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A Survey of Transformer Graph Neural Network Graph Attention Network and Capsule Network Approaches for Cardiovascular Disease Prediction

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Abstract
Cardiovascular disease is one of the important causes of morbidity and mortality in the world and early diagnosis and accurate prediction are required. The recent developments of Artificial Intelligence (AI) technologies have simplified the prediction of cardiovascular disease diagnosis by analyzing a variety of health-related data such as the analysis of an electrocardiogram (ECG), electronic health records (EHRs), medical images, data from wearable devices and even genomic data. The present review reviews advanced architectures of AI for cardiovascular prediction, including multimodal learning architectures, Capsule Networks (CapsNets), Graph Attention Networks, Graph Neural Networks and Transformer models. Methods that model specific temporal relationships in clinical data using a transformer architecture are effective for capturing temporal dependencies in sequential clinical data, whereas methods that model the relationships among various patients, diseases, and healthcare events using graphs are effective for modeling complex relationships. CapsNets are hierarchical feature representations for cardiovascular signal and image analysis. Moreover, multimodal AI enhances the predictability by combining multiple healthcare data sources, and Explainable Artificial Intelligence (XAI) techniques boost transparency and clinical trust. While there is great progress, there are issues with data heterogeneity and interpretability, computational complexity, external validation, privacy, and regulatory compliance. Clinically deployable cardiovascular prediction systems are likely to continue to be increasingly improved in future developments of multimodal learning, XAI, foundation models, and personalized medicine.
Keywords: Cardiovascular Disease Prediction, Artificial Intelligence, Transformer Models, Graph Neural Networks, Graph Attention Networks, Capsule Networks, Multimodal Learning, Explainable Artificial Intelligence

1. Introduction

Heart diseases are one of the significant causes of death across the globe. Cardiovascular diseases (CVDs) including coronary artery disease (CAD), Heart Failure, Arrhythmias, Myocardial Infarction, and Stroke are the leading contributors towards global healthcare issues. The rise in risk factors such as diabetes, obesity, hypertension, and lack of physical activity highlights the importance of accurate and fast disease prediction in CVDs. The early detection of at-risk patients is crucial for prevention activities and clinical decision-making [1]. With the use of EHRs, ECG, wearables, and medical imaging, cardiovascular datasets have become abundant. Unfortunately, because of the complexity of these datasets, classical statistical methods can be insufficient, and there is an opportunity for development of CVD prediction using AI technology [2].

Machine Learning (ML) and Deep Learning (DL) methods have gained traction in the prediction of CVD by discovering intricate patterns from clinical data. DL models resolve the shortcomings associated with traditional methods through automatic feature extraction and representation learning [3]. Transformers are the state-of-the-art deep neural networks that effectively model the long-term temporal dependencies of sequential health data and have shown impressive results in predicting cardiovascular risks from Electronic Health Records (EHRs) [4].

Graph Neural Networks(GNNs) and Graph Attention Networks(GATs) are suitable for modelling patient-disease-event association, which leads to better predictions [5]. Contrarily, Capsule Networks (CapsNets) preserve the relationship between features and exhibit encouraging performance in identifying abnormalities from cardiovascular signals [6]. This literature survey studies the recent advancements in the domain of Transformers, GATs, and CapsNets for the prediction of CVDs.

2. Background and Foundations

Prediction in regard to CVD has become one of the most important topics to study as the prevalence of heart diseases is increasing, hence the requirement for early interventions. The most frequently used risk prediction tools include statistical and clinical ones. However, they do not take into account the interaction of a number of risk factors. In connection with the developments in the field of AI, the process of analyzing clinical data has become more manageable. ML and DL are some examples of the applications of AI which have shown their efficacy in uncovering disease-related patterns [7].

The increasing number of healthcare data has led to further developments in AI-assisted cardiovascular prediction. The data obtained from electrocardiogram tests are useful indicators of cardiac conditions; moreover, they can be analyzed using AI algorithms which will allow for detection of any abnormality [8]. EHRs contain various data related to patients' history and can thus assist in predicting long-term CVD risks for individuals. Research has found ML models trained on EHR data to be more effective than traditional methods in prediction tasks [9]. In addition, cardiovascular imaging techniques such as echocardiography, computed tomography (CT), and cardiac MRI help diagnose diseases and predict their outcomes [10]. Moreover, wearable and remote monitoring technologies allow the continuous monitoring and predictive analytics of a person's physiology [11].

Nevertheless, there are a variety of issues that need to be addressed in order to make cardiovascular medicine reliable, understandable, and patient-centered [12].

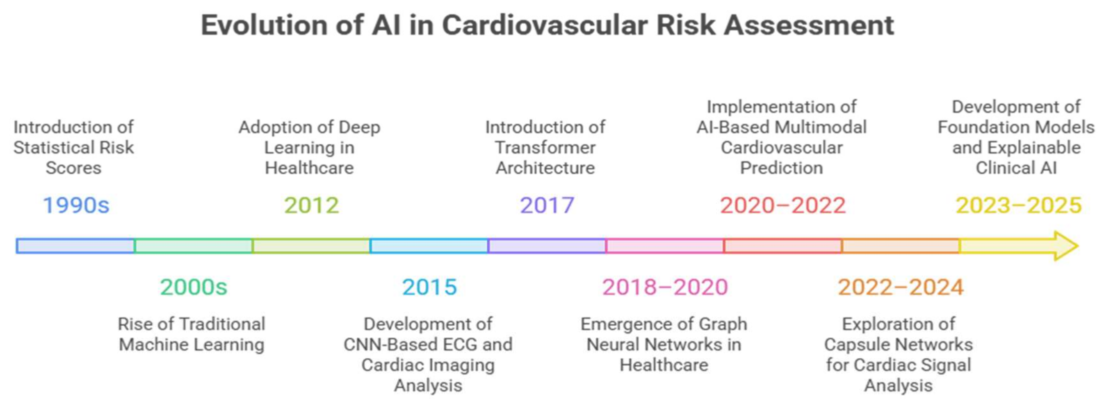

Figure 1. Evolution of AI techniques in cardiovascular risk prediction.

Figure 2 shows how CVD prediction models evolved over time from statistical risk scores to ML techniques and from simple DL to transformers, GNNs, CapsNets, and finally to foundation models.

3. Architecture Foundations

Recent advancements in predicting CVD were associated with new DL architectures. Transformer-based networks utilize self-attention mechanisms to establish the context in sequence data and learn relationships between different features. They can handle multiple modalities (electronic health records, electrocardiograms, medical imaging), perform parallel computations efficiently, and provide high prediction accuracy for CVDs [13].

GNNs and GATs are created to model graph-based medical data where nodes are entities like patients, diseases, and medication, whereas edges are relationships between these. Using message passing and attention mechanisms, these techniques create useful representations and identify significant clinical interactions, which are important for disease association, patient similarity modeling, and medical predictions [14].

CapsNets overcome limitations of traditional convolutional neural networks in maintaining spatial and hierarchical relationships of features. With the help of capsules and dynamic routing mechanisms, they ensure the maintenance of rich feature information in representations. For cardiovascular problems, CapsNets have been proved effective for physiological signals and heart sound analysis as these tasks require considering small relations between different features [6].

4. Related works:

1. Transformer-Based Models for CVD Prediction

Ansari et al. [15] carried out a survey of transformer and LLM-based techniques employed for diagnosing CVDs using ECG signals. Given the shortcomings of the CNN approach in modeling long-range temporal dependency, analyzing existing solutions and proposed a framework for classifying current solutions into single-beat, multi-beat, and full-length ECG-based techniques. It was shown that transformer networks can effectively capture temporal relationships via self-attention mechanisms while LLMs allow for multimodal integration and enhanced diagnostic capabilities. Yet, the high computational cost, positional encodings, hallucinations, and uncertainty quantification pose considerable problems.

Velandia et al. [16] have provided a systematic review of AI algorithms used in interpreting ECGs in diagnosing CVDs. After reviewing more than one hundred papers ranging from 2019 to 2025, the classification was made by the researchers according to different criteria including type of disease, architecture, and new methodological approaches. The findings suggest that ML, DL, and hybrid algorithms surpass traditional methods in terms of diagnostic effectiveness while providing better sub-clinical disease detection and wearables. However, there are some drawbacks associated with the use of the aforementioned technologies.

