AI-Enabled ECG Combined with Dry Electrode Sensors for Population-Based Screening of Atrial Fibrillation

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Abstract

This study assessed the performance of a deep neural network (PulseAI, Belfast, United Kingdom) used in conjunction with a dry-electrode ECG sensor device (RhythmPad, D&FT, United Kingdom) to detect AF automatically.

Simultaneous pairs of 12-lead ECGs and single-lead dry-electrode ECGs were collected from 622 patients. The 12-lead ECGs were manually overread and used as reference diagnoses. Twenty-two patients were confirmed with AF and had an interpretable 12-lead and single-lead dry-electrode ECG recording. The deep neural network analysed the dry-electrode ECGs, and performance was compared to the 12-lead interpretation. Overall, the deep neural network algorithm yielded a sensitivity of 96% (95% CI, 87%-100%), specificity of 99% (95% CI, 98%-100%) and positive predictive value of 81% (95% CI, 66%-96%) for detection of AF episodes.

When coupled with dry-electrode ECG sensors, the PulseAI neural network allows for large-scale and low-cost screening for AF. Widespread implementation of this technology may allow for earlier detection, treatment, and management of patients with AF.

1. Introduction

Atrial Fibrillation (AF) is the most common form of arrhythmia. It occurs when the natural pacemaker of the heart, the sinoatrial node, is overpowered by chaotic electrical potentials from other cells in the atria. Many of these potentials are then conducted to the A-V node. However, only some potentials create complete contraction of the ventricles, thus creating an irregular rhythm with no P-wave on the electrocardiogram (ECG). When left untreated, AF can lead to stroke. AF causes approximately 25-30% of ischaemic strokes when left untreated. Appropriate treatment of AF patients with anticoagulation can prevent strokes; however, accurate detection remains a challenge, particularly in asymptomatic patients. Some patients experience episodes of AF that are sporadic and intermittent (paroxysmal), making them difficult to detect using traditional clinical methods.

AF is detected in a clinical environment by recording a 12-lead ECG, which is then manually interpreted by the physician and used for diagnosis and treatment. Traditional algorithms depend on lead-specific features to detect QRS complexes and sense the absence of P-waves for AF detection [1-3]. Hand-crafted feature selection may not be transferable to other ECG devices, which record a different ECG lead. Deep learning has emerged as a class of algorithms capable of learning from large datasets without hand-crafted feature selection..

DCNNs have improved the computerized interpretation of ECG recordings from resting 12-lead ECG and ambulatory ECG devices [4-6]. Many single-lead devices have been developed recently to record ECG signals from dry-electrode sensors. These devices are a non-invasive way of assessing abnormal heart rhythms at scale. However, the ECG data generated by consumer smartwatches means physicians cannot review it [4]; therefore, reliance is placed on computer algorithms to interpret the data.

The PulseAI neural network is a device-agnostic algorithm for detecting AF and other arrhythmias from a range of clinical ECG monitors [7]. In this study, we aim to assess the performance of the PulseAI neural network for detecting AF from a commercially available dry-electrode single-lead (Lead I) ECG device.

2. Methods

2.1 Clinical Data

This study involved 660 simultaneous pairs (22 AF) of 12-lead ECGs and Lead I smart device ECGs (SD-ECGs) recorded at the Ashford and St Peter's Hospitals NHS Foundation Trust in the United Kingdom.

