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Recent Trends in ECG-Data Based Solutions for CVD Forecast Using Explainable Artificial Intelligence: A Systematic Review

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Abstract

The field of cardiovascular disease (CVD) prediction utilizing electrocardiogram (ECG) data experienced a substantial change, simply since Explainable Artificial Intelligence (XAI) has emerged. The crucial transition from conventional "black-box" deep learning models to transparent, clinician-centric frameworks is examined in this paper. Factor-ECG, which breaks down complex signals into interpretable latent factors, and Generative Counterfactual XAI (GCX), which offers "what-if" morphological representations, are two significant technological developments. Beyond qualitative heatmaps, objective auditing of model trustworthiness turned out to be enabled by adding a mix of quantifiable XAI metrics (qxAI).

With intermediate (feature-level) fusion tactics outperforming late fusion methods, multimodal integration—specifically, the fusion of ECG with medical imaging and wearable data—has shown improved prediction accuracy. With a growing physician acceptance rate of 66% as of 2024, the global AI in cardiology market is expected to reach USD 1.66 billion by 2031, according to market data. Despite these developments, issues with data privacy, regulatory compliance, and external validation continue to impede clinical application. Future paths are increasingly focused on Federated Learning to provide safe, multi-institutional model training and Digital Twins for customized diagnoses.

Keywords: Black-Box Models; Explainable Artificial Intelligence; Electrocardiogram; Cardiovascular Disease; Machine Learning.

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Introduction

The main reason of demise universally, cardiovascular disorders require prompt and precise diagnosis and treatment. The primary tool for identifying cardiac problems is the electrocardiogram (ECG); nevertheless, human error and the depth of apparent patterns limit the manual interpretation of ECGs. Although artificial intelligence (AI) has turned out criticised due to its "black-box" character, which undermines therapeutic trust, it has historically provided strong prediction performance [2], [10]

To narrow the spacing between algorithmic performance and therapeutic utility, research has shifted toward Explainable-AI (XAI) between 2024 and 2026. Static saliency maps, which frequently offer ambiguous "hotness" across signal segments, are giving way to practical, morphological, and measurable explanations in this period [1],[3]. This study describes the particular approaches, implementation challenges, and market trends that characterize this new area of cardiology.

Technical Advancements in XAI Methods

Several advanced XAI frameworks created especially for the distinct temporal and morphological characteristics of ECG data were introduced between 2024 and 2026.

Generative Counterfactuals (CofE as well as GCX)
By providing "what-if" answers, Generative Counterfactual XAI (GCX) signifies a paradigm shift in interpretability. GCX creates a synthetic version of the patient's ECG that would lead to a different clinical categorization rather than highlighting whatever aspect of an ECG affected a prediction [1][5].

For example, the StyleGAN2-based architecture used in the CoFE (Counterfactual-ECG) framework was trained on almost three million electrocardiograms, with 12 leads sourced from the MIMIC-IV, a repository. [24]. CoFE can vary certain physiological characteristics, such as P-wave amplitude, The variance of RR ranges, and QRS duration, using cross-entropy and Average Measured Mistakes (MSE) to see what happens when the AI's evaluation is impacted by such alterations [12].Investigation displayed offering these alternate ECGs match recognized clinical indications for conditions including elevated hypertension and atrial fibrillation (AF), providing physicians with a more rational proof than traditional accounting methods [1], [5].

Opaque Encoding and A Component ECG
One major challenge in electrocardiogram artificial intelligence is the enormous heterogeneity of the data. Dynamic ECG uses a variant-based Encoding Engine (VAE) to deconstruct intricate ECG appearance through a set of 32 plausible implicit factors [2]. Physicians might comprehend. Owing to this approach, which was trained on more than a million ECGs, different elements (indicating certain structural traits) assist to a diagnosis. Crucially, it has been shown that A component ECG matches the diagnostic efficacy of purely black-box models while significantly increasing openness and reducing the requirement for subjective heat map representations [2].

Quantifiable XAI (qxAI)
To counter the emotive nature of visual justifications, the qxAI concept offers numerical indicators for XAI [10]. Our approach evaluates the Region of Interest (ROI) and employs CVD-specific afterwards to ensure that the AI's "characterization" matches the actual symptoms of the condition.

Studies for qxAI indicate notable improvements in explaining accuracy. For instance, in the ST-elev. (STE) tasks, explainable accuracy rose reached 50.7% to the 70.5% and explainable quality F1-score from 26.1% to 35.8% [10]. In intraventricular block (IAVB) tasks, the F1-score for justifications grew from 49.8% through 71.8% [10]. Methodical modelling that utilizes a trade-off among duration, explanatory consistency, and effectiveness in classification is made possible by this measure.