Jaya Prakash et al. [17] performed a systematic analysis on ML and DL algorithms for ECG beat classification by examining 106 articles that were published between 2014 and 2024, employing PRISMA guidelines. The review focused on ECG preprocessing, feature selection, and classification algorithms such as CNN, RNN, Hybrid model, and attention-based models. The researchers emphasized that the evolution in ECG analysis has led to the use of automated feature learning instead of manual feature selection, resulting in an improvement in accuracy and efficiency.

Zhang et al. [18] discussed the applications of AI to manage heart failure patients, reviewing risk prediction, diagnostics, phenotyping, therapies, and prognoses using ML, DL, and large language models capable of analyzing multiple sources of clinical information, including electronic medical records and images. Overall, the authors concluded that multivariate models showed higher accuracy and provided greater opportunities for personalization compared to monomodal solutions. Nevertheless, limitations associated with the interpretability and generalizability of algorithms and their insufficient robustness limit current models' practical applications.

Myśliwiec et al. [19] performed a narrative review of DL usage in cardiovascular medicine in regard to the use of diagnostic imaging, risk stratification, integration of biomarkers, and clinical decision making. The authors reviewed scientific literature on the use of the mentioned types of DL algorithms applied in echocardiography, magnetic resonance cardiovascular imaging, coronary CTA, and electrocardiography studies. According to the research, DL and especially CNNs and transformer-based algorithms have achieved high performance in diagnosing cardiovascular conditions. However, some limitations were identified.

Chikumo and Ndlovu [20] performed a systematic review on the application of transformers in CVDs' predicting using Electronic Health Records. The analysis was conducted according to the PRISMA guidelines, and 16 publications from the time period of 2020-2025 were used. In particular, the paper focused on transformer models, namely the BEHRT algorithm, and its modifications. According to the research results, transformers demonstrated their ability to analyze long-term temporal relationships and showed high efficiency in predicting cardiovascular conditions. Also, they had an advantage regarding the explanation of the processes.

Kasartzian and Tsiampalis[21] reviewed the latest research on ML and AI application for CVD risk prediction. In the study, researchers investigated how AI algorithms use different sources of information within healthcare to increase the efficiency and scalability of their methodology for evaluating patient risks. The research reviewed scientific literature to assess various ML and DL algorithms used in precision cardiovascular medicine. AI-based techniques were shown to be more effective than traditional ones in terms of recognition of risk-factor interactions, but many challenges are still to be faced.

Ansari et al. [22] reviewed the latest research on the use of DL for detecting and classifying ECG arrhythmias for early diagnosis of CVDs. To that end, various architectures, including CNN, MLP, RNN, and transformer, were studied between 2017 and 2023. According to the study findings, the proposed model outperforms traditional ML-based methods since it is capable of automatically detecting features within the ECG without any manual data preparation; however, several issues still need to be addressed.

Gutierrez-Garcia et al. [23] conducted a systematic review of DL applications for identifying myocardial infarctions through ECG image recognition. Using the PRISMA framework, the researchers analyzed 47 high-quality papers selected out of 361 publications found in six scientific databases. In particular, the paper discusses DL architectures, training procedures, performance metrics, open-access ECG databases, and the application of Vision Transformers in diagnosing myocardial infarctions. In addition to providing the necessary information about advances in diagnostic practices, the paper highlights some crucial issues concerning DL approaches, including heterogeneity of the databases, non-standardized metrics, validation, and safe real-world application.

Xiao et al. [24] examined applications of DL for automatic ECG arrhythmia classification. Specifically, analyzing 368 papers, the researchers aimed at assessing current research trends, identifying challenges, and pointing to future directions regarding the issue. The analysis covered ECG datasets, preprocessing techniques, DL models, performance evaluation, and measures used in this purpose. The review indicated that although CNN models prevailed, there were notable improvements in model performance because of the introduction of hybrids and innovations in architectures. Nonetheless, there were still many issues such as heterogeneous datasets, patient generalizability, data imbalance, clinical validation, and real-world application.

Table 1. Transformer-Based Models for CVD Prediction

Author	Sector	Methods	Key Findings	Contribution	Limitations
Ansari et al. [15]	ECG-based CVD diagnosis	Survey of Transformers and LLMs	Effective long-range ECG modeling	Taxonomy of Transformer/LLM ECG methods	High complexity, hallucinations, uncertainty issues

Velandia et al. [16]	AI-enabled electrocardiography	Systematic review (>100 studies)	AI outperforms traditional ECG interpretation	Comprehensive categorization of ECG AI applications	Bias, limited datasets, regulatory concerns
Jaya Prakash et al. [17]	ECG beat classification	PRISMA review (106 studies)	Automated feature learning improves accuracy	Comparative analysis of ML/DL ECG methods	Data imbalance, poor interpretability
Zhang et al. [18]	Heart failure management	Review of AI, DL, and LLM methods	Improved diagnosis, prognosis, and monitoring	Multimodal AI framework for heart failure	Generalization and validation challenges
Myśliwiec et al. [19]	Cardiovascular medicine	Narrative review of DL applications	Expert-level prediction and imaging performance	Clinical evaluation of DL-based cardiology systems	Limited prospective and multicenter validation
Chikumo & Ndlovu [20]	EHR-based CVD prediction	Systematic review of Transformer models	Superior risk prediction from EHRs	Assessment of BEHRT and related models	Data shift and generalization issues
Kasartzian & Tsiampalis [25]	CVD risk prediction	Review of AI and ML techniques	Better risk stratification than traditional models	Precision cardiology perspective	Standardization and interpretability concerns
Ansari et al. [22]	ECG arrhythmia detection	Systematic review of DL models	DL outperforms conventional ML methods	Comparative review of ECG DL architectures	Dataset imbalance and validation issues
Gutierrez-Garcia et al. [23]	Myocardial infarction detection	PRISMA review of DL ECG-image studies	Accurate MI detection using DL and ViTs	Overview of architectures, datasets, and trends	Limited dataset diversity and validation
Xiao et al. [24]	ECG arrhythmia classification	Systematic review (368 studies)	CNNs dominate; hybrids improve performance	Comprehensive ECG DL research synthesis	Generalization and deployment challenges

2. Graph Nural Networks and Graph Attention Networks in Clinical Disease Prediction

Boll et al. [26] examined the potential application of GNNs for predicting clinical risks based on the analysis of EHRs. Based on the review, 50 articles published during the years of 2009 – 2023 were considered, with the emphasis on architectural features of the models used in these papers, data sets and predictions conducted by researchers. GNNs, in particular, GATs, have been effective in modeling relations among patients, diagnoses, and clinical events as well as eliminating drawbacks typical of classical ML algorithms. Nevertheless, the problem of EHR heterogeneity, the combination of multimodal data, scalability, and interpretable algorithms persists.

Vaida and Huang [27] examined multimodal GNNs, particularly their capacity to integrate multiple data sources in healthcare practice, including EHRs, medical images, genomics data, and clinical notes. In particular, the study analyzed three kinds of GNNs, namely Graph Convolutional Networks, Graph Attention Networks, and hybrid frameworks incorporating transformer models, CNNs, and temporal encoders. Thus, the effectiveness of multimodal GNNs in capturing intra-modal and inter-modal relations and enhancing clinical decision-making through attention-based data fusion was confirmed by the research. However, some problems related to data heterogeneity, computational demands, scalability and others remain topical.

Ali et al. [28] investigated the existing body of literature concerning the use of GNN approaches for diagnosing Alzheimer's disease on the basis of unimodal and multimodal brain images. The research focused on architectures like GCNs, GraphSAGE, GANs, and Graph Isomorphism Networks used on several datasets including ADNI, OASIS, TADPOLE, and UK Biobank. It was observed that GNN-based approaches have the potential to identify meaningful relationships between imaging variables and clinical data and hence improve diagnostic capabilities and accuracy. Dataset heterogeneity, lack of generalizability, computational complexity, interpretability, and standardization of evaluations were discussed as future issues.

