

REVIEW

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Deep learning and electrocardiography: systematic review of current techniques in cardiovascular disease diagnosis and management

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Abstract

This paper reviews the recent advancements in the application of deep learning combined with electrocardiography (ECG) within the domain of cardiovascular diseases, systematically examining 198 high-quality publications. Through meticulous categorization and hierarchical segmentation, it provides an exhaustive depiction of the current landscape across various cardiovascular ailments. Our study aspires to furnish interested readers with a comprehensive guide, thereby igniting enthusiasm for further, in-depth exploration and research in this realm.

Introduction

Electrocardiogram (ECG) have been widely employed across various clinical disciplines. ECG represents one of the earliest non-invasive diagnostic methods in medicine, exerting profound influence on the field of cardiology [1]. However, accurate ECG interpretation typically necessitates substantial physician expertise, thereby fostering the gradual emergence of automated diagnostic technologies. In the 1970s, machine learning (ML) was introduced for automated ECG analysis, employing algorithmic modeling, image learning, and feature extraction to facilitate automated diagnosis [2]. Nevertheless, this approach was constrained by predefined rules and reliance on human-defined patterns, resulting in inadequate differentiation of subtle ECG differences and a relatively high rate of misdiagnosis. Consequently, ECG automated diagnostic programs have attracted considerable attention.

Over the past several decades, the rapid advancement of computational technology has catalyzed substantial growth at the intersection of computer science and biomedical research, generating numerous novel opportunities in healthcare diagnostics, therapy, and prognosis. Artificial Intelligence (AI), epitomizing the "Fourth Industrial Revolution", emulates human cognitive processes to harness sensor data for automated



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diagnostic solutions, enabling the identification of diverse abnormal patterns for diagnosing various diseases [3, 4]. Deep Learning (DL), a branch of AI, utilizes data-driven modeling, autonomous data recognition and learning, to generate powerful models, particularly suitable for handling heterogeneous data and dynamically changing ECG diagnoses [5].

The purpose of this review is to systematically survey the existing DL methods in conjunction with ECG and cardiovascular diseases, establishing a clear understanding of research hotspots. This review aims to clarify the current state of research concerning DL, ECG, and cardiovascular diseases, elucidate the future trends of DL and ECG applications in clinical settings, facilitate the advancement of research on DL, ECG, and clinical diseases, and expedite their translation into clinical practice for patient benefit.

Deep learning and the convergence with ECG

In the field of DL, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have emerged as pivotal architectures. CNNs, initially conceptualized by LeCun et al. [6, 7] in 1989, excel in image feature extraction due to their local connectivity and weight sharing properties, making them ideal for ECG feature extraction [8, 9]. Their evolution has led to advanced models like AlexNet [10], ZFNet [11], VGGNet [12], GoogLeNet [13], and ResNet [14], enhancing DL performance. Conversely, RNNs, introduced by Rumelhart et al. [15] in 1986, are tailored for sequential data handling, with their ability to maintain context information via feedback loops. However, to tackle the vanishing gradient problem when dealing with long-term dependencies, LSTM [16] and GRU [17] were developed. The Convolutional Recurrent Neural Network (CRNN), a hybrid model born in 2015 [18], combines CNNs' spatial feature extraction prowess with RNNs' temporal dependency management, proving especially beneficial in ECG signal analysis. Meanwhile, Autoencoders (AEs) [19], another DL component, learn efficient data representations through compression and reconstruction, offering a powerful tool for dimensionality reduction and noise removal. Generative Adversarial Networks (GANs) [20], introduced by Goodfellow et al. in 2014, stand out for their capability to capture data distributions and generate new samples. They have been successfully applied to ECG data augmentation and denoising, overcoming the challenges posed by imbalanced or noisy data [21, 22]. This overview encapsulates the vibrant progression of DL, highlighting how researchers continuously innovate and refine these architectures to address limitations and broaden their applicability across various domains. This groundwork serves to offer readers a comprehensive insight into DL before delving into its specific applications in cardiovascular diseases.

The ECG data analyzed in our review were sourced from various channels, including: (1) exports from bedside ECG machines or cardiac monitors [23]; (2) data collected via ambulatory ECG devices [24]; (3) segments retrieved from public or specialized databases [25]; and (4) data derived from wearable devices [26]. These conventional ECG segments necessitate further processing before use. The data are stored in formats like SCP-ECG, DICOM, HL7 aECG, GDF, and more, which are designed to retain ECG waveforms, patient data, acquisition parameters, and diagnostic measurements. The ECG data processing workflow typically involves three stages: signal extraction and pre-processing, feature extraction, and classification. Given the low frequency and amplitude

