INFORMATION BRIEF (RAPID REVIEW)

ARTIFICIAL INTELLIGENCE-ELECTROCARDIOGRAPHY FOR CARDIOVASCULAR DISEASES

Malaysian Health Technology Assessment Section (MaHTAS)
Medical Development Division
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PURPOSE

To provide brief information on the effectiveness and safety of Artificial Intelligence Electrocardiography for Cardiovascular Diseases following request from the Primary Healthcare Section, Family Health Development Division, Ministry of Health, Malaysia.

BACKGROUND

Atrial fibrillation (AF) is the most common arrhythmia encountered in clinical practice, marked by rapid and disorganised electrical activity in the atria that impairs effective contraction. Over time, structural remodeling such as fibrosis and damage to conductive tissues contributes to its persistence. Age is the leading risk factor, with AF incidence rising globally alongside increased life expectancy. Additional triggers include genetic predisposition, inflammation, stress, and comorbid conditions like hypertension, heart failure, myocardial infarction, and diabetes. Early recognition of these risk factors is essential to prevent disease progression.[1]

Atrial fibrillation (AF) affects an estimated 37 million people globally, with its prevalence projected to rise significantly. By 2050, over 16 million Americans are expected to develop AF, highlighting the urgent need to implement effective preventive strategies. Atrial Fibrillation is associated with several severe outcomes, including increased mortality risk, cardiovascular events, stroke, heart failure, and kidney disease, with heart failure having the most significant absolute risk increase. These complications underscore the importance of early and accurate diagnosis. Although 12-lead electrocardiography (ECG) remains the gold standard for diagnosing AF, it has limitations due to its low sensitivity, especially in detecting paroxysmal or asymptomatic cases. The growing use of artificial intelligence (AI) in healthcare offers potential improvements for detecting and diagnosing AF and other cardiovascular diseases.[1]

The integration of artificial intelligence (AI) with electrocardiography (ECG) represents a profound technological shift in cardiovascular diagnostics. Historically, ECG analysis relied on rule-based interpretation, often limited by the time constraints and subjective nature of human review. Through the application of deep learning algorithms, AI-ECG swift from identifying existing abnormalities to performing complex prognostic risk stratification. This technology is reported to reduce diagnostic latency, enhance detection rates of subtle cardiac pathologies and augment the efficiency of clinical workflows across various care settings, including emergency departments, primary care, and remote monitoring.[2]

Within ECG diagnostics in particular, remarkable AI analysis by means of deep-learning convolutional algorithms have enabled rapid interpretation utilising ECG features as an ideal substrate for this process. Nowadays, several groups across the globe have large digital ECG databases linked with clinical datasets, which have in turn revealed the utility of AI in identifying signatures and patterns that are unrecognisable by conventional ECG interpretation. Accordingly, neural networks that can identify these patterns have been used to find various heart conditions and pathologies including left ventricular (LV) systolic dysfunction, atrial fibrillation (AF) and arrhythmia syndromes, as well as hypertrophic cardiomyopathy (HCM).[3]

Artificial intelligence (AI) has been applied across various fields for decades, but its use in cardiovascular disease is relatively recent. In ECG diagnostics, AI is primarily used in two ways: automated ECG interpretation which has been available for many years and continues to evolve and, more recently, the extraction and analysis of raw data to uncover insights beyond human visual perception and traditional interpretation methods. Cardiac signals on a standard ECG are shaped by complex processes, including signal filtering to enhance amplitude, as well as influences from body electrical activity, anatomical variations, and cardiac rotation. Consequently, large volumes of digital data are required to develop machine learning (ML) models capable of performing complex mathematical tasks and optimising solutions using the computational power of modern software.[2]

Deep learning (DL) is a subset of ML that uses neural networks with many layers to mimic the learning process of the human brain. More specifically, each neuron represents an equation with parameters that are adjusted during network training, thus the representation of the input is learned by the network itself. A frequently used model is a subtype of neural networks called convolutional neural networks (CNNs), which are particularly useful for finding patterns in images and signal data such as ECG. Supervised or unsupervised techniques can be used and CNNs have evolved from deep neural networks. A neural network consists of two serial components, the feature extraction layers and subsampling (pooling) layers, which then utilise the feature extraction output as their input to further analyse the data and generate the ultimate output **(Figure 1)** [3]