Lu and Uddin [29] provided a review of graph ML methods for disease prediction from EHRs. The authors evaluated the use of GNNs and shallow graph embedding methods in healthcare predictions. The authors evaluated node classification and link prediction models and found that the use of graph-based models improves the system's ability to detect the relationship among patients, diseases and clinical factors in the EHRs. However, implementation barriers are the interpretation of the model, dynamic graph modeling and heterogeneous data from healthcare.

Zhang et al. [30] presented a literature review on GNNs with brain imaging for neurological disorder diagnosis. Zhang et al. discussed graph construction, graph convolution, graph pooling, and graph prediction techniques for medical diagnosis. They critically evaluated GNN approaches applied to various neurological diseases by different imaging techniques and data sets. The literature survey indicated the effectiveness of GNNs in capturing non-Euclidean relations and structural dependencies in medical imaging data, surpassing traditional DL techniques. Nonetheless, there is data heterogeneity, data scarcity, computation complexity, interpretation problems, and standardization issues in evaluation yet to be solved.

Vrahatis et al. [31] performed a review of GATs to discuss the methodologies employed and application areas and classified GAT models into global attention models, multiple-layer GAT, spatial GAT, embedding-based GAT, and variational attention models. Various applications of GAT models to recommendation systems, image processing, sentiment analysis, anomaly detection, and medical fields were discussed. It was evident from the review that attention mechanisms allow for better interpretability and adaptive feature extraction in contrast with classical GNN models. Nonetheless, benchmarking and cardiovascular studies were underrepresented.

Khemani et al. [32] discussed GNNs by analyzing major concepts, architectures, datasets, applications, challenges, and future work opportunities. The study analyzed different architectures, namely Graph Convolutional Networks, GraphSAGE, and Graph Attention Networks, along with the message-passing process. The review showed that GNNs efficiently exploit the relational and non-Euclidean nature of input data by capturing dependencies in interconnected entities and modeling the irregular data representation. Thus, scalability, computational expenses, graph construction and representation and other issues became the central problems.

Zhang et al. [33] performed an extensive literature review concerning image-based disease diagnosis by the Graph Neural Network. Specifically, this paper explored the ability of the GNNs to incorporate the spatial irregularity in medical images that is not possible with the traditional convolutional neural network. The authors analyzed different types of GNNs, such as Graph Convolutional Networks and Graph Attention Networks, with an emphasis on various disease diagnosis tasks. The review showed that GNNs are able to capture spatial relationships between different segments of medical images, leading to improved accuracy in disease diagnosis.

Paul et al. [34] conducted a review of GNNs by looking at different types of architectures, techniques, datasets, and applications. Key architectures of GNNs discussed include Graph Convolutional Networks, GraphSAGE, and GATs and the use of the message passing approach for relational learning. This paper pointed out the advantages of GNNs in overcoming challenges in traditional DL approaches, which fail to capture non-Euclidean data, node-edge relations among other issues such as in applications within text mining, recommenders, and biomedical. Domain-specific applications, especially within healthcare and heart disease prediction, have not been investigated.

Liang et al. [35] discussed the application of GNNs in learning on non-Euclidean structures of data. The paper discussed different architectures for GNNs based on spectral and spatial convolution techniques, explaining their theoretical foundation and the learning processes involved as well as applications in learning on graphs. As seen in the findings, GNNs offer an effective way of extending standard neural networks through the representation learning of graph-structured data and modeling relational dependencies. Increased applications are also witnessed in IoT applications.

Table 2. GNNs and GATs in Clinical Disease Prediction

Author	Sector	Methods	Key Findings	Contribution	Limitations
Boll et al. [26]	Clinical risk prediction using EHRs	Survey of GNN-based healthcare prediction studies	GATs effectively model complex clinical relationships	Comprehensive analysis of GNNs for EHR prediction	EHR heterogeneity, scalability, interpretability issues
Vaida & Huang [27]	Multimodal healthcare analytics	Review of multimodal GNN fusion frameworks	Improved prediction through multimodal	Analysis of GNN-based fusion strategies	Data heterogeneity, high

			integration		computational cost
Ali et al. [28]	Neuroimaging-based disease diagnosis	Review of GNNs for Alzheimer's diagnosis	Multimodal GNNs improve diagnostic accuracy	Comparative evaluation of GNN architectures and datasets	Limited generalizability and standardization
Lu & Uddin [29]	Disease prediction using EHRs	Review of graph ML methods	GNNs capture patient-disease relationships effectively	Overview of graph learning in healthcare prediction	Interpretability and dynamic graph challenges
Zhang et al. [30]	Neurological disorder diagnosis	Review of GNNs with brain imaging	Effective modeling of non-Euclidean imaging data	Framework overview for imaging-based diagnosis	Small datasets, computational complexity
Vrahatis et al. [31]	Graph Attention Networks	Comprehensive review of GAT architectures	Attention mechanisms improve graph representation learning	Structured taxonomy of GAT developments	Lack of benchmarking and clinical validation
Khemani et al. [32]	Graph-based DL	Review of GCN, GraphSAGE, and GAT models	GNNs model complex relational dependencies	Comprehensive overview of GNN concepts and techniques	Scalability and graph construction issues
Zhang et al. [33]	Image-guided disease diagnosis	Review of GNN applications in medical imaging	Improved diagnosis through spatial dependency modeling	Analysis of GNNs for image-based diagnosis	Limited annotated data and interpretability
Paul et al. [34]	Graph neural network applications	Comprehensive review of GNN architectures	Effective learning from non-Euclidean data	Broad synthesis of GNN models and applications	Limited healthcare-specific evaluation
Liang et al. [35]	Non-Euclidean data learning	Survey of spectral and spatial GNNs	GNNs outperform traditional methods on graph data	Theoretical and practical overview of GNNs	Scalability and dynamic graph challenges

3. Capsule Networks and DL Architectures for Cardiovascular Signal and Image Analysis

Haq et al. [36] conducted a thorough survey on CapsNets, their architectural evolutions, changes and constraints, and applications. The performance of different variations of CapsNet in pattern recognition, image classification and other related applications in health have been analyzed. The results showed the CapsNets have potential to overcome the shortcomings of the conventional CNN in terms of preserving the spatial structure and hierarchical representations and learning the complex representations with less number of samples. However, some problems in real-world application are high computational costs, routing inefficiencies, scalability issue and long training time.

Khoulqi and El Ouazzani [37] discussed CapsNets and CNN for medical image analysis and Decision Support System. Research conducted from 2018 to 2025 was analyzed and assessed for their performance, interpretability, and robustness in healthcare applications. The results showed that CapsNets solved the problems of CNN by maintaining spatial relations and generalizing the anatomical variation among the patients, which facilitated the reliability of diagnosis and clinical decision-making process. Routings, however, are complicated and require high computation needs, and there is a lack of large-scale validation and integration issues.

Ribeiro et al. [38] delivered an in-depth overview of the research on CapsNets, including foundations, routing and architectural variations, and applications. The study surveys the progress in capsule learning and investigates the connection between the capsule and the attention mechanism in a transformer model. The applications were considered from computer vision, graph learning, natural language processing, and medical imaging. The CapsNets are good at capturing part-whole hierarchical relationships and effectively represent learning beyond CNN, the review pointed out. Nevertheless, challenges include the computational cost, routing instability, scalability, and lack of a standardized evaluation framework.

Akinyelu et al. [39] surveyed ML, convolutional neural networks, capsule neural networks, and vision transformers to identify ML solutions for brain tumor diagnosis with magnetic resonance imaging (MRI). This study summarized the recent advances of CNN, ML, ViT and CapsNet based approaches and compared the performance of them on the diagnostic tasks. The results showed that CapsNets could solve the CNN's problem of rotation and spatial transformation, and maintain the hierarchical feature relationship. Despite this, computational complexity, small-scale validation and scalability to various medical imaging applications are still major challenges.

