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Artificial Intelligence-enhanced electrocardiogram analysis: the need to develop image-based algorithms.

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Take Home Messages

- Contemporary artificial intelligence-enhanced electrocardiogram algorithms exhibit levels of diagnostic accuracy comparable with expert clinicians.
- The ability of artificial intelligence-enhanced algorithms to detect patterns unrecognisable by the human eye offers true promise to expand the utility of the electrocardiogram.
- Most algorithms have been developed using digitised electrocardiogram signal data and are therefore unable to interpret paper-based electrocardiograms.
- Image-based algorithms can facilitate paper-based artificial intelligence-enhanced electrocardiogram analysis ensuring algorithm availability to all healthcare professionals.

Introduction

Artificial intelligence has the potential to revolutionise the care pathway for patients with cardiovascular disease through its ability to rapidly analyse the vast volumes of data acquired during routine clinical care (Figure 1).(1) The electrocardiogram is a widely available diagnostic tool which records the heart's electrical activity as a graph of voltage versus time.(2) Numerous studies have already demonstrated the potential artificial intelligence-enhanced electrocardiography has to improve patient care.(3) The aim of this editorial is to summarise the latest developments in artificial intelligence-enhanced electrocardiography and to discuss potential barriers limiting integration into clinical practice.

Automated electrocardiogram interpretation

In routine clinical care, the electrocardiogram is typically interpreted by a healthcare professional and used to distinguish normal versus abnormal and subsequently diagnose cardiovascular disease. Electrocardiogram interpretation is often challenging, and incorrect diagnoses can lead to adverse outcomes for patients.(4,5) This has led to interest in the use of computer-generated electrocardiogram interpretation. Initially, automated algorithms were developed to make measurements using electrocardiogram signal points and define disease states such as myocardial infarction and arrhythmia.(6) Unfortunately, these were often prone to errors limiting their integration into clinical care. More recently, improvements in computational power have led to the application of machine learning to facilitate automated electrocardiogram diagnosis. Contemporary artificial intelligence-based algorithms have been demonstrated to have similar degrees of diagnostic accuracy compared with experienced clinicians working in cardiology departments.(7) The development of accurate, automated artificial intelligence-enabled electrocardiogram diagnostic algorithms offers the potential to optimise clinical workflows and reduce diagnostic error.

Detection of patterns unrecognisable by the human eye

Beyond automated electrocardiogram interpretation, artificial intelligence-enhanced electrocardiography may be able to detect patterns unrecognisable by the human eye.(3) For example, studies have shown that artificial intelligence-enhanced electrocardiography can accurately estimate patient characteristics such as age and gender(8) as well as serum electrolyte levels.(9) Such characteristics were previously considered unidentifiable from electrocardiograms using rule-based, computer-generated algorithms or human interpretation. Whilst further studies are required to validate such findings, these studies highlight the potential for artificial intelligence-enhanced electrocardiography to identify patterns unrecognisable by the human eye.

Studies are also demonstrating the feasibility of artificial intelligence-enhanced electrocardiography as a screening tool for cardiovascular disease. Arrhythmias such as atrial fibrillation are often paroxysmal in nature leading to low diagnostic yields from single electrocardiograms. Whilst prolonged cardiac monitoring presents a solution, such an approach can be time-consuming and costly. Artificial intelligence-enhanced electrocardiography has been demonstrated to detect the electrocardiographic signature of atrial fibrillation from a sinus rhythm electrocardiogram(10) and prospective studies have subsequently confirmed the effectiveness of such an approach for atrial fibrillation screening.(11) Beyond arrhythmias, artificial intelligence-enhanced electrocardiography can also screen for structural disorders such as left ventricular systolic dysfunction(12) and aortic stenosis.(13) The electrocardiogram is widely available in almost all healthcare settings and the use of artificial intelligence-enhanced electrocardiography could therefore facilitate rapid, population-based disease screening thereby facilitating earlier diagnosis and referral for specialist care.

In patients with pre-existing disease, artificial intelligence-enhanced electrocardiography may also be able to risk stratify patients. For example, in a study of over 7 million patients, artificial intelligence-enhanced electrocardiography was shown to be capable of accurately identifying patients with coronary artery disease and amongst these patients, artificial intelligence-enhanced electrocardiography was able to accurately predict risk for acute coronary events and mortality.(14) Artificial intelligence-enhanced electrocardiography could also facilitate longitudinal disease monitoring. In hypertrophic cardiomyopathy, artificial intelligence-enhanced electrocardiography has been used to create artificial intelligence-enhanced electrocardiogram hypertrophic cardiomyopathy scores for patients, and these scores have been demonstrated to correlate with metrics traditionally used to monitor patients such as left ventricular outflow tract gradient with Valsalva and NT-proBNP levels.(15) In patients with pre-existing disease, artificial intelligence-enhanced electrocardiography could therefore be used to risk stratify patients and guide treatment decision making.

