

REVIEW

Open Access



Clinical significance, challenges and limitations in using artificial intelligence for electrocardiography-based diagnosis

Cheuk To Chung¹, Sharen Lee¹, Emma King¹, Tong Liu², Antonis A. Armoundas^{3,4}, George Bazoukis^{5,6*} and Gary Tse^{2,7*} 

Abstract

Cardiovascular diseases are one of the leading global causes of mortality. Currently, clinicians rely on their own analyses or automated analyses of the electrocardiogram (ECG) to obtain a diagnosis. However, both approaches can only include a finite number of predictors and are unable to execute complex analyses. Artificial intelligence (AI) has enabled the introduction of machine and deep learning algorithms to compensate for the existing limitations of current ECG analysis methods, with promising results. However, it should be prudent to recognize that these algorithms also associated with their own unique set of challenges and limitations, such as professional liability, systematic bias, surveillance, cybersecurity, as well as technical and logistical challenges. This review aims to increase familiarity with and awareness of AI algorithms used in ECG diagnosis, and to ultimately inform the interested stakeholders on their potential utility in addressing present clinical challenges.

Keywords: Electrocardiography, Artificial intelligence, Machine learning, Deep learning, Cardiovascular diseases

Introduction

An increasing number of research studies are currently investigating the potential use of artificial intelligence (AI) in different aspects of medicine [1–4]. In particular, there is increasing evidence supporting the role of AI in the field of electrocardiography (ECG). The ECG is a simple and inexpensive diagnostic tool that provides valuable guidance in assessing and monitoring cardiovascular diseases. Both performing and interpreting ECGs are skilled tasks requiring significant training and experience

to achieve competency, and as such are susceptible to human error.

Application of supervised and unsupervised machine learning (ML) algorithms in ECG analysis and interpretation has shown considerable promise [5]. Supervised ML such as Artificial Neural Networks (ANNs) and Support Vector Machine (SVM) can be trained to learn a classification function given a set of labelled data. Contrarily, unsupervised ML can detect potential correlations in data without labels [6]. In addition to ML, the recent advent of deep learning-based (DL) analysis of ECGs can assist clinicians in different clinical scenarios, such as cardiovascular diseases (arrhythmias, cardiomyopathies, valve diseases, etc.) and non-cardiovascular diseases, for diagnosis, prognosis, and risk stratification [7–12]. Instead of being fed with handcrafted vectors, on which ML algorithms rely, the DL approach uses the end-to-end learning strategy, which programmes the system to learn the necessary features from the raw data [13]. The

*Correspondence: gbazoukis@med.uoa.gr; gbazoukis@yahoo.gr; garytse86@gmail.com

²Tianjin Key Laboratory of Ionic-Molecular Function of Cardiovascular Disease, Department of Cardiology, Tianjin Institute of Cardiology, Second Hospital of Tianjin Medical University, Tianjin 300211, China

⁵Department of Cardiology, Larnaca General Hospital, Inomenon Polition Amerikis, Larnaca, Cyprus

Full list of author information is available at the end of the article



© The Author(s) 2022. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

benefit of deep neural networks is its ability to identify novel intervariable relationships independent of human-selected feature extraction, which can offer an enormous previously unrecognized insights in healthcare diagnosis and treatment [7]. This review aims to discuss the clinical significance and implications of the use of AI algorithms on ECG (AI-ECG) analysis and interpretation as well as the associated clinical challenges and limitations (Fig. 1).

Clinical significance

Cardiovascular disease

With regard to cardiovascular conditions, the use of AI-ECG algorithms for rhythm identification and ECG interpretation can be more accurate in interpretation than existing ECG software [14]. AI-based ECG analysis showed high accuracy in diagnosing hypertrophic cardiomyopathy [15], with an area under the receiver operating characteristic curve (AUC) of 0.98, sensitivity of 92% and specificity of 95%. Moreover, AI-based ECG analysis could also be used for screening first-degree relatives of patients with dilated cardiomyopathy [16]. For the rare catecholaminergic polymorphic ventricular tachycardia with apparently normal ECGs at rest [17, 18], subtle repolarization abnormalities may be detected by machine learning methods [19].

Energy waveform ECG analysis using ML techniques has also been successfully employed in identifying patients with left ventricular (LV) dysfunction, reducing the need for echocardiography exams in asymptomatic patients [20]. Similarly, AI-based analysis of ECGs was able to identify patients with dyspnea caused by LV systolic dysfunction, which outperformed the use of NT-proBNP as a marker of LV failure [21].

