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Cover Story

New Care Delivery

Artificial Intelligence and Cardiology: Reaching New Frontiers

Author: Dr. Rafael Vidal-Perez | Cardiac Imaging Consultant | Cardiology Department | Hospital Clinico Universitario de A Coruña | A Coruña, Spain

Part of the new care delivery in cardiology is the use of artificial intelligence tools that are proving their utility in this evolving field. Electrocardiography has been considered an important diagnostic tool but also could have a role in the prediction of events. One important event to predict is atrial fibrillation due to its causal relationship with stroke, something that could be prevented in many cases with the start of anticoagulation. Artificial intelligence has shown potential value in predicting atrial fibrillation using simple tools as 12-lead electrocardiography. These strategies, based on electrocardiography, could have a role in other scenarios. External validation of this algorithm will be the key to AI success in daily clinical practice.

Key Points

- Decision-making process in medicine is a complex task.
- Incorporation of artificial intelligence tools in the field of cardiology into daily decision-making will improve care.
- Artificial intelligence has a potential value in predicting atrial fibrillation using simple tools as 12-lead electrocardiography.
- ECG patterns evaluated by artificial intelligence could help in the diagnosis of important diseases with an important impact on prognosis

Decision-Making in Cardiology

Nowadays, the decision-making process in cardiology, as a part of medicine, is a complex task that, in an ideal world, is based on the availability of reliable and objective evidence, fast access to knowledge, as well as the proper interpretation of available facts with the incorporation of patient benefit-risk ratios into every step; however, the experience of the practice of cardiology in the real world has taught us that this evidence is not always available, assimilation of knowledge takes time and decisions regarding each individual case may not always be objective (Bonderman 2017).

It is known that the most errors in decision-making have been attributed mainly to two elements. One of them is bias, such as for example, categorising minorities (social bias), and the other one is noise, which means that decisions are prejudiced by irrelevant factors, such as current mood, time since the last drink or even the current weather, as highlighted by Kahneman (2016). If you take all this information together, there is clear room for improvement with respect to generating evidence, structuring knowledge and translating it into clinical decisions

Probably the incorporation of artificial intelligence (AI) tools in the field of cardiology into daily decision-making will improve care delivery. But it is necessary that cardiologists retain the last step in the control of the system, keep an eye on the decisions and have the authority to change algorithms in cases that go wrong.

In this evolving field, AI is showing that simple tools like electrocardiography (ECG) could bring us a lot of potential information converting the ECG into a powerful instrument for prediction.

Electrocardiography as a Predictor of Events

One of the best telemedicine tools is ECG, and it is well known from the beginning of the twentieth century. It is also one of the first examples of telemedicine. In the early 1900s, Einthoven transmitted heart tracing via telephone lines from the local hospital to the laboratory where his string galvanometer was located (Einthoven 1906). ECG plays a fundamental role in diagnosis but could predict future events

On this topic, one of the focus is atrial fibrillation (AF) prediction, as AF is an important cause of stroke, a real public health problem due to the mortality and disability situations after one episode (Alkhouli 2019). A widely available, low-cost, and non-invasive test that facilitates the identification of patients who are likely to have AF would have important diagnostic and therapeutic implications and the ECG could fit in this definition.

For instance, up to a third of strokes have no known cause - so-called embolic stroke of undetermined source (ESUS) (Hart 2014). Many of these strokes are related to AF, which can be under-detected due to its paroxysmal and often asymptomatic nature (Martin 2015). Patients with ESUS are at high risk of a recurrent stroke, and when atrial fibrillation is documented, anticoagulation might reduce mortality and reduce the risk of recurrent stroke (Lip 2018). However, empirical use of anticoagulants following a ESUS event, whether with warfarin or a direct oral anticoagulant, has not been shown to be beneficial and increases risk of bleeding (Hart 2018; Mohr 2001). Therefore, determination of whether AF is present is crucial to guide therapy.

Artificial Intelligence and Atrial Fibrillation Prediction

Significant elements were developed in the last years to show the value of AI for AF prediction, and recently Paul A. Friedman and his group at Mayo Clinic published important results about this topic (Attia 2019a). They showed that ECG in sinus rhythm could predict the AF in the follow-up. They developed an AI-enabled ECG using a convolutional neural network (CNN) to detect the electrocardiographic signature of atrial fibrillation present during normal sinus rhythm using standard 10-second, 12-lead ECGs.

