Using artificial intelligence to spot heart failure from ECGs: is it prime time?

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Heart failure (HF) is affecting 1-3% of the general adult population globally, with escalating socioeconomic costs.[1] Approximately 6% of the adults ->45 years have asymptomatic left ventricular systolic dysfunction (LVSD)[2], with a ~~of whom a~~ third of this population ~~has~~found to have moderate-severe LVSD (LV ejection fraction ≤40%)[2]. Indeed, individuals with LVSD could be asymptomatic for some time before clinical diagnosis, while the disease is often discovered when it is already too late. Screening the general population with echocardiography is impractical, and such a programme would have major health economic implications. Therefore, there is an unmet need for novel diagnostic tools to enable early detection of LVSD, leading to timely deployment of therapeutic measures to modify the natural history of the disease.

In the recent years, artificial intelligence (AI) has transformed our ability to interpret medical imaging data.[3] Indeed, AI-models help to automate the segmentation of anatomical structures of interest across various imaging modalities[4], and can recognise, aggregate and classify hidden patterns from medical images. This ~~enabling~~ enables early diagnosis or even prognosis, in a way that is not possible in routine clinical interpretation,[4,5] and such approaches are currently in use in clinical practice, saving lives and reducing healthcare costs.[6] In a similar way, electrocardiograms (ECG) could be processed by AI-models to recognise invisible patterns, critical for the diagnosis of a range of cardiac diseases. Indeed, pioneering work by the Mayo clinic team in deep ECG phenotyping has demonstrated the ability of AI to predict the probability of a variety of cardiovascular diseases, such as atrial fibrillation from sinus-rhythm ECG[7], aortic stenosis, hypertrophic cardiomyopathy, cardiac amyloidosis and others.[8, 9] In the context of diagnosing heart failure, Akbilgic *et al.*[10] has shown that AI-ECG interpretation could help to predict 10-year risk of HF in the

Atherosclerosis Risk in Communities (ARIC) dataset, with prediction performance comparable with clinical risk calculators.

In this issue of the *European Heart Journal*, Dhingra *et al*.[11] evaluated a novel AI-ECG algorithm that was previously trained to detect the probability of LVSD based on single lead ECG images. Notably, the AI-ECG model was evaluated in a large population drawn from the United States (using electronic health records from 5 hospitals and an outpatient medical group based in southern New England), and externally validated in two primary prevention, community-based cohorts in the United Kingdom (UK Biobank) and Brazil (ELSA-Brazil) with a total of >280,000 individuals. Although the training dataset is from a single healthcare system and it is not representative of the US population, the algorithm appeared to have remarkable generalizability in the ethnically diverse UK and Brazilian cohorts, despite the widely recognised racial variations in ECG patterns.[12]

In the study by Dhingra *et al*.[11] the higher probability of LVSD detected by the AI-ECG model was associated with an increased risk of incident heart failure, a signal that was independent from traditional risk factors, and incremental to convenient risk stratification scores such as PCP-HF. Unlike the previous AI-ECG algorithm that was trained in the ARIC cohort to predict the risk of future clinical diagnosis of HF,[10] the current AI-ECG model was initially developed using contemporary pairs of 12-lead ECG and echocardiograms within 15 days apart.[13] A positive AI-ECG score was also demonstrated to stratify the risk of incident LVSD among individuals with LV ejection fraction ≥40% at baseline.[13] This supports the relevance of LVSD as a factor preceding clinical heart failure in the AI-ECG score, rather than a consequence of the heart failure syndrome, highlighting the predictive value of this

new technology.[10] However, the clinical impact of early treatment for asymptomatic LVSD detected by AI-ECG is yet to be evaluated in future randomised clinical trials.

Another key feature of the AI-ECG model described by Dhingra *et al*.[13] is the use of ECG images (rather than raw digital time/voltage ECG data) as an input parameter.[13] In the model development, images of ECG waveforms in the standard clinical format were resized and transformed into >10 million trainable parameters as input to the convolutional neural network (EfficientNet-B3 architecture).[13] This approach eliminates the constrains of extracting raw ECG voltage data which is vendor-specific and not always accessible.[8, 10] Nevertheless, Dhingra *et al*.[13] were limited to the use of ECG waveforms plotted from raw ECG voltage data because scanned ECG images were not captured in the UK Biobank and ELSA-Brazil cohorts.[11] In the real world clinical setting, the ECG waveform data could be prone to loss of quality from manual scanning or photo taking of the ECGs. Further performance evaluation of the image-based AI-ECG model through head-to-head comparison to raw digital based AI ECG interpretation models would potentially help to clarify the inter-operability and scalability of the AI-ECG in the clinical setting.

As patients with chronic heart failure are likely to have multiple ECGs taken during follow up visits, exploring the longitudinal changes of AI-ECG score at different disease stages would be attractive to guide monitoring and treatment strategies. Importantly, integrating multi-dimensional clinical data (e.g. blood biomarkers, cardiac imaging, clinical information etc) in addition to ECG, could totally transform the way we diagnose, risk-stratify and manage heart failure and a wide range of other cardiovascular diseases in the immediate future (Figure). The rapid adoption of mobile and wearable technologies also means that single lead ECG is being collected at mass scale, and such AI algorithms could rapidly enhance the socioeconomic value of these “non-medical” devices. Overcoming the

interoperability and screening of noisy ECG waveforms from such devices is likely to be a challenge, and this could potentially be addressed using different AI approaches. There is no doubt that the ability to predict future heart failure from ECG waveforms, as presented by Dhingra *et al*.[13] is a major step towards implementing low-cost population screening in search of the hidden signs of heart failure.

Figure Artificial intelligence in the diagnosis and management of heart failure. BNP, brain-natriuretic peptide; CMR, cardiac magnetic resonance imaging; CT, computed tomography; ECG, electrocardiogram; ECHO, echocardiogram; LVSD, left ventricular systolic dysfunction.

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