Another area for AI implementation is the identification of patients who may benefit from anticoagulation following an embolic stroke of unknown source (ESUS). A probability greater than 0.2, of underlying atrial fibrillation (AF) determined by AI-ECG analysis, in patients with ESUS was associated with increased AF detection during ambulatory cardiac rhythm monitoring [22]. Recent work has demonstrated that ML algorithms can detect AF by restitution analysis of normal sinus rhythm ECGs with k-nearest neighbour (k-NN) algorithm [23]. With respect to AF detection, traditionally handcrafted algorithms cannot provide a rich data representation as they are unable to accurately detect P-waves due to their low signal-to-noise ratio and overlapping with the T-waves, which reduces their performance [24]; by contrast, DL algorithms are able to “view” the complexity of the signal holistically by understanding the relationships that exist between parameters [24]. The presence of

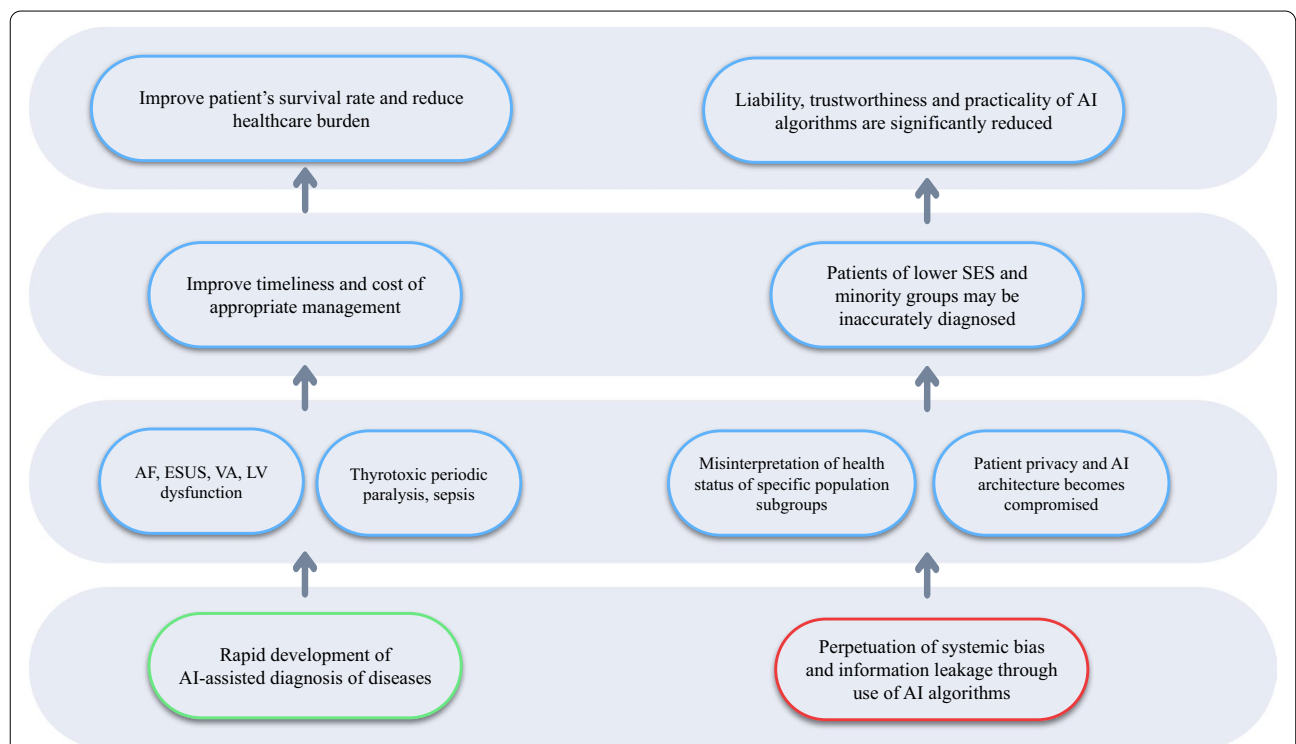


Fig. 1 Flow diagram summarising the clinical significance, challenges, and limitations of using artificial intelligence (AI) for electrocardiography (ECG)-based diagnosis

artifacts in ECG images may pose a challenge in the use of convolutional neural network (CNN) in image training. However, the recent, introduction of recurrent neural networks (RNN) can further minimize potential bias and discriminate AF from normal sinus rhythm [25]. Consequently, if AI enhanced ECG analysis is implemented and adopted, it may save unnecessary inspection time and costs on follow up diagnostic tests or monitoring devices. While there is still limited supporting evidence for systematic screening for AF, as well as associated cost implications [26], targeted screening, systemic opportunistic screening or smartphone algorithms, may be a more cost-effective option when using AI-enhanced ECG systems. With an increasing consumer adoption of wearable healthcare technologies [27, 28], the incorporation of AI-enhanced algorithms for AF screening [29–32] would be expected to AF-related morbidities in the long-term [33, 34].

Regarding ventricular arrhythmias, AI analysis of ECGs can be used to identify the site of origin, aiding catheter ablation procedures and quality of care in the ICU [35, 36]. In the setting of valvular diseases, AI-based ECG analysis has been proposed as an accurate screening tool for the identification of patients with moderate to severe aortic stenosis in the community [37]. Furthermore, promising results have been proposed for the identification of mitral regurgitation using AI-based ECG [38]. ML algorithms have been implemented in the hospitalized patients to improve the quality of care. Specifically, most alarms in bedside monitors have been found to be false. ML algorithms have been implemented in this setting by reducing false alarms improving the quality of care in hospitalized patients [39, 40].

Non-cardiovascular disease

Beyond the role of AI-based analysis of ECG data in the management of cardiovascular disease, AI can be used for the analysis of ECG data to aid the management of various non-cardiovascular diseases. AI has been used to identify the ECG-age of patients. Interestingly, it was found that patients with ECG-age more than eight years greater than their chronological age have higher mortality rates [9].

