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AI-Driven ECG: The Smart Future of Cardiology

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Introduction

For over a century, the electrocardiogram (ECG) has been a cornerstone of cardiovascular diagnostics—offering a noninvasive, accessible, and rapid assessment of cardiac electrical activity. It remains vital in detecting arrhythmias, myocardial infarction, conduction abnormalities, and structural heart diseases. Yet, its interpretation has traditionally depended on clinician expertise, which can lead to inconsistent accuracy.[1,2]

Studies reveal that nearly one-third of ECG readings contain major errors. A 2020 meta-analysis found a median interpretation accuracy of only 54% among physicians, rising modestly to 67% after educational interventions. These persistent gaps highlight the limitations of human interpretation despite training efforts.[3]

Such challenges have fueled interest in more advanced solutions. ►**Table 1** contrasts traditional ECG interpretation with artificial intelligence (AI)-driven approaches in terms of accuracy, scalability, and clinical relevance. The need for automated ECG analysis is particularly pressing in low- and middle-income countries, where over 75% of global cardiovascular deaths occur and access to expert cardiologists is limited.[4]

Recent advances in AI, especially deep learning, are reshaping ECG analysis. AI algorithms can process vast data sets, detect subtle patterns beyond human perception, and deliver highly accurate predictive insights. These tools have demonstrated promise in diagnosing latent or asymptomatic conditions such as left ventricular (LV) dysfunction, atrial fibrillation (AF), hypertrophic cardiomyopathy (HCM), and cardiac amyloidosis (CA)—often before symptoms emerge (►**Table 2**).

AI, particularly machine learning and deep neural networks, is rapidly becoming a transformative force in cardiology. The following sections explore key clinical applications where AI-enhanced ECG has shown significant diagnostic and prognostic value.[5,6]

Understanding the AI Engine: Convolutional Neural Networks

AI models that analyze ECGs typically rely on convolutional neural networks (CNNs), a class of deep learning algorithms especially well-suited for recognizing patterns in visual or time-series data. In the context of ECG interpretation, CNNs process the raw waveform as a series of voltage-time signals and learn to identify subtle features that may be imperceptible to the human eye.

CNNs operate by passing the input ECG data through multiple layers, each designed to extract specific signal

Table 1 Comparison of traditional versus AI-driven ECG interpretation

Feature	Traditional ECG analysis	AI-driven ECG analysis
Interpretation speed	Minutes to hours	Seconds
Interobserver variability	High	Minimal
Diagnostic accuracy	Depends on clinician expertise	High (if trained on robust data)
Detection of subtle abnormalities	Limited	Enhanced sensitivity
Continuous monitoring	Not feasible	Enabled with wearable AI devices

Abbreviations; AI, artificial intelligence; ECG, electrocardiogram.

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المقالة باللغة العربية

تخطيط القلب الكهربائي المعزز بالذكاء الاصطناعي – المستقبل الذكي لطب القلب

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ظل تخطيط القلب الكهربائي (ECG) لأكثر من قرن حجر الأساس في تشخيص الأمراض القلبية الوعائية، حيث يوفر تقييماً سريعاً وغير جراحي للنشاط الكهربائي للقلب. ولكن يعتمد تفسيره تقليدياً على الخبرة السريرية للطبيب، مما قد يؤدي في بعض الأحيان إلى أخطاء تشخيصية نتيجة نقص الخبرة. تشير الدراسات إلى أن نحو ثلث قراءات تخطيط القلب تحتوي على أخطاء كبيرة، حيث تبلغ دقة التشخيص بين الأطباء حوالي 54%، وترتفع إلى 67% بعد التدخلات التعليمية. أدى ذلك إلى الاهتمام المتزايد بالذكاء الاصطناعي(AI) ، وخاصة التعلم العميق، لتحسين تحليل تخطيط القلب.