Options For Multisensory Merging and Synthesis

Its ability to forecast is increased by combining ECG scans using more applicants' tests, such as ventricular radiology (MRI), ultrasound, and diagnostic EHR information.

Fusion of ECG and Visualization
For the purpose of extracting ECG features, recent schemes have integrated 1D-CNNs with visual-based neural systems [5][8]. They use XAI approaches like Grad-CAM, respectively (Class Activation Mapping using Gradient Weights) and SHAP (SHapley Additive exPlanations) to provide interpretations that transcend both paradigms. For example, an approach may indicate that a diminished ejection fraction in scans and specific QRS enlargement in the ECG elevate a likelihood of a heart attack [5][8].

Investigation of Relative Merging
an extensive scholarly debate focused on the optimal fusing strategy for heterogeneous ML models. Investigation has shown that early fusion frequently outperforms latter (decide-level) combining [9]. Mixing abstractions from the moment, amplitude, and temporal-

frequency phases before the last class tiers allowed algorithms to achieve great precision indices of about 97% [6]. This approach is alongside improving efficiency but also rendering it more tolerant with distortion in discrete data sources [9].

Therapeutic Implementation: Constraints And Resilience

Notwithstanding the engineering superiority of these approaches, they remain significant barriers to their application from investigation to the hospital.

Bridging Ambiguity and Credibility
Credibility is the primary barrier. Explicitness and handling ambiguity are both essential. Modern versions increasingly use spatial prediction models or Probabilistic tiers to highlight when the AI is doubtful about an appropriate diagnosis [12]. Rules state that AI should only deal with reliable scenarios by itself; low-credibility or extremely uncertain ECGs must be tagged for manual assessment [2].

Testing and Extrapolation
resent study is sometimes constrained by the use of controlled databases like MIT-BIH or MIMIC-IV. Researchers emphasize the necessity of getting objective confirmation from a range of practical settings and integrating physician feedback into a trained loop [1], [9]. Without hypothetical clinical trials that track patient effects, the actual efficacy of XAI remains uncertain [2], [9].

Enterprise Adherence and Business Prospects

Intelligent technology in cardiac care is a rapidly expanding economy. The worldwide demand is projected to rise from USD 838.87 mm in 2025 to 1.66 billion dollars by 2031 at an average yearly increase (CAGR) of 12.11%. [Web-Source].

Movers of the demand involve:

- Healthcare professionals Engagement**:** In 2024 A surveys by the US Healthcare Group revealed that 66% of physicians used clinical AI in their daily operations, an upsurge versus years past [Web-Source1].
- Wrist Innovation: The emergence of wearables equipped with or without ECG readings (using PPG for testing) has created a vast data chain for artificial intelligence computation, allowing community-wide AF surveillance [Web-Source2].

Yet, rapid growth is hampered by strict adherence to regulations demands and the ongoing challenge of processing massive volumes of delicate medical data while maintaining secrecy [Web Source].

Promising Opportunities

The next era of ECG-based investigation is expected to focus on precise customization and scattered data usage.

Virtual replicas of the cardiac system
E-twins, which are remote replicas of a patient's cardiovascular system, represent a novel method to personalized therapy. By combining ECG impulses with hereditary information and biological frameworks to simulate the effects of various treatments or perhaps the onset of disease, e-twins allow for highly tailored treatments [Web Source].

Explicitness and FL
FL, or Federated Learning is gaining popularity as a framework to overcome the challenges of conventions & data security concerns. Due to FL, crucial ECG traces are still available from the community institution, allowing paradigms to be studied at different healthcare facilities [Web Source]. This distributed methodology allows machine learning models to learn from a variety of inputs while strictly adhering to data security guidelines.

Conclusion

Clinical openness is giving way to experimental accuracy with the introduction of "an artificial intelligence-augmented Electrocardiogram reading that can be interpreted" [13]. Techniques like GCX and Factor-ECG have provided the "how" and "why" behind machine learning predictions, while qxAI has provided variables to support those interpretations. As the firm expands and technological designs like supervised training and a virtual twins continue to progress, the emphasis must remain on complete medical testing and the seamless integration of these devices into existing medical procedures. The ultimate goal is a partnership in which Technology enhances the cardiologist's expertise to better results for patients through timely and understandable CVD detection.

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