Sepsis can be identified by the application of DL algorithms on ECG data [41], while hyperglycemia has been identified by an ML algorithm using ECG data with an AUC of 0.945, sensitivity of 88%, and specificity of 85% [42]. ML-based ECG analysis has also been applied to the non-invasive evaluation of physiological parameters, including cardiovascular and cerebrovascular hemodynamics [43]. An AI-ECG system in combination with routine blood chemistries can aid the early diagnosis of thyrotoxic periodic paralysis, facilitating the timely initiation of appropriate management [9, 44]. Moreover, recent studies have also demonstrated the use of DL models and ECG to assess electrolyte imbalances [45]. This methodology is economical, and data can be easily obtained with wearables. Electrolyte imbalance is a marker for numerous endocrine diseases such as diabetes insipidus and hyperparathyroidism [46]. AI-based ECG analysis was also found to achieve a high negative predictive value for COVID-19 and, therefore, can be used as a rapid screening tool in identifying healthy individuals [47]. The performance of the aforementioned AI-ECG algorithms is summarized in Table 1. The variation in sensitivity and specificity may be attributed to variability in the cohort size of each study. As AI technology becomes more refined and accessible, it can offer increased diagnostic efficiency

Table 1 Summary of the different AI-ECG algorithms of included studies

Study	Year	Machine learning technique	AUC	Specificity (%)	Sensitivity (%)
Adedinsawo et al. [21]	2020	Convolutional neural network	0.890	87	74
Attia et al. [47]	2021	Convolutional and residual neural network	0.767	10.2	98
Cohen-Shelly et al. [37]	2021	Convolutional neural network	0.850	74	78
Cordeiro et al. [42]	2021	Deep neural network	0.945	85	87.6
Kwon et al. [41]	2021	Residual neural network	0.901	–	–
Kwon et al. [45]	2020	Convolutional neural network	0.873	–	–
Lin et al. [44]	2021	Convolutional neural network	0.986	69.2	88.9
Potter et al. [20]	2021	Random forest classifier	0.830	72	85
Rabinstein et al. [22]	2021	–	–	75	63
Shrivastava et al. [16]	2021	Convolutional neural network	0.955	44.8	98.8
Siontis et al. [15]	2021	Convolutional neural network	0.980	95	92

for a range of conditions, thus resulting in more prompt and efficient care.

Challenges and limitations

Professional liability

Despite its promising potential, several issues must be addressed regarding the clinical implementation of AI. More importantly, a framework for successful implementation is mandatory [1, 48, 49]. With greater AI involvement in clinical decision-making, our previous perception of the dynamics of practitioners' fiduciary relationship with their patients will be challenged. Another issue that has raised ethical concerns for AI implementation in clinical practice is physicians' professional liability in the case of an incorrect decision [48, 50]. Inexperienced clinicians may blindly trust the diagnosis of AI algorithms. Consequently, a complication or medical malpractice may be further perplexed, since both healthcare professionals and AI developers are involved.

From a legal perspective, frameworks that apply to existing medical products may not apply to the liability of AI technology. Due to current medical malpractice laws, some healthcare professionals may be incentivized to use AI as a confirmatory tool rather than a sole diagnostic method to prevent liability issues [51]. When dealing with misuse or mismanagement, the concept of accountability is essential for the use of AI in clinical decision-making. Therefore, the indications and possible adverse effects in using an AI algorithm should be stated clearly by the manufacturing company, in a similar way to the other conventional medical products.

Systemic bias

AI algorithms may be subjected to "learn" from biased data. This can be attributed to three main causes: model bias due to the overrepresentation of a majority class; model variance due to inadequate data for minority groups; and outcome noise caused by the undesired effect of unobserved variables [52]. As ECG features vary between races, the generalizability of DL algorithms could be affected by patient selection bias [53].

Also, due to the reliance on electronic health records, it is inevitable that some data will be missing or inaccessible from each data set. For example, there may be fewer data available for specific population subgroups, such as citizens of lower socioeconomic status, as they may have performed fewer diagnostic tests due to limited access to health services [54]. In such case, a system may misinterpret the lack of healthcare usage or a small sample size as a lower disease burden. Similarly, health records collected from wearables may skew the sample population towards socio-economically advantaged individuals [51].

The influence of bias on AI-ECG algorithms is manifested among others in two studies, aiming to detect aortic stenosis [55] and AF [56], in which the accuracy of disease detection is lower amongst populations with a lower disease prevalence. In the case of AF, the problem is exacerbated by the paroxysmal and often undetectable nature of AF, leading to inaccurate data and incorrect diagnosis of patients at baseline or follow-up. When data has been limited to either positive or negative labels, this results in a modest effect on the overestimation of test performance.

In research studies that employ small volumes of data, traditional statistical methods may be superior to ML, which performs better for large datasets [35]. Even when the representation of minority groups exists in a data set, insufficient sample size will be of little use to the development of AI algorithms, which require an exhaustive collection of health records. This leads to the phenomenon known as underestimation that leads algorithms to approximate mean trends in order to avoid overfitting [57]. AI-ECG algorithms may also be prone to overfitting, resulting in poor performance in test sets with limited generalizability [58].