Bulbul et al. [40] id a systematic review of DL models for cardiac monitoring diagnosis of CVD. Over 80 publications that deal with different architectures for the detection of arrhythmia and myocardial infarction (MI) were studied. The sensitivity and specificity of DL models in ECG classification tasks were found to be high from the results of the meta-analysis. The effectiveness of the models in improving diagnostic accuracy and early diagnosis of CVDs in remote healthcare settings has also been mentioned. Standardized evaluation protocols, explainability, uncertainty modeling and external validation, however, are important problems that remain to be addressed for clinical adoption.

Moreno-Sánchez et al. [41] did a systematic review of ECG-based data driven approaches to CVD diagnosis and prognosis. The study reviewed the ML and DL models used for ECG signals, including datasets, modalities, disease types, and algorithmic approaches. The review demonstrated that AI ECG interpretation has been found to be beneficial for diagnostic efficiency, clinical decision making and early detection of disease. It also covered topics such as Explainability, Bias and Ethics under the umbrella term of Trustworthy AI. Nonetheless, standardization of datasets, external validation, interpretability, and generalization remain challenging tasks to accomplish.

Petmezas et al. [42] did a systematic review of DL methods used on the electrocardiogram (ECG) for various clinical applications. Research articles published from 2020 to 2021 were studied and categorized according to the application area such as CVD diagnosis, blood pressure estimation, sleep analysis, and biometric recognition. One of the key points the review mentioned was that the most prevalent methods are convolutional neural networks and hybrid DL architectures, which enhance feature extraction and minimize the need for manual signal processing. But there are limited possibilities of dataset standardization, population generalization, physiological variability assessment and clinical validation.

Al Hinai et al. [43] performed a systematic review of DL applications in resting electrocardiograms for diagnosis of structural cardiac diseases. This study tested end-to-end DL models, including convolutional neural networks, to detect various diseases, including myocardial dysfunction, hypertrophy, and ischemic heart disease. DL methods showed high diagnostic performance and, in many cases, better than traditional ML methods and rule-based techniques, helping to facilitate early detection and clinical screening. Yet there are many limitations, such as lack of external validation , small sample sizes, the imbalance of the data sets, and limited interpretability.

Table 3. CapsNets and DL Architectures for Cardiovascular Signal and Image Analysis

Author	**Sector**	**Methods**	**Key Findings**	**Contribution**	**Limitations**
Haq et al. [36]	Capsule Network architectures	Comprehensive CapsNet survey	Preserves spatial and hierarchical features	Overview of CapsNet variants and applications	High complexity, routing inefficiency
Khoulqi & El Ouazzani [37]	Medical image analysis	Review of CNNs vs CapsNets	CapsNets improve robustness and generalization	Comparative evaluation of CNN and CapsNet models	Computational cost, limited clinical validation
Ribeiro et al. [38]	Capsule learning and representation learning	Comprehensive CapsNet survey	Better part-whole relationship modeling	Analysis of routing mechanisms and architectures	Scalability and evaluation challenges
Akinyelu et al. [39]	Brain tumor diagnosis	Survey of ML, CNN, CapsNet, and ViT methods	CapsNets handle rotations and transformations effectively	Comparative assessment of advanced DL models	High complexity and limited scalability
Bulbul et al. [40]	ECG-based CVD diagnosis	Systematic review and meta-analysis of DL models	High sensitivity and specificity in ECG diagnosis	Quantitative evidence of DL effectiveness	Limited explainability and external validation
Moreno-Sánchez et al. [41]	ECG-based CVD diagnosis and prognosis	Systematic review of ML and DL ECG approaches	AI improves diagnosis and risk prediction	Focus on trustworthy AI and ECG analytics	Poor standardization and

					interpretability
Petmezas et al. [42]	ECG signal analysis	Systematic review of DL-based ECG applications	CNNs dominate ECG interpretation tasks	Comprehensive overview of ECG DL applications	Generalization and validation issues
Al Hinai et al. [43]	Structural cardiac disease detection	Systematic review of DL on resting ECGs	High diagnostic accuracy for cardiac abnormalities	Demonstrated screening potential of DL-based ECGs	Small datasets and limited interpretability

4. Multimodal Data Integration and AI-Based Cardiovascular Risk Assessment

Liu et al. [44] performed a systematic review of the ML-based CVD risk prediction for primary prevention. The study was conducted after the screening of 1757 records according to PRISMA and SANRA guidelines, 22 eligible studies were retrieved. The results showed that complex interactions among clinical variables could be well captured by ML techniques and that they are better suited to achieving a more precise personalized risk stratification than traditional statistical methods. These methods attempt to overcome limitations of traditional risk scoring systems using longitudinal patient information. But there are still challenges in terms of external validation, interpretability, outcome heterogeneity, data quality, and regulatory issues.

Zhou and Wang [45] reviewed multimodal data fusion strategies for accurate coronary artery disease risk prediction. The study consisted of a PRISMA-based evidence synthesis approach of imaging, genomic, wearable and Electronic Health Record data, an analysis of 39 studies. The review showed that multimodal integration provides a notable boost to cardiovascular risk prediction over traditional clinical risk scores. Advanced ML methods, especially DL and Graph Neural Networks, are effectively exploited to model cross-modal interactions and patient risk trajectories. But there are challenges with data heterogeneity, algorithmic bias, validation, and workflow integration.

Yang et al. [46] highlighted the recent advances of multimodal AI in CVD diagnosis, prediction, and management. It investigated the integration of electrocardiograms, medical imaging, Electronic Health Records, genomic information and wearable sensor data through advanced data fusion techniques. The review showed that multimodal AI frameworks provided a wide spectrum of data on patient health and improved disease prediction, clinical decision-making, treatment planning, and patient monitoring accuracy over single-modality approaches. Graph Neural Network models have many advantages, but they still face challenges such as interoperability, data standardization, interpretability, privacy issues and implementation.

Fortuni et al. [47] discussed the application of AI in various cardiovascular imaging modalities like echocardiography, cardiac CT, cardiac MRI, nuclear cardiology, and electrophysiology. In this review, emphasis was placed on ML and DL techniques to address image acquisition, segmentation, diagnosis, risk stratification, and multimodal integration. According to this review, AI could aid in optimizing workflow, reducing variations in diagnosis, and predicting CVDs using a variety of imaging and clinical data sources. However, issues of transparency, quality data, validation, regulation, and generalization remain significant.

Cai et al. [48] have undertaken a systematic review on AI models used in predicting CVD and suggested a new approach called the Independent Validation Score (IVS). In total, 79 studies with 486 prediction models were included in this analysis, and the quality of methods used was assessed with PROBAST. The results proved the potential of AI models in improving CVD risk evaluation by means of sophisticated learning algorithms and various clinical variables. The findings showed that there are definite benefits in applying AI in evaluating cardiovascular risk based on learning algorithms and clinical variables. However, some important limitations should be addressed including geographical limitations of datasets, lack of independent validation, and reporting biases.

Chowdhury et al. [49] reviewed the usage of ML and in the management and prediction of cardiovascular disorders. Some applications include cardiac image analysis, disease detection, outcome prediction, and optimization of clinical decision-making. The paper discussed the power of ML to analyze clinically relevant information without requiring manual labor. This contributes to better diagnostic procedures, optimal use of resources, and personalization of cardiovascular health management. However, certain issues still persist with regard to using AI in this field.

Boadla et al. [50] discussed the application of AI in diagnosing and predicting CVD from multiple cardiac images. In their work, they reviewed the development of AI in different cardiac image technologies such as x-ray imaging, CT, MRI, nuclear imaging, and wearable devices. The study pointed out that ML and DL models help diagnose coronary artery disease, detect arrhythmias, manage heart failure, and personalizing treatments among others. However, some challenges associated with implementation include lack of data standardization, validation, regulation, ethics, and interoperability among others.

Milosevic et al. [51] reviewed the use of AI in multimodal cardiovascular imaging through the integration of multimodal data from cardiac MRI, CT, echocardiography, chest X-ray and Electronic Health Records. The review concentrated on the use of multimodal learning in image registration, image segmentation, image fusion, image classification, and disease prediction. The results indicated that the multimodal techniques are more effective than the unimodal techniques in terms of the accuracy of diagnosis and disease prediction. But there are still challenges in multimodal imaging.