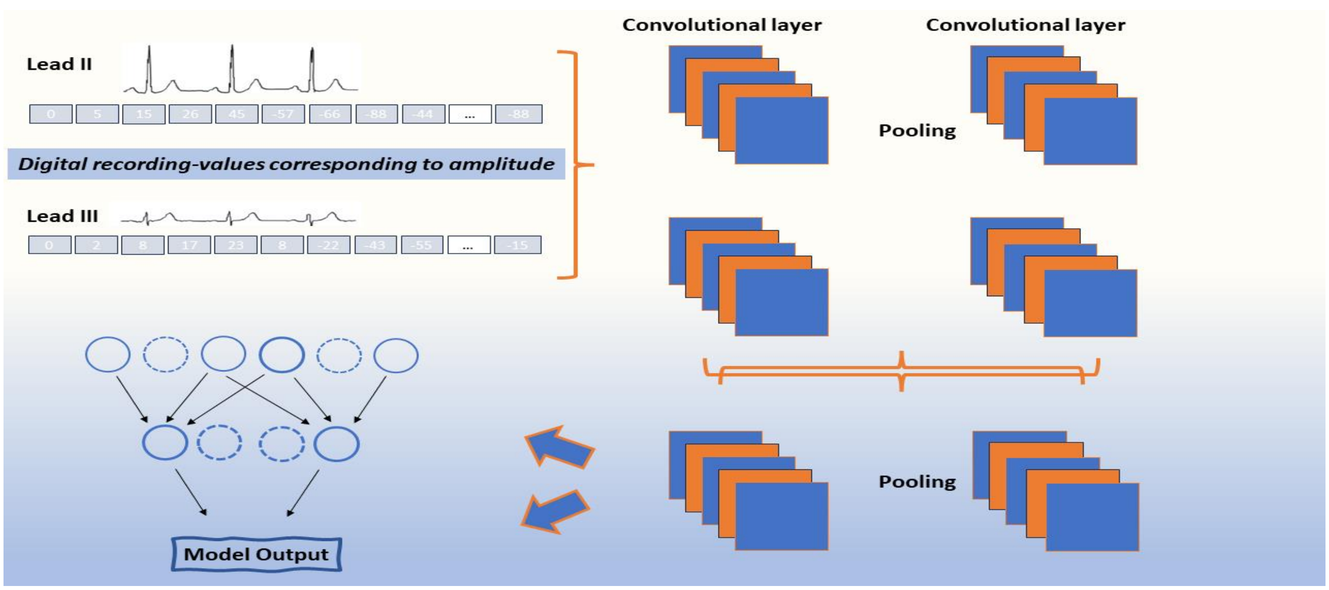

Figure 1: Generic development of a convolutional neural network using the 12-lead ECG [1]

The ECG analogue signal is converted to a digital recording, resulting in a list of numerical values corresponding to the amplitude of the signal, feeding sequential layers of convolutions until the final model output is reached.

EVIDENCE SUMMARY

A total of 58 titles were retrieved from the scientific databases via OVID, PubMed and general search engines [Google Scholar], using the search term; *artificial intelligence echocardiography, cardiovascular diseases* and tricog ecg. The last search was conducted on 19th November 2025. The articles were found to be relevant and included in this review which comprised of one systematic review, one RCT, one case control study, five cohort studies and two observational study (a total of ten articles)

EFFICACY/ EFFECTIVENESS

AI-ECG diagnostic in Acute Coronary Syndrome

Fawzy et al. (2025) conducted a systematic review to evaluate the diagnostic accuracy of artificial intelligence (AI) algorithms applied to 12-lead electrocardiograms (ECGs) for detecting acute coronary syndrome (ACS). This review comprised of 24 studies with 119,000 study subjects involved (adults with suspected ACS in acute care settings). Primary outcomes were sensitivity and specificity, and secondary outcomes included positive predictive value (PPV), negative predictive value (NPV), and accuracy. Artificial intelligence models, mainly deep learning-based (66.7%), demonstrated sensitivity of 68% to 98% and specificity of 41% to 98% for ACS, with STEMI/OMI detection showing sensitivity 68% to 97% and specificity 68% to 99%. Comparisons with clinicians indicated AI outperformed them in sensitivity (90% of studies), PPV (100%), and AUROC (all 8 studies reporting), while clinicians had better NPV in 70% of studies. Compared with commercial non-ML software, AI had higher sensitivity (86%) and PPV (83%). Only one study evaluated AI versus real-time clinician interpretation. High or unclear risk of bias was noted in 88% of studies, and transparency was limited, with only three studies providing public code. Despite heterogeneity preventing meta-analysis, the review concluded AI-ECG models show high potential to improve early ACS diagnosis, particularly for ruling out disease, while complementing clinical judgment.[4]