of ECG signals, coupled with interference from electromyographic activity, power line frequency, and baseline wander, preprocessing is essential to ensure accurate feature extraction and optimal model classification performance. Preprocessing techniques encompass both traditional and modern approaches. Traditional techniques include the use of FIR and IIR digital filters, while modern methods involve wavelet transform and adaptive filtering. Fourier and wavelet transforms are prevalent preprocessing tools, with the wavelet transform often preferred for its variable window length, providing superior resolution in both time and frequency domains, and greater accuracy than the Fourier transform [25]. Deep learning's role in ECG preprocessing is twofold: enhancing the model's data extraction capabilities through efficient filtering, and improving noise robustness through data augmentation strategies, such as the introduction of noise. The selection of these techniques hinges on the specific application, model architecture, and dataset size. Feature extraction strategies are categorized into hand-crafted methods, such as wavelet transforms, SVMs, kernel independent component analysis, and principal component analysis, and feature learning-based deep learning methods. The latter have significantly improved ECG signal classification accuracy and efficiency through automatic feature extraction, end-to-end models, attention mechanisms, management of multi-label imbalances, and deep transfer learning. ECG signal classification algorithms are divided into morphological methods, which include template matching and structural description, and methods based on signal features that emphasize waveform differences. The former is prone to noise interference and has a high computational cost and low accuracy, while the latter offers higher accuracy but may suffer from overfitting due to a lack of detailed heartbeat annotations. Manual classification and feature extraction methods, while valuable, have limitations in terms of accuracy and computational complexity for classifying ECG abnormalities and are being supplanted by DNN-based feature learning methods. DNNs enhance classification accuracy through autonomous feature extraction and minimize human intervention. CNNs, with their strength in processing one-dimensional temporal data, often serve as the basis for ECG signal analysis algorithms, enabling the construction of deep algorithmic models that effectively classify abnormal ECG [27]. The advent of deep learning models has undoubtedly advanced the accuracy of ECG signal classification and reduced reliance on human intervention, thus facilitating the integration of ECG with computational technologies and promoting the development and clinical adoption of innovative technologies.

Materials and methods

A systematic review was conducted to identify and aggregate published original studies that reported on DLlearning analyses of ECGs for the assessment of cardiovascular disease. The manuscript was prepared in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines [28]. This study utilized the Web of Science (WoS) platform, a multifaceted citation index database consisting of SCI, SSCI, A&HCI, CCR, and IC. The search strategy employed the following keywords: ('Deep learning') AND ('Electrocardiography' or 'ECG' or 'EKG') AND ('cardiovascular disease' or 'heart disease') with a publication date range from January 1, 2017, to September 30, 2023. This search yielded 1123 articles, which were systematically screened to exclude meeting abstracts

($n = 221$), proceeding papers ($n = 134$), non-English papers ($n = 150$), irrelevant articles ($n = 180$), duplicate articles ($n = 33$), no open access ($n = 197$) and poor quality ($n = 10$) articles, resulting in the selection of 198 high-quality articles post-discussion and voting by the research team. The data extraction in this process was carried out independently by multiple reviewers, with the aim of minimizing bias and errors as much as possible. The screening process is illustrated in Fig. 1. In this study, to elucidate the evolving trends and directions of deep learning applications in electrocardiogram (ECG) research, we conducted a statistical analysis of the publication years of the included articles (Fig. 2), the number of diseases investigated (Fig. 3), and the databases utilized (Fig. 4). For the graphical representation of our findings, we employed GraphPad Prism version 10.1.2 software. For bibliometric analysis and visualization of the selected literature, VOSviewer version 1.6.19 was used to map co-occurrences among countries/regions (Fig. 5) and keywords (Fig. 6). In Fig. 5, each dot denotes a distinct country, with its size reflecting the number of publications from that country. The lines connecting the nodes represent collaborative relationships between countries, where the thickness of the lines indicates the intensity of cooperation—thicker lines signify stronger collaborative ties. Figure 6 follows the same convention. Additionally, we summarized and ranked the top ten countries and regions based on article count (AC), citation count (CC), average citations per article (ACP), and total link strength (TLS) for the included articles (Table 1). We also summarized and ranked the top ten countries and regions based on the occurrences