Amal et al. [52] conducted an analysis on how ML could be employed for data fusion involving multimodal healthcare data for better cardiological care. The research focused on exploring the process through which various types of data such as electronic medical records, radiology images, genomic data, and data from sensors in wearable technology can be fused together through ML and DL methods. The results showed that data fusion has the capability to yield complementary information about patients, thereby improving their diagnosis, prognosis, and treatment.

Li et al. [53] highlighted the use of AI and biomechanical models for predicting cardiovascular disorders. Methods for integrating clinical risk factors, medical imaging, and hemodynamic simulations using ML algorithms were explored to improve diagnosis and assessment of risks. The research observed that ML models could overcome the limitations of traditional methods by enabling rapid prediction, minimizing manual efforts, and facilitating surrogate modeling in computational fluid dynamics. Moreover, combining ML with biomechanics increases the precision of predictions and personalized modeling. Nevertheless, such models are complicated, posing several problems regarding verification and computation, along with the availability of data.

Table 4. Multimodal Data Integration and AI-Based Cardiovascular Risk Assessment

Author	Sector	Methods	Key Findings	Contribution	Limitations
Liu et al. [44]	EHR-based CVD risk prediction	Systematic review of ML models	Improved personalized risk stratification	Assessment of ML-based EHR prediction models	Poor interpretability, limited validation
Zhou & Wang [45]	Multimodal CAD risk prediction	Review of multimodal data fusion strategies	Multimodal data improves prediction accuracy	Framework for multimodal cardiovascular risk assessment	Data heterogeneity and workflow integration issues
Yang et al. [46]	Multimodal cardiovascular AI	Review of multimodal AI frameworks	Better diagnosis and risk prediction	Integration of ECG, imaging, EHR, genomics, wearables	Interoperability and privacy challenges
Fortuni et al. [47]	Cardiovascular imaging AI	Review of AI across imaging modalities	Enhanced diagnosis and risk stratification	Multimodal imaging-based cardiovascular assessment	Transparency and validation concerns
Cai et al. [48]	AI-based CVD prediction	Systematic review of 486 AI models	AI improves cardiovascular risk prediction	Proposed Independent Validation Score (IVS)	High bias and limited external validation
Chowdhury et al. [49]	AI in cardiovascular healthcare	Review of AI and ML applications	Improved diagnosis and personalized care	Comprehensive overview of cardiovascular AI applications	Interpretability and deployment challenges
Boadla et al. [50]	Multimodal cardiac imaging	Review of AI-driven imaging techniques	Improved disease detection and treatment planning	Analysis of multimodal cardiac imaging AI	Standardization and regulatory barriers
Milosevic et al. [51]	Multimodal cardiovascular imaging	Review of multimodal learning methods	Better diagnostic and predictive performance	Integration of imaging and EHR data	Limited datasets and real-world validation
Amal et al. [52]	Multimodal cardiovascular care	Review of data fusion and ML techniques	Enhanced diagnosis and personalized management	Framework for multimodal healthcare integration	Interoperability and scalability issues
Li et al. [53]	AI and cardiovascular biomechanics	Review of ML and biomechanical	Improved prediction and risk assessment	Integration of biomechanics with AI models	Model complexity and limited clinical validation

		modeling			

5. ML and AI Applications for Cardiovascular Disease Diagnosis and Monitoring

Gul et al. [54] conducted a systematic review on ML and ensemble learning approaches for CVD prediction. In particular, reviewed approaches involved decision tree classifiers, support vector machines, artificial neural network, random forest, and ensembles. Through the review, it was found that ensemble models can enhance the prediction accuracy, stability, and generalization by integrating several models and data fusion methods. These methods are effective in solving problems related to high-dimensional, imbalanced and noisy healthcare data. But there are a number of challenges to address to make it viable in practice, such as model interpretability, computational complexity, data quality, and clinical deployment.

Teshale et al. [55] performed a systematic review of AI models for CVD risk prediction with time-to-event outcomes. It examined 33 investigations that used ML and DL models in a survival framework, such as Random Survival Forest, Survival Gradient Boosting and DeepSurv. The review showed that the DL survival models could work well with the cardiac data with censored data, and could predict better than the traditional methods. It also pointed towards a growth in XAI methods. However, social determinants of health, gender-stratified analyses, interpretability and clinical generalizability are still limited.

Li et al. [56] performed a systematic scoping review of the DL models used for the prediction of cardiovascular risk markers and CVDs from retinal fundus images. 24 papers were studied which are mainly related to cardiovascular prediction using CNN. The results showed that DL models can successfully identify cardiovascular risk information from the retina images, and that they can achieve better performance in most of the cases compared to the traditional clinical risk scoring methods when used in conjunction with traditional cardiovascular risk factors. However, there are still challenges, including limited external validation, lack of prospective investigations, limited dataset diversity, and comparing with existing frameworks.

Moradi et al. [57] was a scoping review of artificial AI applications in cardiac imaging modalities such as echocardiography, computed tomography angiography (CTA), and cardiac magnetic resonance imaging (CMR). The review included the evaluation of AI approaches applied to image acquisition, image analysis, and cardiovascular events prediction. It was revealed that AI improves image quality, reduces diagnostic errors, accelerates the process, and performs equally well as an experienced physician. Such methods are applied to enhance cardiovascular diagnosis and risk evaluation. But there are issues of generalizability, validation in differences in healthcare environments, and assessment in resource-limited settings.

Zhou et al. [58] did a study on DL methods for heart disease prediction under the scope of 64 articles that appeared from 2018 to 2023. The authors classified the methods into conventional DL, extended DL and integrated DL (IDL). The review pointed out that DL models are able to automatically learn complex features from clinical data and outperform traditional methods in predicting heart disease in real time. Integrated frameworks include additional improvements in feature representation and prediction accuracy. But, the lack of a large public dataset, data imbalance and generalization and robustness issues persist.

Cuevas-Chávez et al [59] performed a systematic review on the use of ML, Internet of Things and Internet of Medical Things technologies in the prediction and monitoring of cardiovascular diseases. A study reviewed 164 journal articles on wearable devices, sensing technologies, ML algorithms, datasets and cardiovascular applications. Neural network, ensemble methods, random forest and XGBoost were found to provide significant improvement in the prediction performance and enable prediction of a patient’s status through an IoT based health care system. However, some of the challenges are limited availability of publicly available data, privacy issues, heterogeneity of devices and large scale deployment issues.

Manetas-Stavrakakis et al. [60] have carried out a systematic review and meta-analysis of AI technologies for atrial fibrillation detection. The study reviewed 14,770 records and 31 diagnostic accuracy studies were included that tested AI-enabled PPG and single-lead ECG systems. The results showed that AI had high pooled sensitivity and specificity, surpassing the performance of traditional screening methods, and allowed for an automated diagnosis in a short time. These techniques help detect and monitor CVD at an early stage. Variability in unclassified recordings, heterogeneity between AI, and limited evidence for long-term outcomes, however, remain issues.

Denysyuk et al. [61] carried out a systematic review of automated CVD diagnosis with ECG data. A total of 103 publications were analyzed in this study during the years 2017–2022, and the ML and DL techniques used for the identification, classification and recognition of disease from ECG were evaluated. In particular, Convolutional Neural Network (CNN) and Support Vector Machine (SVM) AI approaches have been proven to contribute to automated cardiovascular diagnostics, according to the review. It also explored uses of publicly available datasets in the development of models. But there are some drawbacks such as dataset heterogeneity, absence of standard assessment procedure, and generalization issues.

Błaziak et al. [62] performed a systematic review of predictive models using AI in heart failure management. The study investigated ML models that are trained on data from external sources for four use cases: mortality prediction, risk assessment for rehospitalization, evaluation of treatment response and monitoring medication adherence. The results have shown that ML approaches are generally better than traditional statistical risk scores, thus improving clinical decision-making and facilitating the implementation of personalized healthcare strategies. These models also aid in improving the patient outcomes. However, few of the studies have been externally validated, limiting their reliability and broad clinical use.