Chandola N. et al. (2023) conducted an observational study comparing the performance of the smartphone-based Spandan ECG device with the Tricog Insta ECG platform in detecting abnormalities specifically Ischemic Heart Disease (IHD) and Myocardial Infarction (MI) against diagnosis provided by experienced cardiologists in India. A total of 309 individuals were initially recruited, but 31 were excluded due to human error during ECG recording or baseline artifacts. The final analysis therefore included 278 eligible participants, all of whom had their ECGs evaluated using the Tricog Insta ECG portal. Participants ranged in age from 18 to 70 years, with a mean age of 45 years; 53 were female (20.8%) and 225 were male (79.2%). The Tricog platform correctly interpreted 276 cases. Among the participants, 26 cases of IHD and 123 cases of MI were identified, totaling 149 abnormal findings, while the remaining 129 were classified as normal. Within the IHD group, 7 were female and 19 male, with a mean age of 50.5 years. The MI group included 17 females and 106 males, with a mean age of 45.5 years. Overall, the study concluded that while computerized ECG interpretation offers valuable guidance, discrepancies between systems highlight the need for AI-based tools to serve as supportive aids rather than definitive diagnostic instruments.[5]

Naik G et al. (2025) conducted a prospective cohort study evaluated a hub-and-spoke STEMI management program implemented in Goa, India from 2019 to 2022. Using existing public healthcare facilities (one government medical college and two private hospitals functioned as 24-hour cath-lab hub), the model linked twelve peripheral centers acted as spokes, equipped with cloud-connected ECG machines, emergency supplies and thrombolytic drugs. Medical officers received intensive training, and ECGs were transmitted via Tricog Health India's tele-ECG service for rapid confirmation. Among 2050 STEMI patients, complete data for 1325 showed that 74.3% of eligible patients received thrombolysis substantially higher than prior Indian registries. Treatment timelines were rapid, with a median door-to-ECG time of 7.9 minutes and door-to-needle time of 18.5 minutes, meeting or exceeding guideline standards. Safety outcomes were favorable, with inappropriate thrombolysis in only 0.22% of cases, in-hospital mortality of 9.4%, and low complication rates. The study demonstrated that leveraging existing infrastructure with cloud-based ECG interpretation can markedly improve timely reperfusion therapy in resource-limited settings.[6]

AI-ECG diagnostic in Left Ventricular Systolic Dysfunction

Bachtiger et al. (2022) conducted a prospective, multicentre observational study to evaluate an artificial intelligence (AI) algorithm applied to single-lead ECG recordings obtained via an ECG-enabled stethoscope, aiming to validate its use as a point-of-care screening tool for detecting left ventricular ejection fraction (LVEF) ≤ 40%. The study assessed a convolutional neural network (AI-ECG), previously validated for reduced LVEF detection using 12-lead ECG input, retrained here to interpret single-lead ECG data exclusively. This study involved 1,050 patients with mean age 62 years (51% male; 41% non-White) and was conducted across seven NHS sites in London. Participants underwent single-lead ECG recordings at standard auscultation sites, with echocardiography-derived LVEF as the reference. This study found AI-ECG model accurately identified LVEF ≤40%, performing best at the pulmonary position (AUROC 0.85; sensitivity 84.8%; specificity 69.5%). Combining pulmonary and handheld positions improved performance (AUROC 0.91; sensitivity 91.9%; specificity 80.2%), with consistent results across age, sex, and ethnicity. The study concluded that AI analysis of single-lead ECGs via an ECG-enabled stethoscope enables rapid, low-cost and non-invasive screening for HFrEF, potentially facilitating earlier diagnosis and more efficient use of echocardiography resources.[7]