تتميز الخوارزميات المدعومة بالذكاء الاصطناعي بقدرتها على معالجة كميات هائلة من البيانات، واكتشاف أنماط دقيقة قد لا تلاحظها العين البشرية، وتقديم تنبؤات تشخصية عالية الدقة. وقد أثبتت هذه التقنيات فعاليتها في تشخيص حالات مثل **الرجفان الأذيني، خلل الوظيفة البطينية اليسرى، اعتلال عضلة القلب الضخامي، والداء النشو اني القلبي**، حتى قبل ظهور الأعراض .

تعتمد نماذج الذكاء الاصطناعي، وخاصة الشبكات العصبية التلافيفية (CNNs) ، على تحليل إشارات تخطيط القلب الزمنية لاكتشاف التغيرات الدقيقة في الموجات الكهربائية. على سبيل المثال، يمكن للذكاء الاصطناعي التنبؤ بخطر **الرجفان الأذيني** من خلال تحليل تغيرات موجة P وفترة PR ، حتى عند المرضى الذين يظهرون إيقاعاً جيبيّاً طبيعياً. كما يمكنه اكتشاف **خلل الوظيفة البطينية اليسرى** من خلال تغيرات طفيفة في مركب QRSوموجة T ، والتي قد لا يلاحظها الأطباء .

في مجال **اعتلال عضلة القلب الضخامي**، تصل دقة النماذج المدعومة بالذكاء الاصطناعي إلى 95%، مما يجعلها أداة فحص فعالة، خاصة للرياضيين المعرضين للخطر. كما يمكنها اكتشاف **الداء النشو اني القلبي** من خلال تحليل التغيرات الكهربائية المبكرة، مما يسمح بالتدخل العلاجي في مراحل أولية. بالإضافة إلى ذلك، يمكن للذكاء الاصطناعي التنبؤ بفرط بوتاسيوم الدم من خلال تحليل تغيرات موجة T واتساع مركب QRS ، مما يسهم في الوقاية من الاضطرابات الخطيرة .

رغم هذه الإنجازات، تظل هناك تحديات تتعلق بدقة النماذج عبر الفئات السكانية المختلفة، وضرورة التحقق السريري الواسع، بالإضافة إلى القضايا الأخلاقية مثل خصوصية البيانات والتحيز الخوارزمي. ومع ذلك، يعد دمج الذكاء الاصطناعي في تحليل تخطيط القلب خطوة واعدة نحو تشخيص مبكر، رعاية أكثر تخصيصاً، وتخفيف العبء على الأنظمة الصحية .

Table 2 Current AI applications in ECG and their clinical utility

AI application	Clinical utility/Significance
Arrhythmia detection (e.g., AFib, VT, PVCs)	Improves diagnostic accuracy and early detection of arrhythmias often in asymptomatic patients. Enables timely intervention and reduces stroke risk
ECG interpretation assistance	Enhances efficiency and consistency in reading ECGs, especially in high-volume settings. Reduces interobserver variability
Prediction of left ventricular dysfunction	AI models can detect reduced ejection fraction (e.g., LVEF $< 40\%$) from surface ECGs alone, facilitating early heart failure diagnosis even before symptoms or echo abnormalities appear
Detection of silent myocardial ischemia or infarction	AI-enhanced ECG can identify subtle patterns indicative of ischemia or prior MI not recognized by standard interpretation, especially useful in diabetics or atypical cases
Hyperkalemia or hypokalemia prediction	Detects electrolyte disturbances from ECG patterns before lab confirmation, allowing quicker clinical decision-making
Risk stratification (e.g., sudden cardiac death, AFib recurrence)	Identifies patients at higher risk for adverse events and guides monitoring or therapy escalation. For example, predicting need for ICD in nonischemic cardiomyopathy
Disease screening in asymptomatic populations	Facilitates mass screening for conditions like hypertrophic cardiomyopathy, AFib, or heart failure with preserved EF (HFpEF)
Remote monitoring and wearable integration	AI enables continuous rhythm monitoring from smartwatches or patches, filtering noise and detecting actionable events with high accuracy
Early detection of noncardiac conditions	Emerging use of AI to predict conditions like sleep apnea, anemia, and even COVID-19 through ECG pattern analysis