Challenges to artificial intelligence-enhanced electrocardiography implementation

Despite the array of potential benefits associated with artificial intelligence-enhanced electrocardiography, numerous barriers limit the integration of artificial intelligence-enhanced electrocardiography into routine clinical care. These barriers will need to be overcome to ensure artificial intelligence-enhanced electrocardiography supplements existing clinical workflows. Barriers associated with artificial intelligence-enhanced electrocardiography include those typically associated with the use of artificial intelligence in healthcare such as patient/physician trust and the requirement to ensure that algorithms are externally validated in prospective studies.(16) A problem unique to the electrocardiogram, however, is the format through which it is encountered (Figure 2). Whilst digital electrocardiograms are available, paper-based electrocardiograms remain in use in numerous clinical settings. Most artificial intelligence algorithms currently rely on digitised signal data and are therefore unable to analyse paper-based electrocardiograms, which are typically scanned or photographed and uploaded into electronic health records. Some image-based algorithms have been developed.(17) However, there is a need to ensure that more are developed to facilitate artificial intelligence-enhanced analysis of paper-based electrocardiograms.(18) This will ensure that artificial intelligence-enhanced electrocardiogram analysis can be applied regardless of the electrocardiogram format encountered.

Conclusion

Artificial intelligence-enhanced electrocardiography has the potential to transform the clinical utility of the electrocardiogram. Studies have demonstrated that artificial intelligence-enhanced electrocardiography can facilitate rapid, automated diagnosis, screen for disease, and guide treatment-decision making for patients with pre-existing disease. Nevertheless, numerous challenges currently limit implementation into routine clinical care. The development of image-based algorithms presents a key step towards ensuring that all healthcare professionals can utilise artificial intelligence-enhanced electrocardiography.

Figures

Data Resources

Electrophysiology and devices: Electrocardiograms, electroanatomic mapping data, wearable devices, implantable loop recorders, pacemakers, defibrillators.
Imaging: Computed tomography, magnetic resonance imaging, echocardiography, nuclear imaging.
Intervention: Angiography, valve imaging.
Heart failure: Clinical data, serum biomarkers, imaging modalities, device-derived data.

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Artificial Intelligence in Cardiology

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Cardiovascular disease management

Prior to diagnosis: Prevention, screening, diagnostic assistance.
Patients with established disease: Risk stratification, disease phenotyping, treatment decision making, longitudinal monitoring.

Figure 1. Applications of artificial intelligence in cardiology.

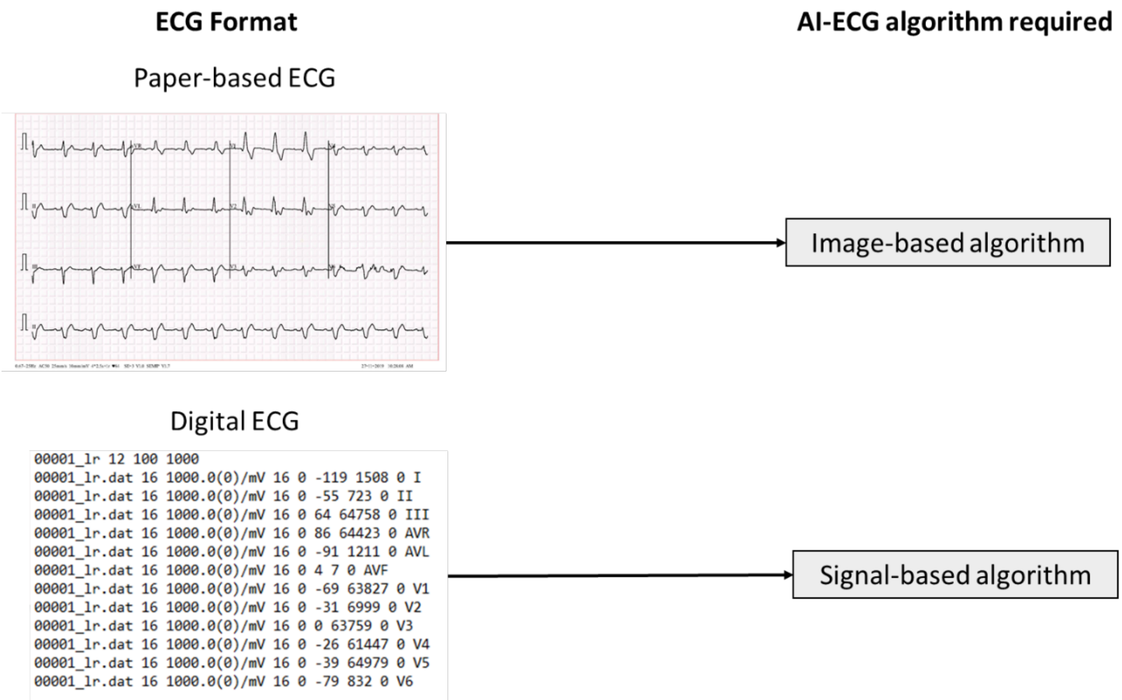

Figure 2. Electrocardiogram formats typically encountered, and the type of artificial intelligence-enhanced electrocardiogram algorithms required for analysis. The top left figure shows an image of a paper-based electrocardiogram obtained from the "ECG Images dataset of Cardiac and COVID-19 patients".(19) The bottom figure is a .HEA file obtained from the PTB-XL dataset,(20) a large, publicly available signal-based electrocardiogram dataset. AI = artificial intelligence; ECG = electrocardiogram. Files obtained from both datasets are available under a Creative Commons Attribution 4.0 International license.

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