AI-ECG diagnostic in Hypertrophic Cardiomyopathy

Siontis KC et al. (2021) conducted a cohort study to evaluate the diagnostic performance of an AI-ECG model in detecting hypertrophic cardiomyopathy (HCM) in a paediatric population. Using data from the Mayo Clinic's digital vault (2000 to 2020), the retrospective study included patients aged 18 years or younger. Hypertrophic Cardiomyopathy cases were identified via ICD-9 and ICD-10 codes and confirmed by echocardiography, while controls were non-HCM patients who had both ECG and echocardiograms during the same period. After age and sex matching, the final cohort comprised 300 confirmed HCM cases and 18,439 controls (case-to-control ratio: 1:61.5). Each participant's 12-lead digital ECG was analysed using a pre-trained AI convolutional neural network (AI-CNN), which generated a probability score for HCM. Model performance was assessed across subgroups defined by sex, age, ECG characteristics, and genetic variant status. The study results demonstrated AI-ECG showed strong diagnostic accuracy, with mean probability scores of 92% in HCM cases and 5% in controls. It achieved an AUC of 0.98 (95% CI: 0.98 to 0.99), sensitivity of 92%, specificity of 95%, a negative predictive value of 99%, and a positive predictive value of 22%. Performance was consistent across sexes, genetic subtypes and improved with age ranging from an AUC of 0.93 in children under 5 to 0.99 in adolescents aged 15 to18 year-old.[8]

AI-ECG diagnostic in Atrial Fibrillation

Noseworthy PA et al. (2022) conducted a non-randomised interventional trial to evaluate the effectiveness of AI-guided targeted screening approach for detecting previously unrecognised atrial fibrillation (AF) among individuals with stroke risk factors but no known AF. A total of 1003 participants with mean age 74 years-old from 40 U.S. states who had undergone routine ECGs were prospectively enrolled. Artificial Intelligence algorithm was applied to these ECGs to stratify participants into high-risk (n=633) and low-risk (n=370) groups for AF. All participants wore continuous heart rhythm monitors for up to 30 days, with real-time data transmission. The study result demonstrated AF was newly detected in 48 high-risk participants (7.6%) and 6 low-risk participants (1.6%) with odds ratio of 4.98 (95% CI, 2.11 to 11.75; p=0.0002). Compared to matched real-world controls receiving usual care, AI-ECG increased AF detection in the high-risk group (10.6% vs. 3.6%; p<0.0001), though not in the low-risk group (2.4% vs. 0.9%; p=0.12), over a median follow-up of 9.9 months. These results demonstrate that AI-guided risk stratification can effectively target individuals most likely to have undiagnosed AF, improving screening efficiency and detection rates compared to standard care.[9]

Jo YY et al. (2021) conducted a retrospective cohort study using Sejong ECG dataset to detect atrial fibrillation (AF) using depp learning model (DLM) or AI-ECG in South Korea. This study involved 128,399 patients's ECGs, to develop and internally validate an explainable deep learning model (DLM). Study result demonstrated area under the receiver operating characteristic curve for DLM with 12-leads ECG range from 0.997 to 0.999, while DLM with VAE using 6-lead and single-lead ECGs achieved AUCs of 0.990 to 0.999. Analysis for features such as rhythm irregularity and absence of p-wave yielded AUCs of 0.961 to 0.993 and 0.983 to 0.993 respectively. These results demonstrate that the DLM can accurately detect AF across diverse ECG datasets while providing interpretable insights into its predictions, supporting its potential clinical application with enhanced transparency.[10]

Christopulos et al. (2020) conducted a prospective cohort study to evaluate whether AI-ECG could predict the future development of atrial fibrillation (AF) in participants from the Mayo Clinic Study of Aging (MCSA). The study involved 1936 participants with median age 75.8 years and no prior AF, followed for a median of 7.4 years. The study demonstrated throughout the follow up period, total of 333 participants (17.2%) developed AF. The AI-ECG, using a convolutional neural network trained to detect AF signatures in sinus rhythm, was compared to the established CHARGE-AF score. Both independently predicted incident AF (AI-.ECG HR 1.76 per SD; CHARGE-AF HR 1.90 per SD), with similar discriminatory performance (C statistic 0.69 for both). When combined, prediction improved slightly (C statistic 0.72). Participants with high AI-ECG output (>0.5) had AF incidences of 21.5% at 2 years and 52.2% at 10 years. Artificial Intelligence-ECG remained predictive after 8 years (C statistic 0.62), whereas CHARGE-AF's predictiveness declined (C statistic 0.56). The study concluded that AI-ECG provides an independent, efficient, and automated method for long-term AF risk prediction, offering a simple, single-test alternative to traditional clinical risk models.[11]