Abbreviations; AFib, atrial fibrillation; AI, artificial intelligence; COVID-19, coronavirus disease 2019; ECG, electrocardiogram; HFpEF, heart failure with preserved ejection fraction; ICD, implantable cardioverter-defibrillator; LVEF, left ventricular ejection fraction; MI, myocardial infarction; PVC, premature ventricular contraction; VT, ventricular tachycardia.

characteristics—such as wave shapes, intervals, or morphologic anomalies—and gradually build a complex internal representation of the data. These models are trained on large annotated ECG data sets, allowing them to "learn" to predict conditions like AF, LV dysfunction, or even electrolyte disturbances with impressive accuracy.

Unlike traditional rule-based algorithms, CNNs do not require explicit programming of features; instead, they automatically discover the most relevant patterns during the training process. This self-learning ability makes them uniquely powerful in predicting early or atypical presentations of cardiac conditions, positioning them as a transformative tool in cardiology diagnostics.[7]

Prediction Atrial Fibrillation Risk from Sinus Rhythm ECG

Approximately 20% of patients with AF are asymptomatic, and another third present with nonspecific symptoms like fatigue, dyspnea, or light headedness—factors that contribute to underdiagnosis. Additionally, up to 15% of cryptogenic stroke patients are later found to have undetected paroxysmal AF. Early identification or prediction of AF is therefore critical, as it enables timely anticoagulation therapy, potentially reducing stroke recurrence and mortality.[8]

Recent advances in AI have enabled ECG-based predictive modeling of AF, even in patients with normal sinus rhythm. AI algorithms, particularly CNNs, can detect subtle ECG changes such as P-wave morphology alterations and PR interval dynamics suggestive of atrial electrical remodeling or fibrosis.[9]

In a landmark 2019 study, Attia et al developed an AI-enabled ECG model that identified the electrocardiographic signature of AF during sinus rhythm using standard 10-second, 12-lead ECGs. The model demonstrated a sensitivity of about 79% and specificity of 81%.[9] Later studies confirmed that even single-lead ECGs, when analyzed using AI, can successfully predict future AF episodes—supporting its use as a noninvasive AF screening.[10]

Clinical Implications

AI-enhanced ECG analysis shows great potential in identifying high-risk individuals who might benefit from early intervention, such as anticoagulation for stroke prevention.

Limitations

Conditions like structural heart disease (e.g., mitral stenosis or longstanding hypertension) can cause left atrial enlargement, mimicking AF-related changes. Age-related atrial remodeling in elderly patients may also affect prediction accuracy.[10]

Prediction of Asymptomatic Left Ventricular Dysfunction

AI, particularly CNNs, has shown strong potential in detecting subtle ECG markers of LV dysfunction, even in asymptomatic individuals with normal-appearing ECGs. These markers may include minor QRS changes, T-wave abnormalities, or altered voltage patterns that typically escape human detection.

A landmark study by Attia et al (2019, Mayo Clinic) trained a CNN model on large data sets linking standard 12-lead ECGs with echocardiographic LV ejection fraction (LVEF). The algorithm accurately detected LVEF < 35%, achieving 86% sensitivity and 85% specificity.[5] Remarkably, it identified subclinical LV dysfunction in patients whose ECGs were deemed normal by physicians.

Clinical Implications

Early detection: Enables identification of LV dysfunction before symptom onset.

Screening tool: Especially valuable in primary care and resource-limited settings without echocardiography access.