Alskaf et al. [63] performed a review and meta-analysis of DL usage in the diagnosis and prognosis of myocardial perfusion imaging for CAD. Forty-six clinical studies were included in the review that compares myocardial perfusion scintigraphy with stress CMR. The results showed that DL techniques, especially convolutional neural networks, can be used to achieve better diagnostic accuracy, to automate image interpretation, to improve patient risk stratification and to assist in predicting clinical outcome. Lack of real-world validation, however, and small implementation studies are important limitations, as is publication bias.

Moshawrab et al. [64] conducted a methodical literature review of the smart wearable technology for CVD detection and prediction. In accordance with the PRISMA methodology, 87 publications published between 2010 and 2022 were analysed and assessed with respect to wearable devices, sensing technologies, ML models, datasets and performance metrics. The review showed that smart wearables have proven to be effective in supporting continuous monitoring of the human body and accurate prediction and diagnosis of CVDs. It also pointed to a rise in wearable health care systems that are increasingly integrated with AI. But issues of device reliability, data consistency, sensor precision, and deployment issues remain.

Table 5: ML and AI Applications for CVD Diagnosis and Monitoring

Author	Sector	Methods	Key Findings	Contribution	Limitations
Gul et al. [54]	CVD Prediction	ML, Ensemble Learning	Ensemble models improved accuracy and robustness.	Compared ML and ensemble approaches for CVD prediction.	Interpretability, computational cost, data quality issues.
Teshale et al. [55]	CVD Risk Prediction	AI Survival Models (DeepSurv, RSF, SGB)	DL survival models outperformed conventional methods.	Reviewed AI for time-to-event cardiovascular prediction.	Limited SDOH analysis, interpretability, generalizability.
Li et al. [56]	Retinal Imaging-Based CVD Prediction	DL, CNNs	Retinal images can predict cardiovascular risk effectively.	Demonstrated non-invasive AI-based risk assessment.	Limited external validation and dataset diversity.
Moradi et al. [57]	Cardiac Imaging	AI, ML, DL	Improved image quality and diagnostic performance.	Summarized AI applications across cardiac imaging modalities.	Generalizability and validation challenges.
Zhou et al. [58]	Heart Disease Prediction	Conventional, Extended and Integrated DL Models	DL enhanced prediction accuracy and feature extraction.	Categorized and compared DL-based prediction frameworks.	Data imbalance and lack of large public datasets.
Cuevas-Chávez et al. [59]	IoT/IoMT-Based Cardiovascular Monitoring	ML, Neural Networks, RF, XGBoost	Enabled accurate prediction and real-time monitoring.	Integrated AI with IoT healthcare systems.	Privacy concerns and dataset limitations.
Manetas-Stavrakakis et al. [60]	Atrial Fibrillation Detection	AI-based PPG and Single-Lead ECG Systems	Achieved high sensitivity and specificity.	Validated AI technologies for AF screening.	System heterogeneity and outcome evaluation gaps.
Denysyuk et al. [61]	ECG-Based Automated	ML, DL, CNN, SVM	AI improved automated	Comprehensive review of ECG-	Dataset heterogeneity and

	Diagnosis		cardiovascular diagnosis.	based diagnostic methods.	lack of standardization.
Błaziak et al. [62]	Heart Failure Management	ML Prediction Models	ML outperformed traditional risk scores.	Reviewed AI models for heart failure prognosis.	Limited external validation.
Alskaf et al. [63]	Coronary Artery Disease Imaging	DL, CNNs	Improved diagnosis, risk stratification, and prognosis.	Evaluated DL in myocardial perfusion imaging.	Publication bias and limited clinical deployment.
Moshawrab et al. [64]	Wearable-Based Cardiovascular Monitoring	Wearable Sensors, ML Models	Supported continuous monitoring and disease prediction.	Reviewed AI-enabled wearable technologies.	Reliability, sensor precision, and scalability issues.

6. XAI and Interpretability Methods for Clinical Cardiovascular Applications

Ferreira Santos and Dores [65] conducted a narrative review focused on applying large language models in CVD prevention. This literature review compiled literature from 2015 to 2025 and organized applications by the patient, clinician, or healthcare system level. The review found that LLM's improve patient education, clinical documentation, decision support, automated phenotyping and multimodal cardiovascular risk prediction. It also set forth the C.A.R.D.I.O. governance model for responsible AI use. However, certain limitations, such as hallucination, automation bias, temporal knowledge obsolescence, privacy concerns, and lack of clinical validation will hinder wider implementation.

Haupt et al. [66] carried out a systematic review of the XAI techniques in cardiovascular radiological imaging. The authors reviewed 28 articles from 2015 to 2025 that featured cardiac CT, MRI, echo and chest X-rays. The study assessed the performance of four explainability techniques (Grad-CAM, SHAP, LIME, and saliency maps) for making DL systems for cardiovascular diagnostics more transparent. The review showed that XAI techniques can improve the interpretability of models and foster clinical trust and acceptance. But standardized evaluation structures, quantitative assessment techniques and prospective clinical validation are still inadequate.

Ferreira Santos et al. [67] conducted a systematic review of Large Language Models in CVD prevention, diagnosis and treatment. The review of 35 observational investigations was carried out according to the PRISMA guidelines, especially focusing on the use of ChatGPT in patient education, clinical decision support, and cardiovascular risk management. The results showed that LLM models typically give correct and comprehensive answers to cardiovascular related questions and can aid patients and clinicians. But there is some misinformation, hallucinated references, some lack of personalization and some lack of clinical validation that is problematic for some time before it is widely adopted.

Quer and Topol [68] summarized the promise of large language models, multimodal AI, and foundation models for cardiovascular medicine. It is claimed that the use of transformer models based on EHRs, medical imaging, genomics, and biosensors deliver superior performance in disease diagnosis and risk prediction than the current approaches to cardiovascular analytics. They emphasized support for clinician decision-making and automatic patient guidance. But there are serious concerns around privacy, diagnosis inaccuracies, regulation concerns and limited real-world validation.

Hosseini et al. [69] have systematically reviewed the use of AI techniques to enhance the polygenic risk score (PRS) in CVD prediction. A study of 13 research articles used ML methods to process high dimensional genetic data, integrate multimodal information, and select advanced features. The results showed that the use of AI-powered polygenic risk score models could yield better predictive accuracy and aid in personalized prevention strategies, benefiting beyond traditional methods. However, issues of diversity of populations, sex-specific analysis, integration of workflows, and long-term cost-effectiveness evaluation remain unaddressed.

Hoghooghi Esfahani et al. [70] performed a systematic review of the XAI techniques used for the prediction, diagnosis, treatment, and management of chronic diseases. The researchers found that among the explainability methods used in healthcare applications, SHAP, LIME and Grad-CAM were the most common. The review showed that XAI techniques led to better understanding of the models' predictions and boosted trust in AI-based decision-making. These techniques address the need of transparent healthcare systems, while being interpretable. But multimodal handling of data, clinical validation, treatment-oriented applications and regulatory standardization are still in their infancy.