Other cardiac Pathologies

Electrocardiography (ECG) contributes variably to the diagnosis of numerous cardiac pathologies. Recent advancements in artificial intelligence (AI) have enabled the detection of long QT syndrome (LQTS), even when the corrected QT interval (QTc) appears within normal limits.[2]

Bos JM et al. (2021) conducted a retrospective case-control study in Minnesota to assess the effectiveness of an artificial intelligence enhanced electrocardiogram (AI-ECG), powered by deep neural networks, in detecting long QT syndrome (LQTS) more accurately than the corrected QT interval (QTc) alone. The study analysed data from 2059 patients treated at a specialised arrhythmia clinic between 1999 and 2018, including 967 with confirmed LQTS and 1,092 without LQTS. The AI-ECG achieved an area under the curve (AUC) of 0.900 (95% CI: 0.876 to 0.925), outperforming the QTc alone (AUC 0.824; 95% CI: 0.790 to 0.858). Among patients with normal QTc values (<450 ms), AI-ECG improved diagnostic accuracy (AUC 0.863 vs. 0.741). It also effectively differentiated genetic subtypes: LQT1 vs. LQT2/3 (AUC 0.921), LQT2 vs. LQT1/3 (AUC 0.944), and LQT3 vs. LQT1/2 (AUC 0.863). Importantly, the detection of LQTS in the presence of a normal QT interval holds significant potential for enhancing clinical screening strategies. Overall, the AI-ECG demonstrated approximately 80% accuracy in predicting genotype status and showed promise as a simple, cost-effective tool for early detection and risk stratification of congenital LQTS.[12]

Elias P et al. (2022) conducted a retrospective cohort study to assess the use of deep learning analysis of electrocardiography (AI-ECG) to detect moderate or severe aortic stenosis (AS), aortic regurgitation (AR), and mitral regurgitation (MR), individually and in combination. This study involved 77,163 patients who underwent ECG within one year prior to echocardiography from 2005 to 2021. Patients were split into training (n=43,165), validation (n=12,950), and test (n=21,048) sets, with 7.8% of patients having at least one valvular heart disease. Model performance was evaluated using area under the receiver-operating characteristic (AU-ROC) and precision-recall curves, with external validation on an independent dataset. The study result demonstrate in AI-ECG, AU-ROC values are 0.88 for AS, 0.77 for AR, 0.83 for MR, and 0.84 for any valvular disease with sensitivity 78% and specificity 73%. Screening simulations indicated that predictive values depended on disease prevalence, with a positive predictive value of 20% and negative predictive value of 97.6% at 7.8% prevalence. These findings demonstrate that ECG-based deep learning can accurately identify key valvular heart diseases and may provide a foundation for the development of a population-level VHD screening program.[13]

SAFETY

[redacted]edical device obtained Medical Device Authority (MDA) approval on 15th December 2024 (V-Cardia VC 100; GB7691724-192232).[14] No adverse events or evidence retrieved on AI-ECG from the scientific databases.

ORGANISATIONAL

American Heart Association (AHA) supports the integration of artificial intelligence (AI) and machine learning (ML) as strategic tools to advance precision medicine and improve cardiovascular outcomes. In its Position Statement, AHA highlights diverse applications of AI across imaging, electrocardiography, in-hospital monitoring, wearable devices, genetics, and electronic health records. These technologies hold promise for enhancing disease detection, automating analytical processes, and predicting adverse events earlier than conventional non-AI ECG methods. At the same time, the AHA underscores the urgent need for implementation science to ensure that AI-ML tools are applied safely, equitably, and effectively. This requires rigorous clinical validation, transparent system design, and seamless integration into routine care to maximize their positive impact on cardiovascular health.[15]

European Society of Cardiology emphasizes that advances in AI have opened new opportunities in non-invasive diagnostics. In electrocardiography, Convolutional Neural Network (CNN) based analysis enables rapid and accurate interpretation, supporting the detection of conditions such as arrhythmia, left ventricular systolic dysfunction, cardiomyopathy, and valvular heart disease. Artificial intelligence driven ECG still requires rigorous clinical validation, structured professional training, and a clear legal framework before it can be fully integrated into medical practice.[3]

