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Artificial Intelligence can now identify Atrial Fibrillation through Sinus Rhythm

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Atrial fibrillation (AF) is a significant healthcare challenge and is considered a global pandemic, since prevalence rates have increased substantially[1] and AF-related hospitalizations outnumber those of major cardiac conditions such as heart failure and myocardial infarction.[2] AF confers an increased risk of stroke and mortality, thus AF needs to be detected to manage the arrhythmia, but more importantly to also prevent comorbidities and death.[3] Sinus rhythm (SR) in a 10-second 12-lead ECG should not be deceptive to possible AF beyond this short monitoring time. Whilst silent or undetected AF is common, current screening methods are limited and demanding. Continuous monitoring by means of loop recorders is often indicated, particularly in case of embolic stroke with undetermined source (ESUS).[4] Novel and user-friendly wearables to identify arrhythmias have emerged with recent digital advances: wearable ECG technology using automated photoplethysmography (ppg) algorithms have shown feasible and accurate cardiac rhythm detection and will aid in monitoring the dynamic burden of time spent in AF[5], while mobile AF applications are available for patients and health care professionals, for education and guidance in management.[6]

Attia and colleagues aimed to develop and validate an artificial-enabled ECG (AI-ECG) using a trained neural network to detect the electrographic signature of AF during SR.[7] Structural changes in the atria predispose to atrial arrhythmias.[8] Deducting AF in a SR ECG has been attempted previously, by using P-wave and PR interval traces to describe phenomena such as interatrial block.[9] Here, Attia et al. hypothesised that the signature of AF due the structural changes in the atria, could be identified by a trained network, using a 12-lead ECG recorded during SR. Rather than finding the needle in the haystack by prolonged monitoring, authors basically suggest that AI will be able to judge by looking at the haystack if it has a needle hidden in it. P-wave characteristics are likely to be picked up

by the network, but no criteria are predefined or revealed in retrospect. In total, almost 65 million ECGs from a cohort of 210,414 patients ≥18 years with a least one 12-lead SR ECG from the Mayo Clinic ECG laboratory were used to develop, test and validate the network. The authors created three datasets: 1) a set (70% of patient cohort) to train the network; 2) a validation set to optimize the network; and 3) a testing set, to identify the ability of the AI-ECG to detect AF. Mathematical performance of the network demonstrated an impressive area under the curve of the operating receiver curve of 0.90%, a sensitivity 82.3%, specificity 83.5% and overall accuracy 83.4%.

There are several strengths of the approach taken by Attia and colleagues. Firstly, they used a large cohort of patients and consequent ECGs and prevented bias by dividing the patients over three datasets, demonstrating a robust approach. Their findings will be of clinical importance especially in identifying silent AF, and may have significant implications for secondary prevention of patients with ESUS in terms of providing appropriate oral anticoagulation to prevent recurrences of stroke. Furthermore, this approach may lead to a paradigm shift in recording SR rather than AF on an ECG, with a specific focus on identifying structural changes. However, false negatives may also be part of the outcomes and would prevent appropriate therapy. Moreover, the network has been tested to retrospectively identify AF rather than predicting AF. The AI-enabled algorithm would require further validation in a different patient cohort, testing a healthier out of hospital population, and rigorous prospective clinical trial assessment. Advanced refinement may be necessary before the network can be used for primary AF prediction.

In summary, Attia and colleagues are to be congratulated for their innovative approach and the thorough development and local validation of the AI-ECG. Since AI-algorithms have recently reached 'Cardiologist-level' in diagnostic performance[10], this AI-

ECG interpretation is ground breaking by creating an algorithm to reveal the likelihood of AF in ECGs showing SR.

Notwithstanding the limitations, the network can support clinical decision making, helping to relieve the AF-related healthcare burden. Further improvement of available systems, as well as related research is warranted to optimize the identification of AF and appropriate management accordingly. Combining ECG algorithms with age, gender, clinical features and biomarkers[11] may further improve identification of AF patients. Additionally, linking these variables with genetic markers[12], AI enabled algorithms[7] and smart monitoring by means of wearables[5] to diagnose AF and quantify AF burden, promises a safer and more efficient prevention of AF-related complications.

Author statement

Both authors contributed equally in drafting and critical revising the manuscript.

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Declaration of Interest

Dr Hendriks reports that the University of Adelaide has received on his behalf lecture and/or consulting fees from Medtronic and Pfizer/BMS. Dr Fabritz has received institutional research grants and non-financial support from European Union, British Heart Foundation, Medical Research Council (UK), and DFG and Gilead; and is listed as inventor on two patents held by University of Birmingham (Atrial Fibrillation Therapy WO 2015140571, Markers for

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