Extended Single-Lead ECG Monitoring for AF Detection Using Deep Learning

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Abstract

Atrial fibrillation (AF) is the most common arrhythmia in developed countries and is associated with reduced quality of life as well as an increased risk of life-changing events, such as stroke and heart failure. Enabling timely detection of new clinically relevant episodes of AF in patients already diagnosed with the condition would support physicians in improving patient management. This study investigates the effectiveness of convolutional neural networks (CNN) for automated AF detection in 14-day single-lead ECG wearable patch data collected just after a successful electrical cardioversion. Continuous ECG data from 89 patients were segmented into contiguous 10-second intervals and annotated by ECG experts for presence or absence of AF. A CNN was developed to classify AF at the segment level, and generalizability was evaluated on out-of-distribution subjects. The model achieved a sensitivity of 0.87 and specificity of 0.96 on unseen subjects, demonstrating high accuracy for AF recurrence detection.

1. Introduction

Atrial fibrillation (AF) is the most prevalent cardiac arrhythmia [1]. Its presence leads to electrical and structural remodeling of the heart, which in turn promotes the persistence of AF in a self-perpetuating cycle [2]. Electrical cardioversion is a treatment for AF and successfully restores sinus rhythm in more than 90% of AF cases [3]. However, recurrence is expected in approximately 30% of patients in the following 1-2 weeks [3]. Although the clinical relevance of early AF recurrence after cardioversion remains to be fully elucidated, our goal in this study was to utilize these data to develop tools for AF detection. Improving the accuracy of AF detection from single-lead patch ECG is critical because such devices collect very long-term data (large amount of data to review) with lower signal-to-noise ratio.

A range of tools are available for AF detection, including 12-lead ECG, Holter monitoring, mobile cardiac telemetry, handheld devices, wearable patches, biotextiles, smart devices, and implantable loop recorders [4]. These modalities vary in their degree of invasiveness and monitoring duration, spanning from single point-in-time assessments to long-term continuous rhythm tracking. Among these, single-lead ECG patch devices have emerged as an increasingly-popular non-invasive and user-friendly solution for extended ambulatory cardiac monitoring. Notably, 14-day continuous monitoring has been shown to have a higher AF detection rate than 24-hour Holter monitoring, due to the increased recording duration (one vs. multiple day recordings) [5, 6]. Continuous monitoring generates copious amounts of data—a single patient monitored for around 14 days would contain around 120,000 valid ECG segments of 10s depending on both quality of the ECG signals and patient compliance. High-performance AF detection systems could help healthcare providers in triaging the vast amount of data, and streamline the computation of an accurate AF burden.

Several studies have examined AF detection using patch ECGs, including large at-home studies (2,659 participants) [7]. However, investigations focusing on the 14-day period post-cardioversion are limited, with one study including only 16 such subjects [8].

Artificial Intelligence (AI) and more specifically Deep Learning (DL) can automatically detect arrhythmias by learning from preexisting expert rhythm type annotations [9]. Through a series of transformations, DL neural networks learn characteristics (i.e., features) of the ECG signal that are later used to determine the rhythm type, optimized with supervised learning. Validation and test sets from external populations are used for assessing model effectiveness [10]. Such sets help determine whether the features learned during training are specific to the subjects in the training cohort or generalizable to unseen subjects.

The most common DL architectures include convolutional neural networks (CNN), which extract local features from the input and build hierarchical features with more layers. Many works have developed CNNs to detect AF from single-lead ECGs from handheld devices [11]. The most common dataset we have seen to train or validate these models is from the PhysioNet/CinC challenge 2017 [12]. There has also been work done on AF detection using single lead adhesive patch ECGs [9].

While prior work has used DL for AF detection, few have addressed subject-level recurrence, and studies explicitly evaluating generalization to out-of-distribution (OOD) subjects have largely focused on Holter recordings [13]. There have been few studies applying DL to 14-day Zio patch data directly following cardioversion, nor explicitly focusing on subject-level AF recurrence during the post-procedure blanking period. Prior work such as [14] has demonstrated the ability of DL to detect AF on OOD subjects, but this has not been directly examined in the context of post-cardioversion monitoring.

This study evaluates the performance of a CNN for detecting AF from 14-day single-lead ECG wearable patch recordings. We focus on patients with paroxysmal AF who underwent electrical cardioversion and ECGs were collected directly after the procedure. The neural network we developed was evaluated on OOD subjects—achieved a sensitivity of 0.87, a specificity of 0.96, and an F1 score of 0.82.

