Journal of Electrocardiology 90 (2025) 153903

Contents lists available at ScienceDirect

Journal of Electrocardiology

journal homepage: www.jecgonline.com

A practical review of generative AI in cardiac electrophysiology medical education

Shaun A. Hanycz [a], Pavel Antiperovitch [b,*]

[a] Department of Medicine, Schulich School of Medicine & Dentistry, London, Ontario, Canada
[b] Department of Cardiology, Schulich School of Medicine & Dentistry, London, Ontario, Canada

ARTICLE INFO

Keywords:
Artificial intelligence (AI)
Generative adversarial networks (GANs)
Surface electrocardiogram (ECG)
Medical education

ABSTRACT

Generative artificial intelligence (AI) is a component of artificial intelligence that creates synthetic multi-modal output in the form of text, images, and audio. Multiple approaches have been implemented into teaching surface ECG interpretation. However, learner performance remains poor. Generative AI in the form of Generative Adversarial Networks (GANs) is a novel AI model that has the potential to augment trainee ECG interpretation via creation of synthetic ECGs and anatomical depiction of conduction defects. Generative AI may be implemented in medical education to customize trainee surface ECG interpretation to improve learning and retention.

Introduction

Generative artificial intelligence (AI) is a subset of AI that creates new content in the form of multi-modal output (e.g. images, text, audio) that resembles what it initially learned from training (Fig. 1). In electrocardiology, the capability of AI to generate ECGs is an emerging and fascinating advancement with significant implications, particularly for medical education. The rapid evolution of AI underscores the potential of implementing generative AI in the form of Generative Adversarial Networks (GANs) output to optimize trainee education. This review aims to introduce generative AI, summarize current research in the field, and explore ways its potential could transform ECG interpretation for students.

How does generative AI work?

Two common ways to apply generative AI is using Generative Adversarial Networks (GANs) and transformers. Goodfellow et al. first described GANs in 2014 as a form of deep neural networks competing against one another to generate a highly authentic synthetic image [1]. In ECG generation, this consists of two AI networks - the Discriminator network that identifies whether an ECG is "real" or "not real" and a Generator that learns to generate ECGs that look real. The first step is to ensure the discriminator is able to identify real world ECGs from fake ones. The second step is to train the generator, which can create ECGs by trial-and-error until it is good enough to "fool" the discriminator, in an effort for the generator to create authenticity of the synthetic signal [1,2]. GANs provide a unique advantage of creating realistic, synthetic surface ECG signals as depicted in Fig. 1 [2]. Comparatively, in 2017, Vaswani et al. revolutionized large language models (LLMs) with the introduction of the transformer architecture [3]. This architecture utilizes attention, a mechanism by which neural networks keep context when predicting output based on input data [3]. LLMs are not currently suitable for synthetic surface ECG generation due to lack of a training dataset, significant financial capital, and resources required to train them.

Need for generative AI in medical education

Multiple teaching styles have been implemented for surface ECG interpretation without a clear methodology appearing most effective [4]. Despite this, learners continue to have significant difficulty with ECG interpretation [5]. Sibbald et al., 2014 presented data showcasing cardiology fellows performing poorly with the assessment of particular life-threatening diagnoses, including: hyperkalemia, long QT, complete heart block, and ventricular tachycardia [5]. Generative AI can be integrated to reinforce training examples with gold standard labels to provide a customized approach to surface ECG interpretation.

Generative AI may assist medical trainees in understanding mechanisms of conduction system disease, assess intracardiac electrograms, and initiate treatment. By providing anatomically accurate depictions of the cardiac conduction system and mechanisms of arrhythmia,

* Corresponding author at: 339 Windermere Road, London, ON N6A 5A5, Canada.
E-mail address: pavel.antiperovitch@lhsc.on.ca (P. Antiperovitch).

https://doi.org/10.1016/j.jelectrocard.2025.153903

Available online 21 February 2025

generative AI provides an invaluable tool for internal medicine and electrophysiology trainees aiming to appreciate pathophysiology and disease localization. These models provide an avenue for real-time ECG and electrogram creation and illustration of conduction system disease focused on individualized learning. Generative AI lends itself as a model that provides a unique, not previously utilized methodology in ECG interpretation training that is highly personalizable and adaptable as outlined in Fig. 2. For example, deficiencies in arrhythmias secondary to life-threatening metabolic disturbances can be tailored for learners with visual aids augmenting their learning. Comparatively, a separate learner may benefit from an anatomic depiction and an increased number of ECGs depicting ST elevation myocardial infarction.

