018.
[28] "Keras Documentation." [Online]. Available: https://keras.io/. [Accessed: 24-Aug-2018].
[29] "H6, H7, H10 and OH1 Heart rate sensors - Polar Developers." [Online]. Available: https://developer.polar.com/wiki/H6,_H7,_H10_and_OH1_Heart_rate_sensors. [Accessed: 23-Aug-2018].
[30] "GATT Specifications | Bluetooth Technology Website." [Online]. Available: https://www.bluetooth.com/specifications/gatt. [Accessed: 23-Aug-2018].