Algorithms developed in university hospitals often sample data from a Western, youthful and high-income population subgroup [54]. Hence, this may lead to a skewed interpretation of available data rather than a holistic view of the whole population. Resultantly, data deficiency may exacerbate socioeconomic disparities. Interestingly, a study by Noseworthy et al. demonstrated that the performance of a DL AI algorithm in using ECGs to detect left ventricular ejection fraction $\leq 35\%$ was not influenced by the variation of race, even though a homogenous population was used to develop the algorithm, which reflects the unpredictable relationship between race and algorithm systems [53].

However, such an issue may be alleviated if algorithms from single institutions could be amended and integrated with external data sets that represent more racially and socioeconomically diverse population subgroups. It is imperative that diversity exists not just in the sample population but also in developers, healthcare professionals and medical experts in order to ensure that different social groups are sufficiently represented and identify potential discriminatory aspects of the data analysis process.

Surveillance and cybersecurity

Surveillance of the safety and accuracy of a specific algorithm should be ensured by the responsible authorities. Compared to other medical products, surveillance is more important in the case of AI algorithms due to system upgrades that may influence algorithm performance.

It must be noted that some AI systems are designed to be dynamic and can re-calibrate through self-learning. Proactive protection of patient rights and protection of personal data should also be upheld. Among other issues, the increasing anthropomorphization of AI may also pose potential security risks and ethical concerns [59].

Finally, cybersecurity is another topic of interest, as AI algorithms can be a potential target for hacking [60, 61]. Almost all processing stages of the AI architecture, including the initial data inputs, human-machine teaming to the data-conditioning process, are susceptible to cyberattacks [59]. This is a unique type of cyber vulnerability compared to traditional information and technology systems, in which the hardware or software is generally the target of cyberattacks [59].

In that vein, there are four common types of attacks against AI systems [59]. Firstly, attackers can tamper with categorization models and adjust the outcome of the AI algorithm; secondly, data inputted into the AI can be altered by mixing erroneous data with actual data sets, which significantly impacts the AI training process; thirdly, through reverse engineering, attackers can perform multiple adversarial attacks and create knock-off systems; fourthly, backdoor attacks can be stealthily conducted by overriding existing classifications and infiltrating data sets through data “poisoning”. Subsequently, hacking can influence the performance of AI systems and can adversely affect patient outcomes. This makes the prevention of hacking a prerequisite for the implementation of these systems in clinical practice.

As it is inevitable that collaboration and exchange of data between different institutions is necessary to build large data sets required for AI model development [62], another concern pertinent to patient privacy is the use of anonymized data. As the size of the ECG data set increases, existing anonymization techniques may not be effective [63, 64]. Aside from medical information, the identification of demographic variables, socioeconomic class and religious status may contribute to discrimination of specific population subgroups [65]. Moreover, an ECG data ownership conflict may arise when the data are obtained from smartphone-based applications. Hence, it is crucial to establish regulations for all stakeholders and federated learning architectures to safeguard data sharing [62].

In recent years, the US Food and Drug Administration has advanced considerably in developing a rigorous regulatory framework for the medical use of AI [66]. For example, ML apps such as the Apple watch that pose a moderate to high risk to individual user safety have to comply to the regulatory requirements of the FDA [67].

Additionally, there have been considerable efforts towards developing cyberattack detection systems to

protect the e-Health infrastructure. Son et al. developed an intelligent ECG monitoring system to detect arrhythmia occurrence while incorporating anonymous identity schemes and signal scrambling to protect user privacy [68]. To preserve anonymity, a pseudonym was given to each user and a pseudo-random generator-based stream cipher was implemented to safeguard the ECG signal. The study also ensured to utilize a conventional public key cryptosystem to secure the transfer of sensing data from the sensor to the monitoring station.

Technical challenges for incorporating AI-ECG into clinical practice

There are many technical challenges when attempting to incorporate and AI algorithms into clinical practice. The first is standardization of data. Variations in existing ECG input data types, storage formats and interpretation statements unavoidably limit the broad interoperability of ECG data [69]. These formats differ depending on whether the data pertain to resting, ambulatory, bedside or ECG from mobile devices that could cause miscommunication and discrepancies in the understanding of the data. Including standardized reporting statements increases the utility and consistency of ECG interpretation, AI algorithms need a large amount of high-quality data to provide accurate results. This is a major limitation for developing algorithms in the management of rare diseases with limited sample size. In addition, data that are either incomplete, heterogeneous, noisy or ambiguous poses an additional challenge as it could affect the quality of data [51]. Resultantly, this may lead to missing values, redundancy, or data sparsity [51]. However, the collaboration between centers and the development of multicenter registries can help to overcome this issue. Furthermore, the adoption of a unified ECG data format such as the Fast Healthcare Interoperability Resources could improve the aggregation of data, maximize the extraction of useful data and support all diagnostic modalities [70].

ECG data collection should be followed by their proper annotation. In a real-world setting, the population cannot always be well-phenotyped and the quality of ECG data may vary, which may lead to discrepancies between the published performance results of an algorithm and its performance in clinical practice. Consequently, ML algorithms should be used only for the specific population they have been trained for.