Limitations and challenges of generating ECGs

The implementation of Generative AI into medical education has noteworthy limitations. Class imbalance, a scenario where common conditions (ie: normal sinus rhythm) are encountered by GANs much more frequently than rare arrhythmias (ie: bidirectional ventricular tachycardia) resulting in an inability to generate a realistic representation of rare arrhythmias [6]. However, these effects can be partially mitigated by data augmentation, a process by which the size of a dataset can be increased by adding minimally modified versions of the original data [6]. To generate high fidelity surface ECGs, labeled ECG datasets are required [3].These datasets often contain proprietary and clinically sensitive data, which contain multiple regulatory and privacy concerns when employed in medical research and significant financial capital, thereby limiting their use.

Despite these limitations, the utility of AI to improve medical trainee clinical performance is becoming increasingly applied at the level of undergraduate medical education. At the University of Minnesota, trainees have access to a database of over 800 clinical cases with the ability to have immediate feedback and input on their performance via AI. This level of customization provides an opportunity to revolutionize how ECGs are taught to increase trainee competency [7]. The medical imaging community has widely adopted GANs for creation of synthetic images, but also have not yet explored the utility for medical education [8]. This may be a result of logistical challenges including adoption via training programs and quality insurance, or a consequence of the rapid growth of the field.

Need for future studies

Currently, existing image generation models make use of the transformer architecture rather than GANs to generate images [3]. However, these models struggle to produce high-quality, realistic ECGs, primarily due to limited and inadequate input data used during training [3]. To date, no generative AI model has been reported to successfully generate ECGs with diagnostic labels beyond simple sinus rhythm. While efforts are underway to develop generative AI models capable of producing diagnostic-quality ECG signals, progress is hindered by the requirement for large, well-labeled training datasets. This highlights the need for multinational collaboration to build such extensive datasets.

The advances in generative AI highlight the potential for implementation into medical education. Currently, GANs have been primarily utilized in data augmentation but are unable to generate arrhythmias, including those associated with the Brugada syndrome. Once generative AI models are able to create ECGs, they must be tested in rigorous medical education studies to assess the potential for further improvement in learners performance and retention. Although not currently available, the growth of these models highlights that generative AI is a promising modality to provide a personalized and revolutionized approach to surface ECG interpretation.

Ethics approval and consent to participate

Not applicable.

Funding

This research received no external funding.