Salih et al. [71] reviewed methods for evaluation of XAI in cardiology. The study will comprise a comparison between cardiac AI applications and XAI techniques and a research into the quality assessment of the explanation. The review said the XAI methods can help improve the transparency, trustworthiness and interpretability of models by explaining their decision-making process. It also noted the lack of standard practices for explainability assessment, and that the

assessment should be clinician-centric. However, most studies poorly or not at all measured the quality of explanation, and it was difficult to be confident in the clinical deployment of these studies.
Manimaran et al. [72] performed a systematic review of the use of XAI models combining with DL for heart disease classification from ECG data. It reviewed research articles from 2018 to 2024, including datasets, preprocessing techniques, DL architectures, and explainability approaches. However, the review pointed out that explainable DL would help improve the transparency and trustworthiness of automatic ECG analysis through its interpretability which was achieved by using methods such as LIME, Grad-CAM, SHAP and saliency maps. However, there is still a need for improvement in regards to standardization and benchmarking in explainability evaluation.
Band et al. [73] presented their findings from a systematic review on XAI approaches in health care. They compared several techniques including SHAP, LIME, Grad-CAM, Layer-Wise Relevance Propagation, ANCHOR, Contextual Importance and Utility, TraCE and NeuroXAI that were used in different medical fields. The review indicated that the application of XAI methods could help imrove transparency of ML and AI models as the interpretable answers provide greater trustworthiness in predicting future conditions in a patient's healthcare. Nevertheless, there are some challenges concerning consistency in explanation, scalability, standardization, and balance between interpretability and accuracy.
Purwono et al. [74] outlined the multiple techniques of AI in medical imaging. Various methods discussed include Grad-CAM, Integrated Gradients, attention-based models, symbolic inference techniques, and explanation by example in cardiology image analysis, cancer diagnostics, and brain lesion segmentation. It was revealed that XAI increases interpretability, transparency, and trust in AI by doctors in diagnostic imaging. Limitations in terms of the accuracy-interpretability trade-off, ethical concerns, difficulties in integrating XAI into workflows, and challenges associated with complex biomedical data stand in the way.
Hulsen [75] provided his narrative review on the XAI in healthcare that included several concepts, techniques, challenges, and future directions regarding the field. It concentrated on the most important approaches of XAI that aim to overcome black-box ML and DL models in healthcare. The review revealed that XAI techniques have the potential to make AI-based predictions more transparent, reliable, and comprehensible to humans, which could foster greater trust in AI by clinicians and assist in decision support systems. But beside these, there are other issues that are very important, such as the quality of explanations, standardization, regulation, and interpretability and predictability.
Table 6: XAI and Interpretability Methods for Clinical Cardiovascular Applications

Author	Sector	Methods	Key Findings	Contribution	Limitations
Ferreira Santos and Dores [65]	Cardiovascular Prevention	LLMs, Multimodal AI	LLMs improved education, decision support, and risk prediction.	Proposed the C.A.R.D.I.O. governance framework.	Hallucinations, privacy risks, limited validation.
Haupt et al. [66]	Cardiovascular Imaging	XAI (Grad-CAM, SHAP, LIME, Saliency Maps)	XAI increased transparency and clinical trust.	Reviewed explainability methods in cardiovascular imaging.	Lack of standardized evaluation and validation.
Ferreira Santos et al. [67]	Cardiovascular Prevention & Care	LLMs (ChatGPT)	LLMs provided accurate cardiovascular information and support.	Evaluated LLM applications in prevention, diagnosis, and treatment.	Misinformation, hallucinations, limited personalization.
Quer and Topol [68]	Cardiovascular Medicine	Foundation Models, Multimodal AI, LLMs	Multimodal AI improved diagnosis and risk prediction.	Highlighted the potential of foundation models in cardiology.	Privacy, regulatory, and validation concerns.
Hosseini et al. [69]	Genetic Risk Prediction	AI-Optimized Polygenic Risk Scores	AI enhanced genetic risk stratification accuracy.	Improved traditional PRS models using AI techniques.	Population diversity and workflow integration issues.
Hoghooghi Esfahani et al. [70]	Chronic Disease Prediction	SHAP, LIME, Grad-CAM	XAI improved understanding of AI predictions.	Comprehensive review of XAI in healthcare applications.	Limited multimodal support and clinical validation.

Salih et al. [71]	Cardiology AI Evaluation	XAI Evaluation Frameworks	XAI improved trustworthiness and interpretability.	Examined assessment methods for explanation quality.	Lack of standardized evaluation practices.
Manimaran et al. [72]	ECG-Based Heart Disease Classification	DL + SHAP, LIME, Grad-CAM	Explainable DL improved transparency in ECG diagnosis.	Reviewed XAI-integrated ECG classification systems.	Benchmarking and explainability evaluation gaps.
Band et al. [73]	Healthcare AI	SHAP, LIME, Grad-CAM, LRP, ANCHOR, CIU, NeuroXAI	XAI enhanced interpretability and clinical trust.	Comprehensive analysis of healthcare XAI methods.	Consistency, scalability, and standardization issues.
Purwono et al. [74]	Medical Imaging	Grad-CAM, Integrated Gradients, Attention Mechanisms	XAI improved clinician confidence and transparency.	Reviewed XAI techniques in medical imaging.	Accuracy–interpretability trade-off and workflow integration challenges.
Hulsen [75]	Healthcare AI	Explainable AI Techniques	XAI strengthened trust and decision support systems.	Provided conceptual overview of XAI in healthcare.	Regulatory, standardization, and explanation-quality concerns.

5. Research Gaps

1. Lack of robust and efficient transformer models for clinical deployment.

While the transformer model is efficient in capturing long-range temporal dependencies in ECG signals and EHRs, its excessive computational cost, uncertainty management, constraints on positional encodings, and hallucination problems limit its clinical application in cardiac care. In future studies, emphasis should be placed on creating lightweight and robust transformer models for clinical settings [15].

2. Limited cardiovascular-specific GAT research and benchmarking.

However, there have been few research works on applications of GNNs and GATs to the modeling of patient disease relationships within cardiovascular diseases. Additionally, benchmarking frameworks as well as clinically validated datasets for the evaluation of graph neural networks have yet to be established [31].

3. Limited large-scale validation of Capsule Networks in cardiovascular applications.

Capsule Networks provide an edge in terms of superior preservation of spatial and hierarchical information than traditional CNNs; nevertheless, their use in predicting heart diseases is largely understudied. Computational inefficiency and poor routing remain some of the drawbacks hindering their wider applicability [37].

4. Lack of standardized multimodal cardiovascular datasets.

While there have been advances in using multimodal AI models that combine data from ECG, EHRs, medical images, genomic data, and data collected via wearable sensors, the lack of availability of multimodal cardiovascular datasets continues to be a significant hurdle [45].

5. Limited real-world deployment and prospective validation.

Most of the cardiovascular prediction models utilizing artificial intelligence technology show impressive results when assessed using retrospective analysis. Nevertheless, prospective clinical trials and implementations, along with multivariate validations, are still rare in the field [57].

6. Absence of standardized explainability evaluation frameworks.

In spite of the increasing application of methods like SHAP, LIME, and Grad-CAM for making AI more explainable for cardiovascular disease, there is still no standard method for evaluating the quality of the explanations provided. Clinician-oriented assessment criteria need to be defined in future research [71].

6. Research Trends and Key Findings

Recent research has shown a growing interest in the use of AI and DL for predicting, diagnosing, and aiding clinical decisions in CVDs. The scope of research has broadened to include detection of arrhythmia, prediction of heart failure, diagnosis of myocardial infarction, cardiovascular imaging analysis and personalized treatment planning. AI systems can automatically identify clinically relevant data from complex healthcare data, enhancing diagnostic accuracy and aiding in the early detection of disease [22], [47]

One of the largest trends is the generation of multi-modal health care data, such as ECGs, EHRs, cardiac imaging data, genetic data, and data from wearable sensors. By incorporating various data sources, prediction performance can be enhanced, and a more holistic approach to patient assessment can be achieved [9], [45]. Nonetheless, some problems may be found such as data heterogeneity, class imbalance, limited external validation, and poor interpretability. In this regard, the XAI techniques have become important to increase the transparency of AI systems, their reliability, and their clinical use [48], [71].

7. Comparative Analysis

7.1 Transformer-Based Models

In the field of CVD prediction, transformer architectures are particularly popular due to their ability to leverage long-range temporal relationships and context in sequential healthcare data. The self-attention mechanisms enable the analysis of multi-modal information, such as electronic health records, ECG signals and multimodal datasets, which can help to study disease progression, predict disease risks and provide clinical decision making support [15], [18].

7.2 Graph Neural Networks and Graph Attention Networks

Graph-based learning models represent complex relationships between patients, diseases, medications, and clinical events using graphs. Another improvement is the GATs in which the neighborhood nodes are given importance weights to enhance the representation learning. These features are essential for the similarity analysis of patients, disease association modeling, and cardiovascular risk prediction in interconnected healthcare environments [26], [27].