Another concern regarding AI-based analysis of ECG data is the interpretation and incorporation of the algorithm results into clinical practice. Beyond the testing and validation of a proposed algorithm, additional studies are needed to investigate its performance compared to existing diagnostic tools [71]. Therefore, clinicians

must be trained on how to integrate information derived from AI algorithms into their practice, an aspect that is often overlooked in research papers. Overall, designing accessible AI curriculum and training programs may empower practitioners to effectively integrate AI in their clinical practice.

Logistical challenges

Currently, technical variations in coding definitions, electronic health record systems, administrative procedures, laboratory equipment and clinical practice may limit the clinical utility of an algorithm [71]. A large portion of clinical studies have used ECG printouts, possibly because of a lack of access to digital files. If access is a problem, then re-digitalization using recognition software is needed before further application of machine learning techniques [69].

Conclusion

In conclusion, AI-based analysis of ECG signals is expected to revolutionize healthcare diagnostic and prognostic services, in both cardiology and non-cardiology-related diseases. To ensure AI can safely elevate the quality of healthcare services, a framework that regulates the implementation of AI is mandatory. Scientists must be cognizant of the existing limitations of AI-based analysis of ECGs, such as potential bias and actively design interventions to safeguard undesirable outcomes. With such measures, AI can be implemented on a global scale for clinical practice. Ultimately, AI has the potential to offer data-driven clinical decision support systems.

Acknowledgements

None.

Author contributions

CTC and SL: literature search, data extraction and analysis, drafting of the manuscript, critical revision of the manuscript. TL: data interpretation, critical revision of the manuscript. EK, AAA: critical revision of the manuscript. GT, GB: study conception, data analysis and interpretation, drafting and critical revision of the manuscript. All authors read and approved the final manuscript.

Funding

The work was supported by the Institute of Precision Medicine of the American Heart Association (17UNPG33840017) from the AHA, the RICBAC Foundation, NIH Grants 1 R01 HL135335-01, 1 R21 HL137870-01, 1 R21EB026164-01 and 3R21EB026164-02S1.

Availability of data and materials

Not applicable.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

All authors consent to publication.

Competing interests

The authors declare that they have no competing interests.

Author details

¹Cardiac Electrophysiology Unit, Cardiovascular Analytics Group, Hong Kong, China. ²Tianjin Key Laboratory of Ionic-Molecular Function of Cardiovascular Disease, Department of Cardiology, Tianjin Institute of Cardiology, Second Hospital of Tianjin Medical University, Tianjin 300211, China. ³Cardiovascular Research Center, Massachusetts General Hospital, Boston, MA, USA. ⁴Broad Institute, Massachusetts Institute of Technology, Cambridge, MA, USA. ⁵Department of Cardiology, Larnaca General Hospital, Inomenon Politon Amerikis, Larnaca, Cyprus. ⁶Department of Basic and Clinical Sciences, University of Nicosia Medical School, 2414 Nicosia, Cyprus. ⁷Kent and Medway Medical School, Canterbury, UK.

Received: 8 January 2022 Accepted: 13 July 2022

Published online: 01 October 2022

References

- Bazoukis G, Stavrakis S, Zhou J, Bollepalli SC, Tse G, Zhang Q, et al. Machine learning versus conventional clinical methods in guiding management of heart failure patients—a systematic review. *Heart Fail Rev*. 2021;26(1):23–34.
- Sevakula RK, Au-Yeung WM, Singh JP, Heist EK, Isselbacher EM, Armoundas AA. State-of-the-art machine learning techniques aiming to improve patient outcomes pertaining to the cardiovascular system. *J Am Heart Assoc*. 2020;9(4): e013924.
- Au-Yeung W-TM, Sevakula RK, Sahani AK, Kassab M, Boyer R, Isselbacher EM, et al. Real-time machine learning-based intensive care unit alarm classification without prior knowledge of the underlying rhythm. *Eur Heart J Digital Health*. 2021;2(3):437–45.
- Bollepalli SC, Sahani AK, Aslam N, Mohan B, Kulkarni K, Goyal A, et al. An optimized machine learning model accurately predicts in-hospital outcomes at admission to a cardiac unit. *Diagnostics*. 2022;12(2):241.
- Minchole A, Camps J, Lyon A, Rodríguez B. Machine learning in the electrocardiogram. *J Electrocardiol*. 2019;57:S61–4.
- Krittanawong C, Zhang H, Wang Z, Aydar M, Kitai T. Artificial intelligence in precision cardiovascular medicine. *J Am Coll Cardiol*. 2017;69(21):2657–64.
- Siontis K, Noseworthy PA, Attia ZI, Friedman PA. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nat Rev Cardiol*. 2021;18(7):465–78.
- Somani S, Russak AJ, Richter F, Zhao S, Vaid A, Chaudhry F, De Freitas JK, Naik N, Miotto R, Nadkarni GN, Narula J. Deep learning and the electrocardiogram: review of the current state-of-the-art. *EP Europace*. 2021;23:1179–91.
- Lima E, Ribeiro AH, Paixão GM, Ribeiro MH, Pinto Filho MM, Gomes PR, Oliveira DM, Sabino EC, Duncan BB, Giatti L, Barreto SM. Deep neural network estimated electrocardiographic-age as a mortality predictor. *medRxiv*. 2021.
- Tse G, Lee S, Zhou J, Liu T, Wong ICK, Mak C, et al. Territory-wide Chinese cohort of long QT syndrome: random survival forest and cox analyses. *Front Cardiovasc Med*. 2021;8: 608592.
- Lee S, Zhou J, Jeevaratnam K, Wong WT, Wong ICK, Mak C, et al. Paediatric/young versus adult patients with long QT syndrome. *Open Heart*. 2021;8(2):e001671.
- Chung CT, Bazoukis G, Lee S, Liu Y, Liu T, Letsas KP, et al. Machine learning techniques for arrhythmic risk stratification: a review of the literature. *Int J Arrhythmia*. 2022;23:1–3.
- Bodini M, Rivolta MW, Sassi R. Opening the black box: interpretability of machine learning algorithms in electrocardiography. *Philos Trans R Soc A*. 2021;379(2212):20200253.
- Kashou A, Mulpuru SK, Deshmukh AJ, Ko WY, Attia ZI, Carter RE, Friedman PA, Noseworthy PA. An artificial intelligence-enabled ECG algorithm for comprehensive ECG interpretation: Can it pass the 'Turing test'? *Cardiovasc Digital Health J*. 2021;2(3):164–70.

