Intelligent ECG Monitoring Systems

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Proposed Work

Arrhythmias – irregular heart rhythms, can be detected and classified through the monitoring of Electrocardiogram (ECG) signals, allowing for the identification and diagnosis of heart diseases.

There has been some initial work exploring how machine learning applied on ECG signals can be used in the early detection of Arrhythmias [1, 2] utilising the MIT-BIH corpus of 47 unique patients. More recently, [3] has constructed a dataset 500 times larger and shown that a large CNN solution can outperform a trained cardiologist in Arrhythmia detection. Whilst promising, these approaches either identify and leverage ECG waveforms, also known as PQRST segmentation, building features to use in a model – which suffers with individual variability and lower accuracy or, use large end-to-end networks on the raw signal which are computationally intractable on embedded devices. There is also a large variation in the literature of which Arrhythmias the models are trained to detect, with even the most recent and complete dataset not being trained to detect Ventricular Flutter, Fibrillation or Ventricular Hypertrophy [3]. Currently no such solution has both the reliability required for medical use-cases and the computational tractability allowing the models to be utilised inside an embedded device, both of which are paramount for general use.

The authors of [4] have come closest to building models suitable for portable devices. They use a 1D CNN approach to predict 15 classes of Arrhythmia which, due to the reduced computational complexity, they claim is a viable option for mobile devices but the cost of which is an unacceptable accuracy (90%). This is, in part, be due to the use of the older and smaller MIT-BIH dataset where the recent larger collection of ECG recordings could increase the accuracy.

Here this research proposes to push forward the state-of-the-art in embedded ECG signal modeling to produce devices that are both accurate and resourcelite. This project can be broken into five distinct phases which are as follows:

Build, compare and contrast learning machines that utilise human physio- logical signals, ECG in the first instance, to recognise and categorise various Arrhythmias. Emphasis will be on approaches that can offer probabilistic interpretations allowing for more granular decision boundary thresholds and interpretability.

The device will need to capture the ECG signal at a sufficient rate to detect anomalies using the models whilst being memory and power efficient. The next stage will therefore look to reduce resource requirements of machine learning approaches, quantifying any accuracy reductions this causes, in order to be able to embed the models onto wearable devices. We would look to develop new ma- chine learning methods to this end, aiming to increase the predictive accuracy when compared to existing bench-marked models. It is envisioned that this part of the proposed work will be where the majority of the energy will be focused and it is hoped that the models developed in this stage will be applicable, both directly to the ECG signal prediction problem but also generalisable to a wider range of problems which require extreme resource reduction whilst maintaining high accuracy for raw signal classification.

Whilst some portable approaches have been explored utilising mobile devices coupled with ECG signals to predict Arrhythmias [5], using mobile devices for real-time continuous monitoring isn’t resource optimal since it requires the use of Bluetooth. The next stage will therefore aim to identify components and embedded device architectures that would be suitable to produce an intelligent wearable linked to ECG sensors building prototypes ‘mobile-free’. We would also explore the possibility of direct computation through Cellular Neural Net- work processors rather than compiling the learning machines on a programmable device.

Recent work has found that 83% of medical alarms are false in a hospital setting [6] taking up valuable time for clinicians. The problem of false positives could be a particularly pertinent problem for devices utilising captured blood pressure measurements which are sensitive to both physiological responses, such as physical activity, that can closely mimic problematic signs and sensitive to the placement orientation of the devices on particular persons. To overcome these problems, we will need to explore methods in increasing the resilience of the system with additional training ECG signals capturing various human ac- tivity that could otherwise create false-positives, exercising etc. Furthermore, it could interesting to explore treatment-feedback measurements in response alarm signals, for example breathing exercise, such that the responses could improve the classification accuracy further.

There has been some work to explore alternative methods for measuring blood pressure and heart rates, with a promising areas including non-invasive PhotoPlethysmoGraphic (PPG) [7]. This measures blood pressure, using opti- cal sensors where – since blood absorbs infrared light more strongly than general skin tissues, the change in blood volume can be captured and quantified using an LED and photodetector. The PPG measures have successfully been combined with ECG to monitor various cardiatric parameters [8]. A recent paper [9] has used a combination of these two signals with a Cellular Neural Network to filter the PPG signal and validate the ECG readings increasing the viability of these alternative methods. So a further extension to this work would look to incorporate other non-invasive techniques, such as PPG to further strengthen the model.

ECG monitoring measurements are subject to large error and physiological variation and treatment responses have large inter-individual variations making the identification of Arrhythmias challenging. But with 300 million ECGs recorded each year, accurate low-cost monitoring can facilitate the identification of early- signs of potential cardiovascular disease, the leading world-wide cause of human death and reduce misdiagnoses. In summary, we hope in this research to develop computational strategies and machine learning models that allow for intelligent wearable devices that are feasible with hardware restrictions, resilient to false- alarms and accurate in detection of Arrhythmias.

Application Motivation

My conversations with colleagues and initial experiences conducting research have led to me concluding that I have the correct motivations in pursuing a PhD. Firstly, I am insatiably curious, particularly in the underlying mechanisms of why things work. It has never been enough for me to be given an algorithm or equation and to simply accept it on the basis of its utility. I am also extremely keen to share my work with others. This has manifested it- self in a wide array of research domains, co-authoring three papers (one accepted for publication and two in the pipeline) in varying fields; applied game theory and mechanism design, simulating the evolution of agreements and machine learning applied to a multi-view biological problem. The latter of which was an extension of my final year project at undergrad funded through BioProNet which I and my supervisor hope to publish in a high impact journal. My supervisor taught me the importance of presenting research in a way that is both palatable to the widest audience, through interesting figures, and precise and complete for those that may wish to re-produce the work.

Thirdly, I am willing to face hard days and failure on the path to success in the PhD. I am no stranger to feeling completely isolated and unsure of the next steps, although less pronounced than I expect on a PhD, during my summer project I felt like a fish out of water with very limited biological understanding of the metabolic modeling tools I was using and at the time only a basic ma- chine learning understanding with my supervisor away for a few weeks, but I persevered over the weeks and months gaining both an understanding and paper that I am proud of.

Finally, I am not motivated by money but by human progress and the sense that I am playing my part. This is a particularly pertinent reason for my application on the MINDS CDT PhD program, my time at Southampton has already gifted me with a strong mathematical and computational foundation which I hope to build upon and make use of on problems that, to me, represent progress. I am really keen to learn the foundations of electronics which could aid in broadening my approach to the problem and am excited by the prospect of working with a mixed cohort of expertise.

The massive leaps in predictive model benchmarking are not, to my mind, manifesting themselves in real-world systems at their realised potential and I agree that a large bottleneck is the lack of learning machines developed specifically for embedded systems. So for me, a project that is pivoted towards the development of algorithmic learning machines suitable for embedded devices and driven by a medical problem is one which motivates me greatly. Working on hard, interesting problems excites me. I struggle to capture with words the degree by which this sentence I meant. My grade average, 92% undergraduate and 85% currently at masters, I hope communicates just how motivated I am explore new and interesting ways to solve problems.

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