CS236781 – Deep Learning on Computational Accelerators

Final Project

Michael Mendelson-Mints

Dan Kalifa

{michael.me, kalifadan}@campus.technion.ac.il

207193210, 206063497

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Abstract

In the modern world,

1 Introduction

Our work is based on the paper "Detection of Paroxysmal Atrial Fibrillation using Attention-based Bidirectional Recurrent Neural Networks"[4].
Atrial fibrillation (AF or A-fib) is an abnormal heart rhythm (arrhythmia) characterized by the rapid and irregular beating of the atrial chambers of the heart (prevalence of 2% in the adult population). It often begins as short periods of abnormal beating, which become longer or continuous over time [6], and is usually diagnosed by the absence of P waves in the ECG reading. Paroxysmal AF (PAF) is a form of AF that occurs occasionally, and has a higher probability of being undetected. The paper [4] discusses two main concepts:

- Detection of Paroxysmal AF (PAF) using a deep learning architecture with an attention mechanism [1].
- Transferring knowledge from the source domain (ECG readings), to detect AF from pulsatile photoplethysmogram (PPG) readings (the target domain).

The paper shows that the proposed model bypasses baseline models with an AUC of 0.94 on the testing set, and is able to detect AF with a low false-alarm rate. It also discusses the potential of domain transfer to PPG readings obtained from wearable devices to act as a long-term monitoring system which can detect AF in real time.

1.1 Data

The datasets used in the article consists of 2 datasets:

- Holter ECG dataset.
- Smart Watch PPG dataset.

The first dataset consists of 24 hour Holter ECG recordings collected from 2850 patients after been confirmed by a clinical adjudicator and divided into 10-minute segments (after excluding less than 2% segments with a low signal quality index - SQI).
The other dataset consists of pulsatile photoplethysmogram (PPG) recordings from 97 subjects, taken from smartwatches - 44 positive cases and 53 negatives (with other rhythms) for approximately 5-10 minutes.

1.2 Methods

Figure 1 presents an overview of the deep learning architecture, that used for the detection of Paroxysmal Atrial Fibrillation (PAF), and was shown in the paper.

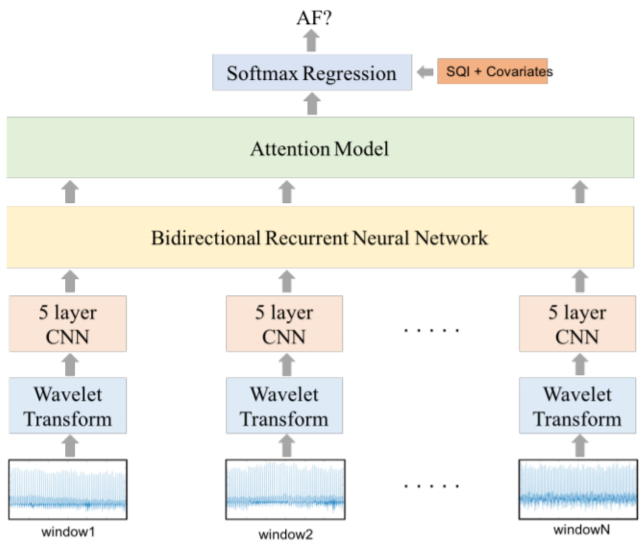

Figure 1: Schematic diagram of the AF detection algorithm

The deep learning architecture that shown includes five main parts:

- Wavelet decomposition – Wavelet transform is capable of extracting time-frequency information from signals of a non-stationary nature, due to its optimal time-frequency resolution trade-offs [3]. The main purpose of applying it is for extraction features from the frequency domain. In the paper's algorithm, the 10-minute segment was split into non-overlapping 30-second windows, and the wavelet transform [5] was applied to each of the windows, resulting in a wavelet spectrogram matrix of size 20 by 300.

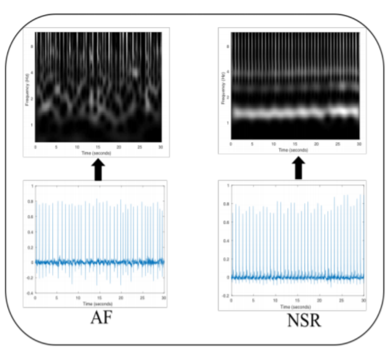

Figure 2: Wavelet power spectrum for 30 second ECG sample. The left panel shows an example of AF segment and the right panel represents a Normal Sinus Rhythm segment

- Feature extraction – A 5-layer CNN receives as input an image of a wavelet spectrogram (for a 30 second window of an ECG reading), which is then fed into 2 successive convolutional layers, a max pooling layer, 2 more convolutional layers and a fully-connected layer. CNNs were shown to achieve good results in extracting important features from images which benefit from invariance of translation and locality of visual features.