7.3 Capsule Networks

CapsNets are able to maintain the relationship of the features in spatial and hierarchical to each other, which is not possible in the traditional Convolutional neural networks. They are represented by complex characteristics using a dynamic approach to routing mechanisms to increase the level of subtleties learned. They have been proven to be effective in various applications such as ECG interpretation, heart sound classification, and cardiovascular signal analysis with the need for preserving features [6].

7.4 Comparative Discussion

The analysed architectures have complementary merits in the context of CVD prediction. Transformer models are a powerful tool for analyzing sequential and multimodal data, graph-based approaches are well-suited for modelling relational healthcare information, and CapsNets are well suited to preserve hierarchical signal features. All of these approaches can be used to solve the various prediction challenges and offer possibilities for clinical decision-support systems.

Table 7: Comparative Analysis of AI Architectures for Cardiovascular Disease Prediction

Feature	Transformers	GNNs	GATs	Capsule Networks
Primary Data Type	Sequential data (ECG, EHRs, time-series)	Graph-structured healthcare data	Graph-structured healthcare data with attention	ECG signals, heart sounds, medical images
Core Mechanism	Self-attention	Message passing and graph aggregation	Graph attention mechanism	Dynamic routing between capsules
Captures Temporal Dependencies	Excellent	Limited	Limited	Moderate
Captures Relational Dependencies	Moderate	High	Very High	Low
Preserves Spatial Hierarchies	Moderate	Moderate	Moderate	Excellent
Multimodal Data Integration	Excellent	Good	Excellent	Moderate
Interpretability	Moderate	Moderate	High	Moderate
Computational Complexity	High	Moderate	High	Very High
Scalability	Good	Moderate	Moderate	Limited
Major Strength	Long-range	Relationship	Adaptive relationship	Hierarchical feature

	dependency modeling	learning	learning	preservation
Major Limitation	High computational cost	Graph construction complexity	Scalability and benchmarking issues	Routing complexity and long training time
Cardiovascular Applications	Risk prediction, ECG analysis, EHR prediction	Patient similarity analysis, disease networks	Cardiovascular risk assessment, multimodal healthcare graphs	ECG classification, cardiovascular signal analysis

Table 7 gives a comparative study between Transformers, Graph Neural Networks (GNNs), Graph Attention Networks (GATs), and Capsule Networks (CapsNets). These comparisons involve their underlying methodologies, abilities to handle datasets, pros and cons, interpretable features, scalability, and computational demands. The Transformer model is known for its superiority in analyzing time series data. GNNs and GATs prove effective in analyzing dependencies between data, whereas CapsNets are efficient in retaining the hierarchical relationship of features.

8. Emerging Trends and Innovations

The latest developments in AI can revolutionize the prediction and management of CVD. Many recent architectures for sequential healthcare data analysis rely on transformer-based models, such as for the analysis of electrocardiograms, longitudinal patient histories and electronic health records. Transformers can capture long-range temporal relationships and context, enhancing risk forecasting and disease surveillance. Furthermore, the use of large language models and foundation models will open the door to more automated decision support, patient education, and multimodal cardiovascular analysis. A current development is the use of multimodal AI frameworks that combine medical imaging, ECG signals, EHRs, genomic information, and lab measurements with wearable devices to provide comprehensive patient evaluation and personalized risk prediction.

Explainability, trustworthiness and real-time healthcare applications also come into focus in the field. To enhance the transparency of and confidence in automated predictions, ExAP techniques are increasingly being introduced into DL systems. In the interim, technologies such as wearable devices, the Internet of Medical Things, and remote monitoring systems allow for ongoing cardiovascular monitoring outside of the clinic. Complex relationships between patients, diseases, and clinical variables are modeled to further improve prediction using GNNs and Graph Attention Networks. Such advancements have resulted in the emergence of smart, patient-centered approaches to cardiovascular healthcare, based on predictive analytics, personalized medicine, and explainable decision support.

9. Key Challenges and Barriers

While advances in AI and DL in predicting CVDs have been made, several limitations continue to prevent their clinical application. The first problem is associated with data-related problems. Heterogeneity, class imbalance, insufficient representation of various groups, missing values, and data acquisition inconsistency reduce the accuracy of predictions [16]. Moreover, models are usually created based on single-center or carefully selected data, which reduces their external validity [48].

Another important limitation is the lack of explainability of models and difficulties associated with applying them in practice. Complex models such as transformers, GNNs, CapsNets, and multimodal models operate as black boxes and pose several challenges [66]. In response to this problem, researchers propose using XAI techniques like SHapley Additive exPlanations, **L**ocal **I**nterpretable **M**odel-Agnostic **E**xplanations, and Grad-CAM [71]. Additionally, AI-driven algorithms require a high capacity regarding computing power, data volume, and complexity of system integration [46]. Moreover, new technologies like Large Language Models come with new risks related to hallucinations, automation bias, and reliability issues [65].

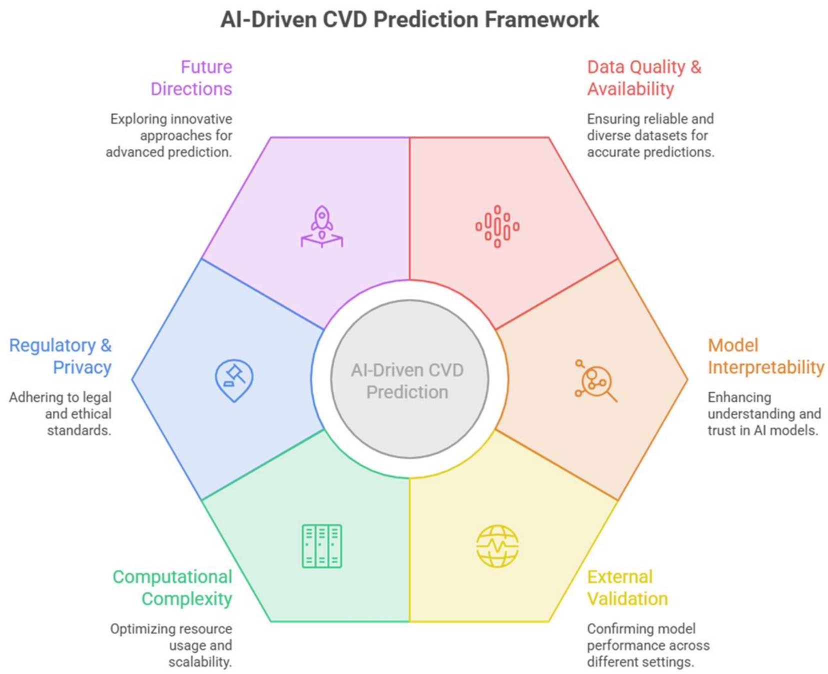

Figure 2. Key challenges and future directions in AI-driven CVD prediction.

Figure 3 depicts Some of the major problems faced by AI models for predicting cardiovascular disorders include data quality, interpretability of the model, validation of the model beyond the environment where it was created, computational difficulty, and possibilities for future research.

10. Conclusion and Future Perspectives

Given the high incidence of CVD, accurate and timely prediction of the condition becomes vital for its diagnosis and prevention. Thus, there is a need to construct highly efficient prediction models utilizing the latest advancements in the field of artificial intelligence, ML, DL, Transformer networks, Graph Neural Networks, CapsNets, multimodal learning, and XAI for predicting CVDs. According to the reviewed articles, using AI allows enhancing the predictive power of models due to automatic pattern recognition in health care-related datasets. Comparison demonstrates the following strengths of Transformer networks – modeling temporal dependency, GNNs – modeling relationships in healthcare-related data, and CapsNets – maintaining the hierarchy of information in a dataset. Additionally, multimodal learning enables more precise prediction of CVDs through multimodal data integration. On the other hand, XAI systems allow improving the transparency and explainability of models. Nevertheless, there are several unaddressed issues related to using AI-based prediction models, namely concerns regarding external validity, fairness, interpretability, and deployment. In the future, researchers should pay attention to constructing standardized methods, multicenter databases, and validated prediction models for different populations. In addition, future improvements are expected in multimodal learning, foundation models, XAI, and wearable technologies for healthcare.

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