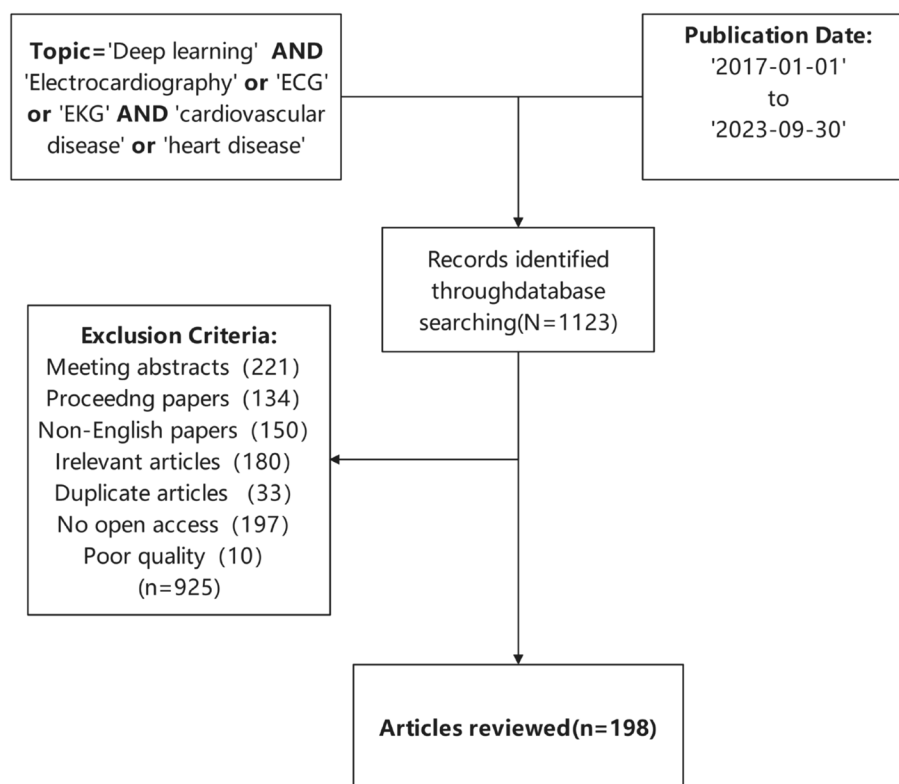


Fig. 1 Screening flowchart

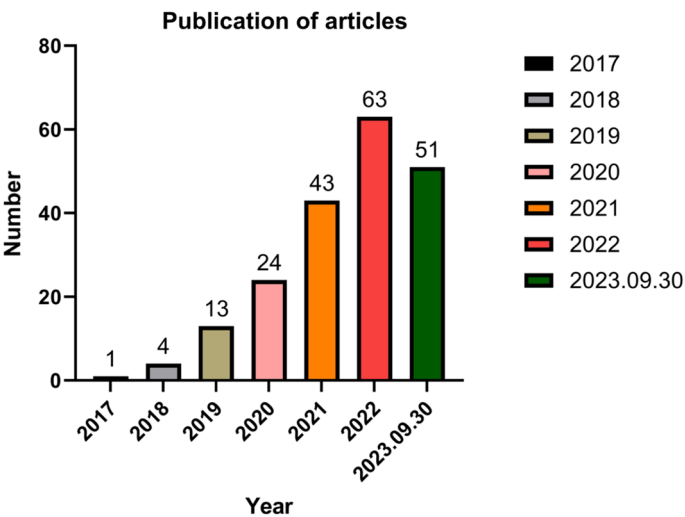


Fig. 2 Publication years of the included articles. The statistical data of the articles included in this study, analyzed across different years, demonstrate a consistent annual increase in trend

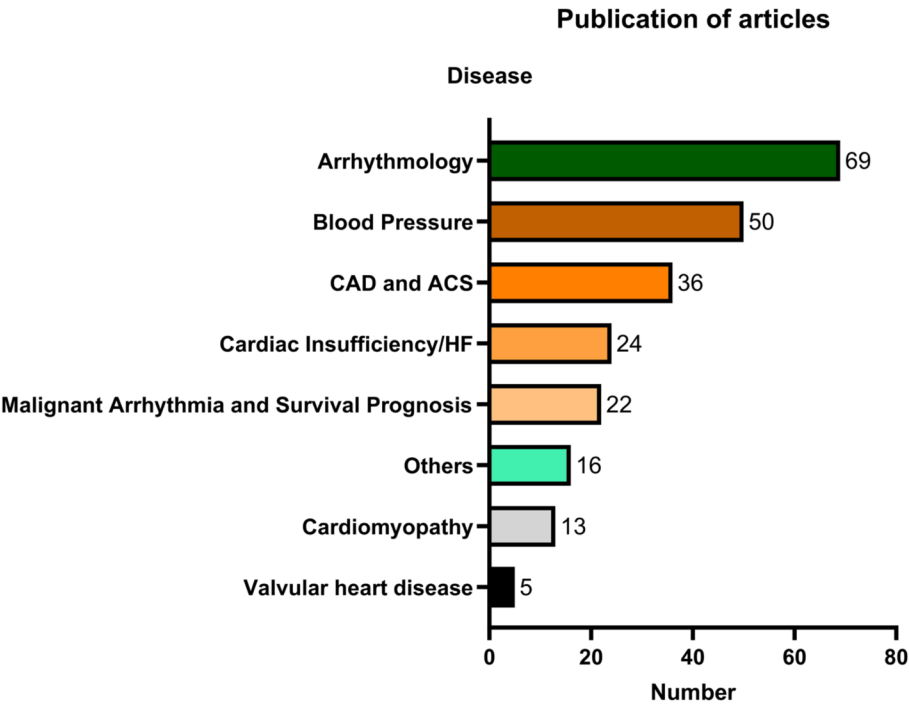


Fig. 3 Disease types in reviewed articles. The study’s statistical analysis by disease type revealed a predominance of arrhythmia research, with less focus on valvular and myocardial diseases

of keywords and their total link strength (TLS) (Table 2). To manage the wealth of information, the studies were classified according to disease types and key details were extracted, including article titles, publication years, source journals, datasets employed, sensors involved, and the specific deep learning application methods