They collected for that standard 10-second, 12-lead ECG acquired in the supine position at the Mayo Clinic ECG laboratory between Dec 31, 1993, and July 21, 2017, with rhythm labels validated by trained personnel under cardiologist supervision. They included 180922 patients with 649931 normal sinus rhythm ECGs for analysis: 454789 ECGs recorded from 126526 patients in the training dataset, 64340 ECGs from 18116 patients in the internal validation dataset, and 130802 ECGs from 36280 patients in the testing dataset. 3051 (8.4%) patients in the testing dataset had verified atrial fibrillation before the normal sinus rhythm ECG tested by the model. A single AI-enabled ECG identified AF with an Area Under the Curve (AUC) of 0.87 (95% Confidence Interval 0.86–0.88), sensitivity of 79.0% (77.5–80.4), specificity of 79.5% (79.0–79.9), which could be interpreted as a good result.

A widely available, low-cost, and non-invasive test that facilitates the identification of patients who are likely to have AF could have important diagnostic and therapeutic implications

Recent advancements in high-quality signal acquisition and the availability of automated hardware ECG setups have facilitated the use of ECG in mass examinations, and many ECG-derived markers have been confirmed as risk factors for incident AF. Both the atrium-related and ventricle-related ECG variables were risk factors for incident AF, with significant hazard risks even after multivariate adjustments. The risk factors included P-wave indices (maximum P-wave duration, its dispersion or variation and P-wave morphology) and premature atrial contractions or runs. In addition, left ventricular hypertrophy, ST-T abnormalities, intraventricular conduction delay, QTc interval and premature ventricular contractions or runs were a risk of incident AF (Aizawa 2017). But this approach has limited efficacy and new tools need to be created, and AI has been the solution.

This AI model tries to find signals in the ECG that might be invisible to the human eye but contain important information about the presence of AF. This AI model was trained using the standard 10-second, 12-lead ECG alone and did not require any other inputs for AF risk assessment. One important thing is that the detection of the AF signal in the ECG relies on this easily obtained 10-second recording as opposed to the more invasive loop recording or cumbersome Holter ECG monitoring (that means 24-48h wearing a device). Also, the addition of multiple ECGs within an individual patient improved the model accuracy and suggested repeated measures might yield even better performance.

The explanation of how ECG in sinus rhythm could predict AF is complex. The authors suggest that the structural changes that precede AF, which might include myocyte hypertrophy, fibrosis, and chamber enlargement, are likely to lead to subtle

ECG changes, allowing for the prediction of underlying AF.

The implications of this study are really important as it supports the hypothesis that subtle patterns on the normal sinus rhythm ECG can suggest the presence of AF. The ability to identify patients with potentially undetected atrial fibrillation using an inexpensive, non-invasive, widely available point-of-care test has important practical implications for atrial fibrillation screening and potentially for the management of patients with prior stroke of unknown cause.

Artificial Intelligence and Electrocardiography Reaching New Frontiers

But there many other things that ECG could show us with the help of the different approaches of AI.

One example is determining serum potassium. Extreme potassium concentration perturbations have well-described ECG manifestations, but more subtle potassium changes may be detectable by Deep Learning of the ECG, and a CNN identified hyperkalaemia with an AUC of 0.85-0.88. This approach may have implications for outpatient titration of medications that disrupt potassium homeostasis or renal function, or for altering dialysis schedules. This approach could give us serum electrolyte concentrations without any blood drawing (Galloway 2019).

Another development, although myocardial diseases causing poor ventricular function are often detectable on the ECG, the ECG itself is not the better screening test for asymptomatic left ventricular dysfunction - a condition that could affect up to 2-5% of the adult population. However, a CNN trained using ECG and echocardiography pairs could reliably detect left ventricular dysfunction (AUC 0.93) (Attia 2019b). This network has performed well in a subsequent validation study at the same institution (Attia 2019c) and is currently being tested in a prospective, cluster-randomised clinical trial called ECG AI-Guided Screening for Low Ejection Fraction, named the EAGLE trial (Yao 2020).

Also, AI has been used for the detection of hypertrophic cardiomyopathy (HCM) based on 12-lead ECG through a CNN, showing an AUC was 0.96 (95% Confidence interval: 0.95 to 0.96) with sensitivity 87% and specificity 90%, which means high diagnostic performance, particularly in younger patients, but this model requires further refinement and external validation (Ko 2020).

Conclusion

Artificial intelligence tools are promising, and they will change the way cardiology is practiced, but physicians need to be prepared for the upcoming AI era. We also need clear results of the utility of AI in daily practice. Many applications are discovered in a short time period, but they need to be replicated in different populations. External validation will thus be the key to AI success.

AI use in ECG interpretation could have important implications for atrial fibrillation screening and for the management of patients with unexplained stroke, but this approach needs further prospective calibration before widespread application for screening a broader, ostensibly healthy population.

Conflict of Interest

None ■

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