Risk stratification: Helps prioritize patients for further cardiac imaging and specialist referral.[11]

Detection of Hypertrophic Cardiomyopathy

AI-enhanced ECG models have demonstrated the ability to detect characteristic electrocardiographic signatures associated with HCM. These include increased voltage, repolarization abnormalities, and alterations in QRS morphology. In a study by Ko et al, the AI model achieved an impressive accuracy for detecting HCM from a 12-lead ECG, with a sensitivity of 95% and a specificity of 92%. Remarkably, the model retained high performance even in cases with subtle or borderline ECG abnorma-lities.[12]

Clinical Implications

A positive HCM prediction by AI should prompt confirmatory testing with echocardiography, cardiac magnetic resonance imaging, and genetic testing. This approach is particularly useful as a screening tool for asymptomatic individuals, especially those planning to participate in competitive or high-intensity sports, where undiagnosed HCM poses significant risk.

Potential Sources of Error

Athlete's heart: Physiological hypertrophy in trained athletes may resemble HCM, potentially leading to false-positive results. Additionally, structural changes due to chronic hypertension (LV hypertrophy) can mimic HCM on ECG and may compromise AI model accuracy.[11,12]

Detection of Cardiac Amyloidosis

CA is associated with significant morbidity and mortality, often due to delays in diagnosis. Timely identification is crucial, particularly in light of emerging disease-modifying therapies that can improve patient outcomes when initiated early. There is, therefore, a growing clinical need for a widely accessible and cost-effective screening tool to facilitate early detection.[13]

CA leads to subtle electrocardiographic abnormalities that may precede the clinical diagnosis. AI-enabled analysis of standard ECGs has demonstrated the ability to detect these early changes, offering a promising avenue for earlier recognition of CA. Recent studies have shown that AI-enhanced ECG models can effectively identify patients with CA. In one such study, various configurations were evaluated, including both single-lead and 6-lead ECG subsets.[14]

Among single leads, lead V5 demonstrated the highest performance, with an area under the curve (AUC) of 0.86 and a precision of 0.78, while other single leads showed comparable efficacy. The 6-lead bipolar configuration yielded an even stronger performance, with an AUC of 0.90 and a precision of 0.85.[14]

These findings suggest that AI-driven ECG analysis holds considerable promise for the early, noninvasive detection of CA, potentially enabling earlier initiation of treatment and improving long-term prognosis.

Prediction of Hyperkalemia

AI models can identify subtle and overt electrocardiographic features suggestive of hyperkalemia. These include peaked T waves, PR interval prolongation, QRS complex widening, and general T-wave abnormalities. These features may be recognized by the AI even when classical signs are not overtly apparent to the human eye.[15]

In a study by Galloway et al (2021), an AI-enabled model applied to standard 12-lead ECGs demonstrated excellent accuracy in detecting hyperkalemia. The model achieved a sensitivity of approximately 82% and a specificity of 88%.[16]

Clinical implications: The early prediction of hyperkalemia by AI-enhanced ECG analysis, particularly in patients with chronic kidney disease or acute renal failure, has significant clinical value. When an AI model flags possible hyperkalemia, immediate confirmation with serum potassium measurement is critical to prevent potentially life-threatening arrhythmias and guide prompt treatment.

Conclusion

AI-enhanced ECG is rapidly transforming cardiovascular care by enabling accurate prediction of conditions such as reduced LVEF, AF, HCM, CA, and even electrolyte imbalances. Its integration into clinical practice promises earlier diagnosis, better risk stratification, and more personalized care. Although still evolving, AI-enhanced ECG analysis has demonstrated strong potential as a noninvasive, scalable tool that can improve patient outcomes and reduce strain on health care systems.

However, several limitations remain. The accuracy of AI algorithms may vary across different populations and clinical settings, highlighting the need for broader validation and real-world testing. Model interpretability, regulatory oversight, and integration with existing health care infrastructure are additional areas requiring refinement. Ethical concerns such as data privacy, potential algorithmic bias, and the risk of overreliance on automated interpretations must also be carefully addressed. Continued research, transparent model development, and responsible deployment will be essential to ensure that AI-enhanced ECG fulfills its promise in a safe, equitable, and clinically effective manner.

Conflict of Interest
None declared.

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