COST/COST-EFFECTIVENESS

Liu WT et al. (2025) conducted a cost effectiveness analysis to evaluate the cost-effectiveness of universal atrial fibrillation (AF) screening using AI-ECG in rural populations aged 65 and older in Taiwan. A lifelong decision-analytic Markov model was employed from a healthcare payer's perspective to compare AI-ECG screening (nurse-administered with physician confirmation) against physician-led ECG screening and no screening. The AI-ECG model, trained on data from 285,108 patients across three Taiwanese hospitals, demonstrated high diagnostic performance with 97.8% sensitivity and 99.1% specificity. AI-ECG screening yielded 16.52 quality-adjusted life years (QALYs) at a cost of $141 per patient, compared to 16.49 QALYs and $39 for no screening, and 16.53 QALYs and $196 for physician screening. The resulting incremental cost-effectiveness ratios (ICERs) were $4,349 (AI-ECG vs. no screening) and $6,132 (physician vs. AI-ECG), both below Taiwan's willingness-to-pay threshold of $32,327 per QALY. The referral rate following a positive AI-ECG result was identified as a key determinant of cost-effectiveness. Findings support AI-ECG screening as a resource-efficient strategy suitable for rural or resource-limited settings, with potential to improve healthcare accessibility and reduce regional disparities in AF care across older age groups.[15]

Thao V et al. (2024) conducted a cost effectiveness analysis to assess the cost-effectiveness of artificial intelligence-enabled electrocardiograms (AI-ECG) for early detection of low ejection fraction (EF ≤ 40%) in routine clinical practice. Utilizing data from the Electrocardiogram Artificial Intelligence-Guided Screening for Low Ejection Fraction (EAGLE) trial, a post hoc economic evaluation was conducted using a decision analytic model combining a short-term decision tree and a lifetime Markov model. The analysis included 22,641 adults (median age 63 years) without known heart failure who underwent clinically indicated ECGs, comparing AI-ECG screening (cost: $100) with usual care (standard ECG, cost: $50). Outcomes were measured in quality-adjusted life years (QALYs) against a $100,000 willingness-to-pay (WTP) threshold. Study results demonstrated AI-ECG screening resulted in slightly higher lifetime costs ($224,950 vs. $224,564) and greater effectiveness (14.85 vs. 14.83 QALYs), yielding an incremental cost-effectiveness ratio (ICER) of $27,858 per QALY and within the WTP threshold. Sensitivity analyses confirmed robustness, with AI-ECG being cost-effective 79.5% of the time, especially in outpatient settings (ICER: $1,651/QALY) and younger populations (ICERs: $13,007–$36,213/QALY). Among high-risk or AI-positive patients, cost-effectiveness further improved (ICERs: $23,435–$13,136/QALY). The findings support AI-ECG screening as a scalable, cost-effective strategy for early detection of low EF, with significant clinical and economic benefits in outpatient and younger patient populations.[16]

No economic evaluations conducted in Malaysia were identified, and evidence on cost are limited. However, in India, the estimated cost of the TRICOG ECG ranges from approximately 50,000 Indian Rupees (RM 2,366) for the basic VCardia ECG Machine to 75,000 Indian Rupees (RM 3,550) for the advanced model.[17]

CONCLUSION

Based on the review, evidence demonstrated AI-enabled electrocardiography (AI-ECG) has moderate to good diagnostic accuracy across multiple cardiovascular conditions. For acute coronary syndrome (ACS), sensitivity ranges from 68% to 98% and specificity from 41% to 98%, often outperforming clinicians in sensitivity and positive predictive value. In atrial fibrillation (AF), AI-ECG effectively detects previously unrecognised cases and predicts long-term risk, complementing traditional scores like CHARGE-AF. For hypertrophic cardiomyopathy (HCM), particularly in older children and adolescents, AI-ECG achieved an area under the curve (AUC) of 0.98, with sensitivity of 92% and specificity of 95%. Economic evaluations demonstrates AI-ECG is cost-effective in screening for AF, heart failure, and VHD. American Heart Association (AHA) and European Society of Cardiology highlight artificial intelligence (AI) and machine learning (ML) as promising tools for advancing cardiovascular care. AI applications, including Convolutional Neural Network–based ECG analysis, enable rapid detection of arrhythmia, ventricular dysfunction, cardiomyopathy, and valvular disease. Deep learning models enhance traditional ECG interpretation, and regulatory approvals support its scalability.

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