15. Siontis K, Liu K, Bos JM, Attia ZI, Cohen-Shelly M, Arruda-Olson AM, Farahani NZ, Friedman PA, Noseworthy PA, Ackerman MJ. Detection of hypertrophic cardiomyopathy by an artificial intelligence electrocardiogram in children and adolescents. *Int J Cardiol.* 2021;340:42–7.
16. Shrivastava S, Cohen-Shelly M, Attia ZI, Rosenbaum AN, Wang L, Giudicessi JR, Redfield M, Bailey K, Lopez-Jimenez F, Lin G, Kapa S. Artificial intelligence-enabled electrocardiography to screen patients with dilated cardiomyopathy. *Am J Cardiol.* 2021;155:121–7.
17. Lee S, Zhou J, Jeevaratnam K, Wong WT, Wong ICK, Mak C, et al. Paediatric/young versus adult patients with congenital long QT syndrome or catecholaminergic polymorphic ventricular tachycardia. *Eur Heart J.* 2021;42(Supplement_1):ehab724.1870.
18. Tse G, Lee S, Bin Waleed K, Hui JMH, Lakhani I. 104 Analysis of clinical characteristics, genetic basis, management and arrhythmic outcomes of patients with catecholaminergic polymorphic ventricular tachycardia from a chinese city. *Heart.* 2022;108(Suppl 1):A77–8.
19. Fridman MD, Tofighi T, Fan CPS, Hamilton RM. Resting ECG measurements can identify abnormalities in children with catecholaminergic polymorphic ventricular tachycardia. *Eur Heart J.* 2021;42(Supplement_1):ehab724.0305.
20. Potter E, Rodrigues CH, Ascher DB, Abhayaratna WP, Sengupta PP, Marwick TH. Machine learning of ECG waveforms to improve selection for testing for asymptomatic left ventricular dysfunction prompt. *JACC Cardiovasc Imaging.* 2021;14:1904–15.
21. Adedinsewo D, Carter RE, Attia Z, Johnson P, Kashou AH, Dugan JL, Albus M, Sheele JM, Bellolio F, Friedman PA, Lopez-Jimenez F. Artificial intelligence-enabled ECG algorithm to identify patients with left ventricular systolic dysfunction presenting to the emergency department with dyspnea. *Circul Arrhythmia Electrophysiol.* 2020;13(8):e008437.
22. Rabinstein A, Yost MD, Faust L, Kashou AH, Latif OS, Graff-Radford J, Attia IZ, Yao X, Noseworthy PA, Friedman PA. Artificial intelligence-enabled ECG to identify silent atrial fibrillation in embolic stroke of unknown source. *J Stroke Cerebrovasc Dis.* 2021;30(9):105998.
23. Huang YH, Alexeenko V, Tse G, Huang CL, Marr CM, Jeevaratnam K. ECG restitution analysis and machine learning to detect paroxysmal atrial fibrillation: insight from the equine athlete as a model for human athletes. *Function (Oxf).* 2021;2(1):zqaa031.
24. Cardiologs. Real-life application of Artificial Intelligence for ECG analysis 2021.
25. Baek YS, Lee SC, Choi W, Kim DH. A new deep learning algorithm of 12-lead electrocardiogram for identifying atrial fibrillation during sinus rhythm. *Sci Rep.* 2021;11(1):12818.
26. Jones NR, Taylor CJ, Hobbs FR, Bowman L, Casadei B. Screening for atrial fibrillation: a call for evidence. *Eur Heart J.* 2020;41(10):1075–85.
27. Cheung ML, Chau KY, Lam MHS, Tse G, Ho KY, Flint SW, et al. Examining consumers' adoption of wearable healthcare technology: the role of health attributes. *Int J Environ Res Public Health.* 2019;16(13):2257.
28. Chau KY, Lam MHS, Cheung ML, Tso EKH, Flint SW, Broom DR, et al. Smart technology for healthcare: exploring the antecedents of adoption intention of healthcare wearable technology. *Health Psychol Res.* 2019;7(1):8099.
29. Yan BP, Chan CK, Li CK, To OT, Lai WH, Tse G, et al. Resting and postexercise heart rate detection from fingertip and facial photoplethysmography using a smartphone camera: a validation study. *JMIR Mhealth Uhealth.* 2017;5(3):e33.
30. Giudicessi JR, Schram M, Bos JM, Galloway CD, Shreibati JB, Johnson PW, et al. Artificial intelligence-enabled assessment of the heart rate corrected QT interval using a mobile electrocardiogram device. *Circulation.* 2021;143(13):1274–86.
31. Wang YC, Xu X, Hajra A, Apple S, Kharawala A, Duarte G, et al. Current advancement in diagnosing atrial fibrillation by utilizing wearable devices and artificial intelligence: a review study. *Diagnostics (Basel).* 2022;12(3):689.
32. Ramesh J, Solatidehkordi Z, Aburukba R, Sagahyoon A. Atrial fibrillation classification with smart wearables using short-term heart rate variability and deep convolutional neural networks. *Sensors (Basel).* 2021;21(21):7233.
33. Rivard L, Friberg L, Conen D, Healey JS, Berge T, Boriani G, et al. Atrial fibrillation and dementia: a report from the AF-SCREEN international collaboration. *Circulation.* 2022;145(5):392–409.