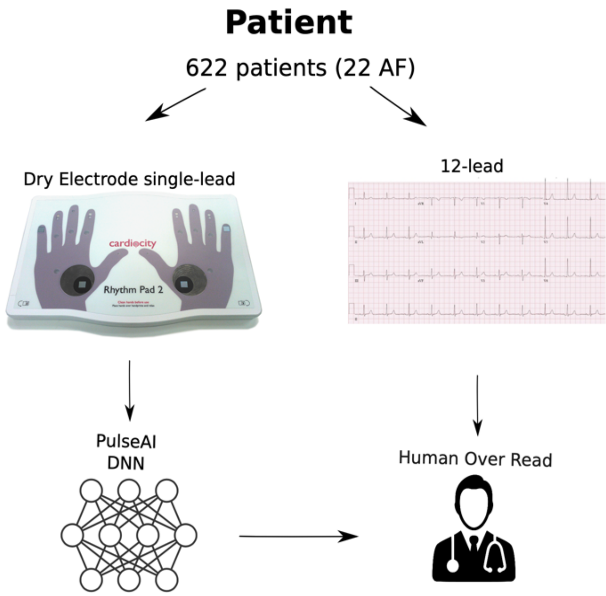

Figure 1. The clinical trial workflow. Each patient had a smart-device ECG (SD-ECG) recording and a clinical 12-lead ECG recording.

The 12-lead ECGs were interpreted by an expert clinician and used as ground truth; we tested the PulseAI neural network algorithm and the traditional R-R algorithm on the SD-ECGs. Results were analysed to the clinical gold standard, the human-overread 12-lead ECG.

2.2. ECG recordings

SD-ECGs were recorded using a dry electrode lead I ECG device (RhythmPad, D&FT, United Kingdom). The device recorded ECG samples in microvolts at 1000Hz or samples per second. All ECGs were downsampled to 256Hz using linear interpolation for analysis by the algorithms. The 12-lead ECGs were recorded on a GE MAC 5500 (GE, Milwaukee, Wisconsin, USA).

2.3. The PulseAI neural network

The PulseAI Deep Neural Network (PDNN) takes raw ECG voltage values as an input time series and produces a single set of classification results. The PDNN architecture is based on residual blocks and is similar to the architecture described by Ribeiro for 12-lead ECG interpretation [8]. The PDNN takes as an input the raw ECG data (sampled at 256 Hz, or 256 samples per second) in microvolts and outputs a single multiclass prediction of the cardiac rhythm. The PDNN is similar to the standard residual network architecture commonly used for computer vision applications but adapted to 1D signals.

The PDNN has nine convolutional layers, consisting of four residual blocks with two convolutional layers per block. Each residual block performs downsampling via max pooling. To help with regularization, we applied batch normalization, rectified linear activation and dropout. The final layer is a fully connected Sigmoid layer that produces a multi-class probability of each ECG rhythm which is then thresholded using class-specific thresholding. In this case, a cutoff of >=0.4 is applied to the neural network output to determine the presence or absence of AF.

The PDNN was trained de novo with random initialization of the weights described by He et al. [9]. We used the Adam optimizer and a mini-batch size of thirty-two. We initialized the learning rate (0.001) and reduced it by a factor of ten when the testing set loss stopped improving for two consecutive epochs. During PDNN training, the weights are altered to minimise differences between the PDNN's output and the reference annotations. We trained the PDNN on a randomly selected single-lead from the 12-lead signal for each training mini-batch to maximize the exposure of the network to different waveform morphologies and amplitudes, allowing for better generalisability.

This process was repeated for all ECGs in the training set, consisting of more than 1 million ECGs from a private internal database previously annotated by clinicians, until the model had fully converged. The model with the lowest loss on the test set was chosen.

2.4. State-of-the-art R-R interval algorithm

The state-of-the-art R-R interval algorithm is based on two stages (1) detection of the QRS complex and (2) statistical analysis of the R-R interval time series. The QRS complexes were detected from the raw ECG signal using the method outlined by Hamilton and Tompkins [10], and R-R intervals were extracted without correction.

The approach outlined by Luo et al. was then applied. The first-order differential R-R interval sequences from the ECG signal were calculated. On the differential R-R series, a polar coordinate transformation on the Poincaré plot was applied to obtain the phase-based distribution. The distribution width and the average distribution height were then extracted and thresholded from the phase-based distribution to classify the AF and non-AF episodes. Further details can be found at [11]. The algorithm was implemented to provide a reference to compare the PDNN results.

2.5. Statistical Analysis

The performance of the algorithms, both PDNN and state-of-the-art R-R interval, against the gold standard human over read 12-lead ECG interpretation was assessed in terms of sensitivity, specificity, positive predictive value and F1 score. Figures are presented as percentages with 95% confidence intervals.