2. Study Subjects

The study (ClinicalTrials.gov Identifier: NCT04267133) included men and women older than 60 years who were medically managed for symptomatic AF, either paroxysmal or persistent, and had symptomatic AF treated by transthoracic electrical cardioversion. Exclusion criteria rejected patients with an implanted device (pacemaker, CRT/CRT-ICD, ICD) with ventricular pacing requirement of 70% or greater; those participating in other clinical trials; subjects unable to cooperate with the protocol due to dementia, psychological, or related reasons; individuals who declined informed consent; and patients unable to operate the device, such as those with Parkinson's disease or those who are blind.

3. Device and Data Collection

The ECG recordings were acquired using the ZioXT ECG patch (iRhythm Technologies, San Francisco, CA, USA). This device features an amplitude resolution of approximately 1 μV and an ECG sampling frequency of 199.8 Hz, supporting continuous ambulatory monitoring over extended periods. Figure 1 details the timeline of the cardioversion procedure and data collection time frame.

4. Methodology

Prior to data preprocessing, ECG data were collected from subjects using a Zio patch single-lead ECG device. Data from 89 subjects were labeled and subsequently divided into three disjoint groups by subject for model development and evaluation. A CNN was trained to classify 10-second ECG segments as AF or non-AF using data from these groups. Model performance was further evaluated on segments obtained from OOD subjects to assess generalizability.

At the subject level, AF recurrence was defined as the occurrence of AF in three consecutive 10-second segments (totaling 30 seconds).

4.1. Data Preprocessing

All recordings were acquired in ISHNE format, containing both raw ECG data and rhythm annotations. Manual adjudication of cardiac rhythm was initially performed by an ECG technician using the M12A (Global Instrumentation LLC, Syracuse, NY), with a randomly selected subset (5%) independently reviewed by a board-certified cardiologist for quality assurance.

AF was annotated by an ECG expert, with episodes defined as lasting at least 15 seconds. Each annotation included the start and end times of AF events. Both AF and atrial flutter events were included during annotation. The ECG data were segmented into contiguous, non-overlapping 10-second intervals. Each segment was assigned a label based on the expert annotations. Atrial flutter segments were dropped, and segments with absolute amplitude exceeding 3 mV or signal energy greater than 3 standard deviations above the mean were excluded. Signal preprocessing included bandpass filtering with a 0.5 Hz low-frequency cutoff and 50 Hz notch filtering to suppress powerline interference.

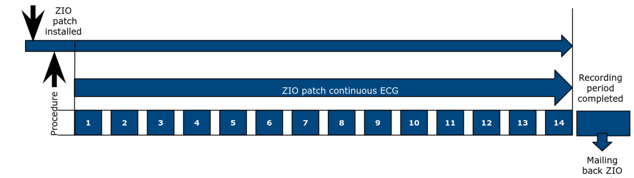

Figure 1: Study Protocol

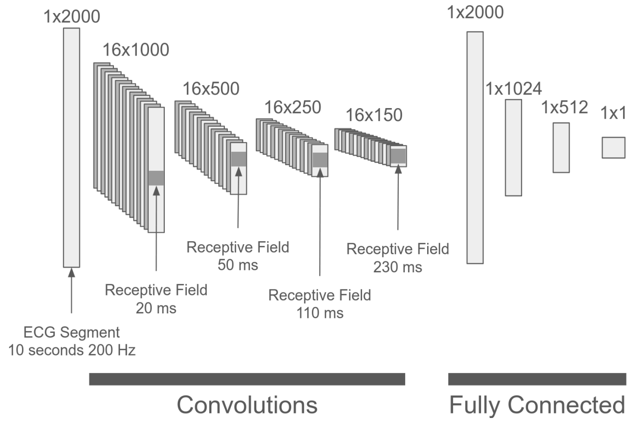

Figure 2: Neural Network Architecture

4.2. Neural Network Architecture

We developed a convolutional neural network containing four convolutional layers and three fully connected layers. Each layer produced feature maps with progressively larger receptive fields approximately 20 ms, 50 ms, 110 ms, and 230 ms, respectively. The 1-D convolutions used a kernel size of 4, stride of 2, and padding of 1. Batch normalization and rectified linear unit activations were applied to each layer, and dropout was employed for regularization. The output feature maps were flattened and passed through three fully connected layers. The final output layer consisted of a single unit with sigmoid activation to output the probability of AF. Figure 2 is an overview of the network architecture.