34. Olier I, Ortega-Martorell S, Pieroni M, Lip GYH. How machine learning is impacting research in atrial fibrillation: implications for risk prediction and future management. *Cardiovasc Res.* 2021;117(7):1700–17.
35. Missel R, Gyawali PK, Murkute JV, Li Z, Zhou S, AbdelWahab A, Davis J, Warren J, Sapp JL, Wang L. A hybrid machine learning approach to localizing the origin of ventricular tachycardia using 12-lead electrocardiograms. *Comput Biol Med.* 2020;126:104013.
36. Bollepalli SC, Sevakula RK, Au-Yeung WM, Kassab MB, Merchant FM, Bazoukis G, et al. Real-time arrhythmia detection using hybrid convolutional neural networks. *J Am Heart Assoc.* 2021;10(23):e023222.
37. Cohen-Shelly M, Attia ZI, Friedman PA, Ito S, Essayagh BA, Ko WY, Murphree DH, Michelena HI, Enriquez-Sarano M, Carter RE, Johnson PW. Electrocardiogram screening for aortic valve stenosis using artificial intelligence. *Eur Heart J.* 2021;42(30):2885–96.
38. Kwon JM, Kim KH, Akkus Z, Jeon KH, Park J, Oh BH. Artificial intelligence for detecting mitral regurgitation using electrocardiography. *J Electrocardiol.* 2020;59:151–7.
39. Au-Yeung WM, Sahani AK, Isselbacher EM, Armondas AA. Reduction of false alarms in the intensive care unit using an optimized machine learning based approach. *NPJ Digit Med.* 2019;2:86.
40. Au-Yeung WM, Sevakula RK, Sahani AK, Kassab M, Boyer R, Isselbacher EM, et al. Real-time machine learning-based intensive care unit alarm classification without prior knowledge of the underlying rhythm. *Eur Heart J Digit Health.* 2021;2(3):437–45.
41. Kwon J, Lee YR, Jung MS, Lee YJ, Jo YY, Kang DY, Lee SY, Cho YH, Shin JH, Ban JH, Kim KH. Deep learning model for screening sepsis using electrocardiography. *Scand J Trauma Resusc Emerg Med.* 2021;29(1):145.
42. Cordeiro R, Karimian N, Park Y. Hyperglycemia identification using ECG in deep learning era. *Sensors.* 2021;21(18):6263.
43. Sadrawi M, Lin YT, Lin CH, Mathunjwa B, Hsin HT, Fan SZ, Abbod MF, Shieh JS. Non-invasive hemodynamics monitoring system based on electrocardiography via deep convolutional autoencoder. *Sensors.* 2021;21(18):6264.
44. Lin C, Lin CS, Lee DJ, Lee CC, Chen SJ, Tsai SH, Kuo FC, Chau T, Lin SH. Artificial intelligence-assisted electrocardiography for early diagnosis of thyrotoxic periodic paralysis. *J Endocrine Soc.* 2021;5(9):bvab120.
45. Kwon J, Jung MS, Kim KH, Jo YY, Shin JH, Cho YH, Lee YJ, Ban JH, Jeon KH, Lee SY, Park J. Artificial intelligence for detecting electrolyte imbalance using electrocardiography. *Ann Noninvasive Electrocardiol.* 2021;26(3):e12839.
46. Papi G, Corsello SM, Pontecorvi A. Clinical concepts on thyroid emergencies. *Front Endocrinol.* 2014;5:102.
47. Attia Z, Kapa S, Dugan J, Pereira N, Noseworthy PA, Jimenez FL, Cruz J, Carter RE, DeSimone DC, Signorino J, Halamka J. Rapid exclusion of COVID infection with the artificial intelligence electrocardiogram. *Mayo Clin Proc.* 2021;96(8):2081–94.
48. Bazoukis G, Hall J, Loscalzo J, Antman EM, Fuster V, Armondas AA. The inclusion of augmented intelligence in medicine: a framework for successful implementation. *Cell Rep Med.* 2022;3(1):100485.
49. Bazoukis G, Hall J, Loscalzo J, et al. The augmented intelligence in medicine: a framework for successful implementation. *Cell Rep Med (in press).*
50. Price W, Gerke S, Cohen IG. Potential liability for physicians using artificial intelligence. *JAMA.* 2019;322(18):1765–6.
51. Griffin F. Artificial Intelligence and liability in health care. *Health Matrix.* 2021;31:65.
52. Barocas S, Selbst AD. Big data's disparate impact. *California Law Rev.* 2016;104:671.
53. Noseworthy P, Attia ZI, Brewer LC, Hayes SN, Yao X, Kapa S, Friedman PA, Lopez-Jimenez F. Assessing and mitigating bias in medical artificial intelligence: the effects of race and ethnicity on a deep learning model for ECG analysis. *Circul Arrhythmia Electrophysiol.* 2020;13(3):e007988.
54. Gianfrancesco M, Tamang S, Yazdany J, Schmajuk G. Potential biases in machine learning algorithms using electronic health record data. *JAMA Intern Med.* 2018;178(11):1544–7.
55. Tseng A, Shelly-Cohen M, Attia IZ, Noseworthy PA, Friedman PA, Oh JK, Lopez-Jimenez F. Spectrum bias in algorithms derived by artificial intelligence: a case study in detecting aortic stenosis using electrocardiograms. *Eur Heart J-Digital Health.* 2021;2(4):561–7.
56. Christopoulos G, Graff-Radford J, Lopez CL, Yao X, Attia ZI, Rabinstein AA, Petersen RC, Knopman DS, Mielke MM, Kremers W, Vemuri P. Artificial intelligence-electrocardiography to predict incident atrial