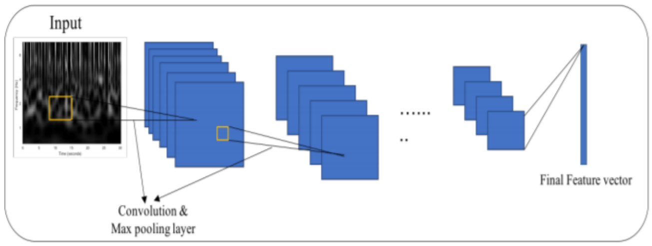

Figure 3: Schematic diagram of the deep CNN layer

- Temporality – The result of all parallel CNN layers (each receiving the next window in a 10-minute ECG reading) is fed into a Bidirectional Recurrent Neural Network, to capture temporal features, and leverage the information flow in both directions of time in the reading.

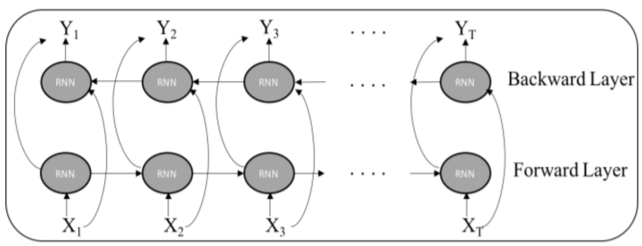

Figure 4: Schematic diagram of the bidirectional recurrent neural network

- Attention – The output of the BRNN is then fed into an attention layer, to capture the most important windows of the input (relying on their temporal and visual features as an indication to the presence of AF).

- Classification – Finally, the attended features are fed into a fully-connected layer and a decision is made based on a Softmax regression, which is also given as input external features for the ECG reading (time series covariates), which are made to capture the quality of the reading (beat-to-beat sample entropy and autocorrelation of the signal).

1.3 Results

The data samples were divided into groups with a different AF burden. an AF burden is the percentage of time from a 10-minute segment spent in AF. It was shown that for an AF burden of $> 5\%$, the model was able to achieve an AUC of 0.94. The model was then compared to a baseline model, and two more models, one without covariates information, and another algorithm proposed by Carrara et al. [2]. the results are detailed in Figure 5.

	Testing set				Training set			
Model	*AUC*	AUC_{pr}	*SPC*	ACC	*AUC*	AUC_{pr}	*SPC*	ACC
Spectrogram	0.92	0.80	0.92	0.92	0.94	0.92	0.93	0.93
Covariates (Baseline)	0.87	0.67	0.77	0.78	0.89	0.80	0.80	0.81
Combined	**0.94**	0.84	0.95	0.94	**0.96**	0.93	0.96	0.96
Carrara et al.	0.91	0.80	0.91	0.91	0.93	0.90	0.94	0.93

Figure 5: Summary of classification performance on different models and a baseline model. The best performing model is the combined one, including both the external features (covariates) and the extracted features from the spectrogram.

The model outperformed all others when compared with the AUC, the Area Under the Precision-Recall curve (AUC_{pr}), the specificity (SPC) and accuracy (ACC).
The model was then used to transfer knowledge from the domain of ECG reading, to a new target domain of PPG readings taken from smart watches. The pre-trained model outperformed a baseline model which was only trained on PPG samples, showing that the domain transfer is plausible, and has applications in real-time AF detection and monitoring using wearable devices.

1.4 Conclusion

In conclusion, the paper [4] provides a well-motivated deep learning architecture for detection of paroxysmal AF, and demonstrates clinically acceptable AF detection accuracies across different recording modalities. Furthermore, the major finding of this study is that combining spectral representation of cardiac pulsatile recordings with traditional indices of heart rhythm irregularity in a deep neural network framework results in better AF classification. This approach facilitates transferring of learned model parameters across recording modalities such as ECG and PPG, thus enabling accurate AF classification in settings with limited access to large patient cohorts for model training purposes. Moreover, the results indicate that the hierarchical architecture of a deep neural network with one or more image-based feature extraction layers, a sequential layer capable of passing temporal information, and an attention mechanism allows for accurate classification of paroxysmal AF.

References

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