4.3. Optimization

Binary cross-entropy was used as the loss function. The network was optimized using AdamW [15] with weight decay [16]. Learning rate scheduling was implemented via cosine annealing with warm restarts [17], updating the base learning rate at every step and doubling the cycle length after each restart to progressively cool the annealing. A threshold of 0.5 was used to discretize the output probability for segment-level classification.

During training, a validation set consisting of OOD subjects was used to monitor model convergence and tune hyperparameters, including learning rate, batch size, and network architecture. All reported evaluation metrics are based on a separate, third set of OOD subjects that were held out until final testing.

5. Results

The AF detection of 10 second ECG segments using the CNN achieved an OOD sensitivity of 0.87, a specificity of 0.96, and a F1 score of 0.82. Figure 3 shows most segments were classified well on most subjects, except for subject 156, which we later discuss in section 6.

At the subject level, there were 4 subjects with recurrence and in all cases AF was detected during the time they were wearing the Zio patch.

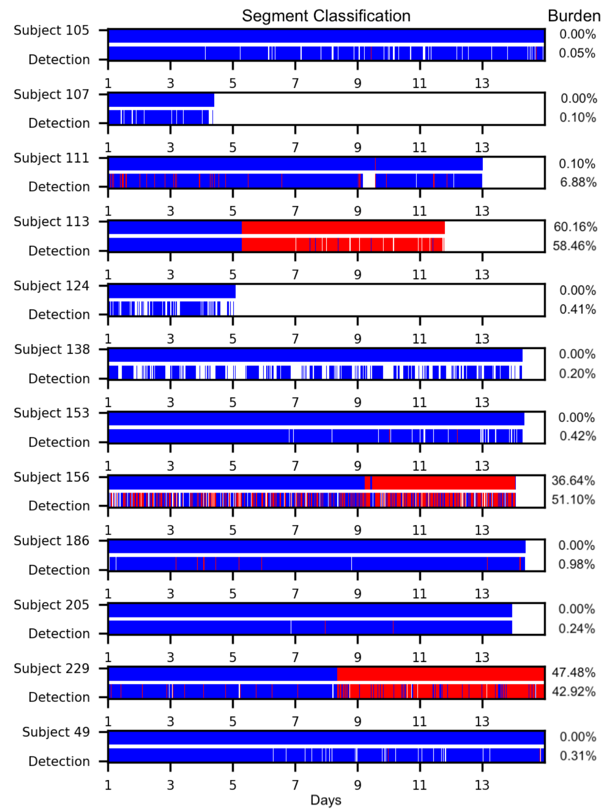

Figure 3: Continuous monitoring labels and AI-detected AF in the OOD test dataset (red = AF, blue = non AF).

6. Challenging ECG Morphologies

In reviewing ECG recordings from subjects with relatively higher false positive rates, several challenging morphologies were noted. Subject 111 exhibited first degree AV block throughout the recording, with atrial flutter occurring several hours before the onset of AF. Subject 156 demonstrated very tall T waves in some segments, as well as fragmented QRS complexes and changes in QRS morphology, as seen in Figure 4. These atypical patterns may contribute to difficulties in accurate AF classification by the model.

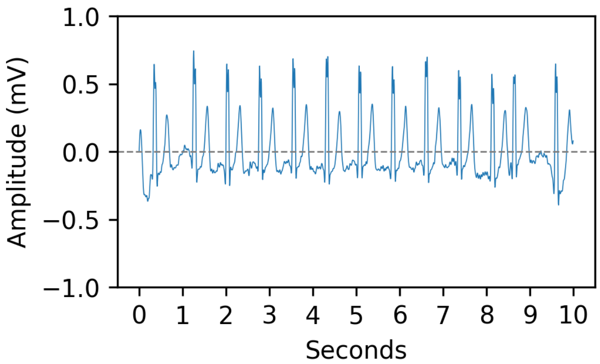

Figure 4: Subject 156

7. Conclusion

In this work, we developed a convolutional neural network to detect atrial fibrillation recurrence using 14-day single-lead ECG patch recordings following electrical cardioversion. The model was evaluated on OOD subjects. These results highlight the potential of deep learning for automated long-term AF monitoring in real-world clinical populations. Future work will focus on expanding the dataset and addressing remaining challenges with atypical ECG morphologies.

Acknowledgments

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