3. Results

Sensitivity for detection of the AF from both algorithms were identical (96% [87%-100%] vs 96% [87%-100%]). However, specificity and positive predictive values were significantly higher by the DNN due to a reduction in false positive detections. The DCNN, therefore, also provided superior performance in terms of the F1 score (88% [75%-100%] vs 15% [11%-20%]).

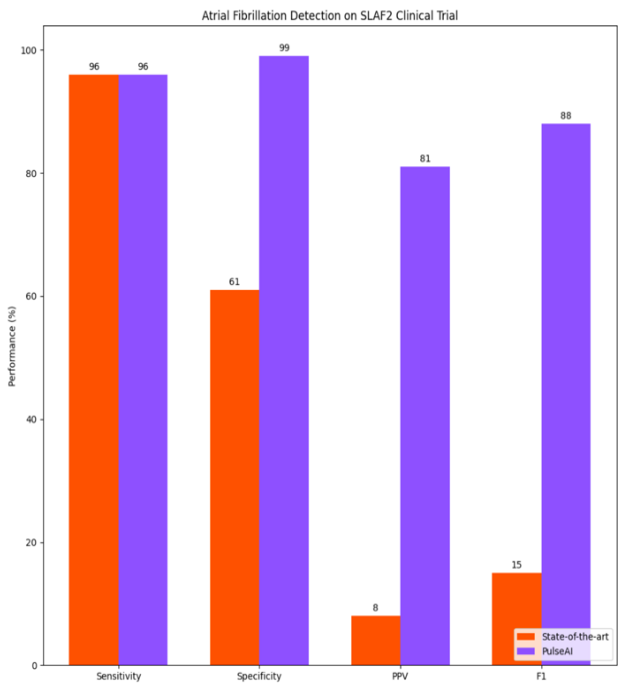

Figure 2. The performance results for the PulseAI neural network compared to a state-of-the-art R-R interval algorithm.

The positive predictive value of the two algorithms differed significantly (81% [66%-96%] vs 8% [5%-11%]). The R-R interval-based approach is much more susceptible to failure due to high signal noise levels. False positives from the traditional R-R interval algorithm were generally due to signal noise and, in some cases, other irregular rhythms, such as sinus arrhythmia and premature atrial and ventricular contractions.

4. Discussion

It is essential for the ECG devices are capable of providing accurate interpretation for AF. Approximately 25-30% of strokes happen because of AF, and there are 450,000 hospitalizations yearly for patients with AF-related issues in the United States alone [12]. In fact, nearly 50 million people worldwide suffer from AF [13]. The most effective way to detect AF episodes is by using ambulatory ECG monitoring [14], and this method is more effective than conventional follow-up for patients who have previously suffered a stroke.

In this study, we observed that the PDNN could detect AF from SD-ECG recordings with high sensitivity, specificity and PPV levels. Previous studies have demonstrated the improved performance of deep neural networks in detecting arrhythmias in comparison to other approaches [5, 14-17]. However, the current study is the first to evaluate the performance of a device-agnostic neural network (PDNN) for cardiac rhythm analysis on a dry-electrode ECG device. Evaluation of the PDNN on the clinical data showed comparable or improved performance with other industry-leading algorithms [17, 18] in detecting AF from clinical ECG monitors.

New smart devices incorporating dry-electrode technology may, for the first time, allow for convenient, cost-effective and scalable capture of ECG recordings for the detection of AF. The large amount of data generated by consumer devices will not allow physicians to review each case in detail, so they will have to rely on ECG interpretation algorithms. Therefore, reducing the number of false positive detections whilst maintaining sensitivity for true AF cases is highly desirable.

5. Conclusions

The findings of this study demonstrate that interpretation of SD-ECG recordings with the PDNN dramatically reduces the number of false positives whilst maintaining the sensitivity for AF detection compared to traditional R-R interval algorithms.

These findings provide further clinical evidence that the PDNN can be device agnostic for detecting AF from single-lead ECG, enabling a range of clinical and consumer-focused applications.

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