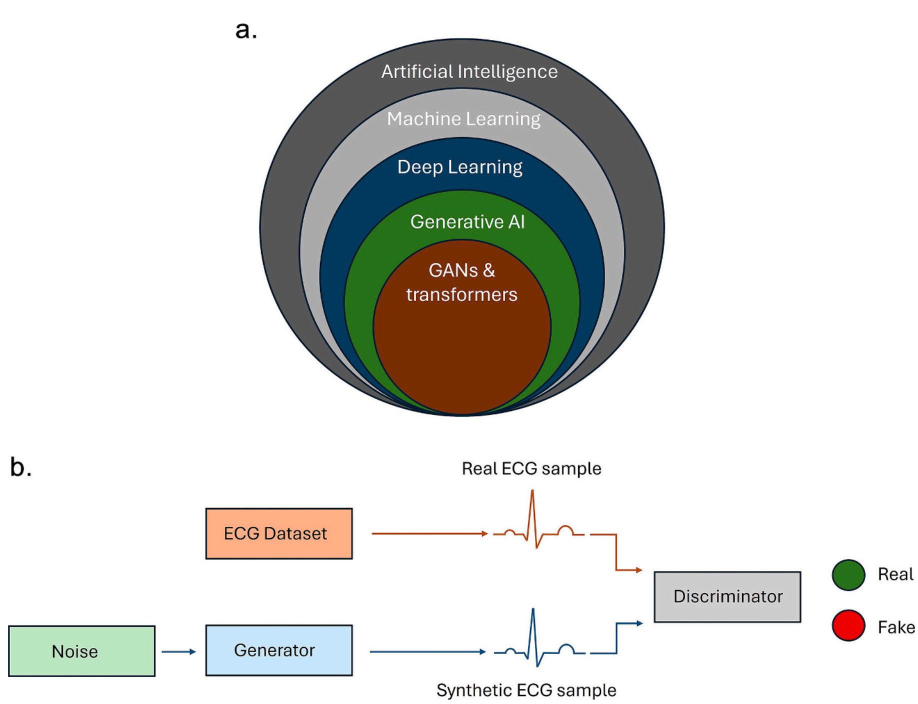

Fig. 1. (a) Graphical representation of the depth of artificial intelligence. (b) GAN architecture consists of two neural networks, the generator and discriminator, competing against one another. The generator produces synthetic ECG data, and the discriminator determines whether the data is real or fake.

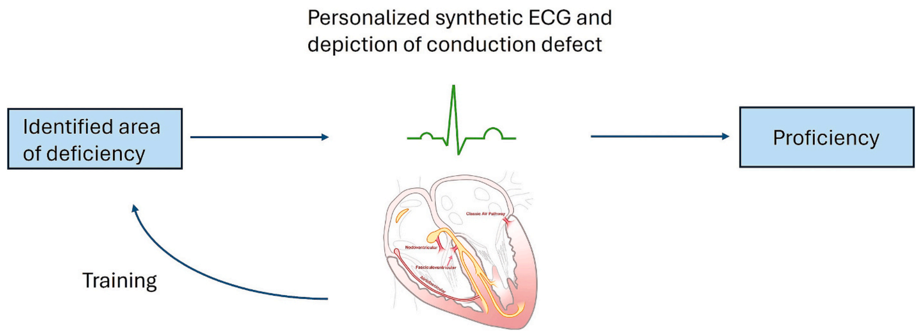

Fig. 2. Proposed mechanism of implementing Generative AI into surface ECG teaching.

CRediT authorship contribution statement

Shaun A. Hanycz: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Pavel Antiperovitch:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declare no conflict of interest.

References

[1] Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, et al. Generative adversarial networks. Neural Inform Proc Syst 2014;27. https://doi.org/10.48550/arXiv.1406.2661.

[2] Berger L, Haberbusch M, Moscato F. Generative adversarial networks in electrocardiogram synthesis: recent developments and challenges. Artif Intell Med 2023;143:102632. https://doi.org/10.1016/j.artmed.2023.102632.

[3] Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention is all you need. Neural Inform Proc Syst 2017. https://doi.org/10.48550/arXiv.1706.03762.

[4] Fent G, Gosai J, Purva M. Teaching the interpretation of electrocardiograms: which method is best? J Electrocardiol 2015;48(2):190–3. https://doi.org/10.1016/j.jelectrocard.2014.12.014.

[5] Sibbald M, Davies E, Dorian P, Yu E. Electrocardiographic interpretation skills of cardiology residents: are they competent? Can J Cardiol 2014;30(12):1721–4. https://doi.org/10.1016/j.cjca.2014.08.026.

[6] Shorten C, Khoshgoftaar TM. A survey on image data augmentation for deep learning. J Big Data 2019;6(1):60. https://doi.org/10.1186/s40537-019-0197-0.

[7] University of Minnesota Medical School. Artificial Intelligence Behind Improved Clinical Skills Assessment and Teaching. https://med.umn.edu/news/artificial-intelligence-behind-improved-clinical-skills-assessment-and-teaching; 2024 (accessed 17 October 2024).

[8] Sorin V, Barash Y, Konen E, Klang E. Creating artificial images for radiology applications using generative adversarial networks (GANs) – a systematic review. Acad Radiol 2020;27(8):1175–85. https://doi.org/10.1016/j.acra.2019.12.024.