- fibrillation: a population-based study. *Circul Arrhythmia Electrophysiol.* 2020;13(12):e009355.
57. d'Alessandro B, O'Neil C, LaGatta T. Conscientious classification: a data scientist's guide to discrimination-aware classification. *Big Data.* 2017;5(2):120–34.
 58. Nagarajan V, Lee SL, Robertus JL, Nienaber CA, Trayanova NA, Ernst S. Artificial intelligence in the diagnosis and management of arrhythmias. *Eur Heart J.* 2021;42(38):3904–16.
 59. Lorenzo P, Stefano F, Ferreira A, Carolina P. Artificial Intelligence and Cybersecurity: Technology, Governance and Policy Challenges. Centre for European Policy Studies 2021.
 60. Klonoff D, Han J. The first recall of a diabetes device because of cybersecurity risks. *J Diabetes Sci Technol.* 2019;13(5):817–20.
 61. LLC M. MW is Short St. Jude Medical (STJ:US) Muddy Waters Research. 2016.
 62. van de Leur RR, Boonstra MJ, Bagheri A, Roudijk RW, Sammani A, Taha K, et al. Big data and artificial intelligence: opportunities and threats in electrophysiology. *Arrhythmia Electrophysiol Rev.* 2020;9(3):146.
 63. Carter RE, Attia ZI, Lopez-Jimenez F, Friedman PA. Pragmatic considerations for fostering reproducible research in artificial intelligence. *NPJ Digital Med.* 2019;2(1):1–3.
 64. Rocher L, Hendrickx JM, De Montjoye Y-A. Estimating the success of re-identifications in incomplete datasets using generative models. *Nat Commun.* 2019;10(1):1–9.
 65. Balthazar P, Harri P, Prater A, Safdar NM. Protecting your patients' interests in the era of big data, artificial intelligence, and predictive analytics. *J Am Coll Radiol.* 2018;15(3):580–6.
 66. Food and Drug Administration. Proposed regulatory framework for modifications to artificial intelligence/machine learning (AI/ML)-based software as a medical device (SaMD). 2019.
 67. Babic B, Gerke S, Evgeniou T, Cohen IG. Direct-to-consumer medical machine learning and artificial intelligence applications. *Nat Mach Intell.* 2021;3(4):283–7.
 68. Son J, Park J, Oh H, Bhuiyan MZA, Hur J, Kang K. Privacy-preserving electrocardiogram monitoring for intelligent arrhythmia detection. *Sensors.* 2017;17(6):1360.
 69. Lyon A, Mincholé A, Martínez JP, Laguna P, Rodriguez B. Computational techniques for ECG analysis and interpretation in light of their contribution to medical advances. *J R Soc Interface.* 2018;15(138):20170821.
 70. Mandel J, Kreda DA, Mandl KD, Kohane IS, Rami RB. SMART on FHIR: a standards-based, interoperable apps platform for electronic health records. *J Am Med Inform Assoc.* 2016;23(5):899–908.
 71. Kelly C, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. *BMC Med.* 2019;17(1):1–9.

Publisher's note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Ready to submit your research? Choose BMC and benefit from:

- fast, convenient online submission
- thorough peer review by experienced researchers in your field
- rapid publication on acceptance
- support for research data, including large and complex data types
- gold Open Access which fosters wider collaboration and increased citations
- maximum visibility for your research: over 100M website views per year

At BMC, research is always in progress.

Learn more biomedcentral.com/submissions