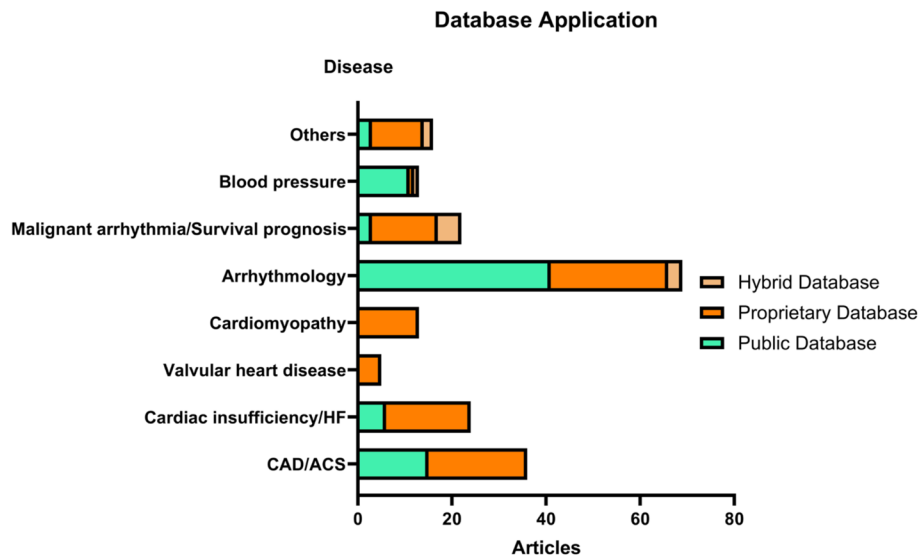


Fig. 4 Types of databases used in the study. Database types commonly used for different diseases: public databases prevalent in arrhythmia research, while CAD/ACS and cardiac insufficiency/HF utilize more proprietary databases

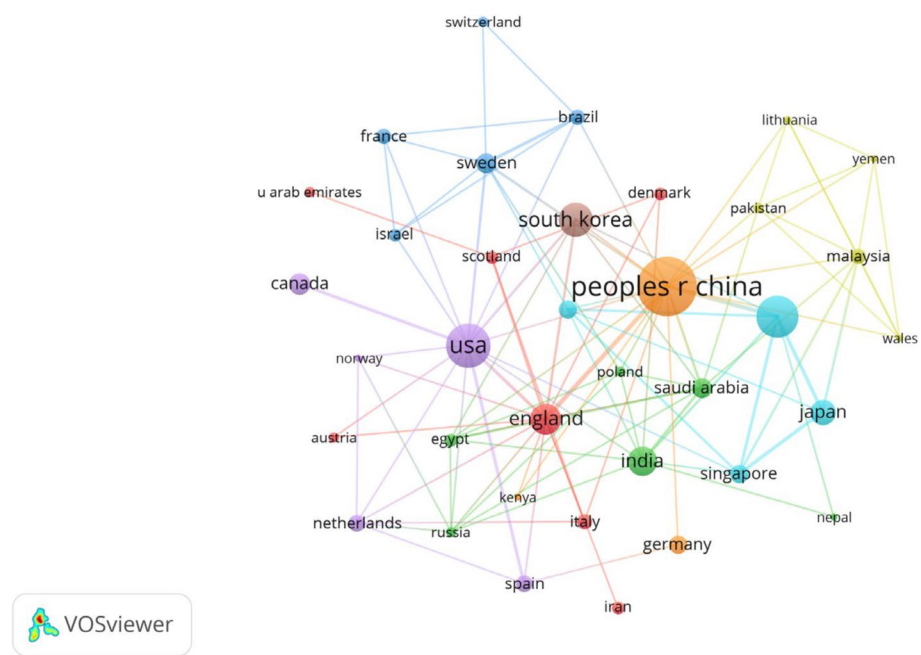


Fig. 5 Principal countries and regions in the study. The top three in article count are China (59), USA (33), and Taiwan, China (30), while the citation count leaders are USA (1237), China (1071), and Singapore (728). In terms of average citations per country, the top three are Malaysia (158.75), Singapore (121.33), and Denmark (71.67). For international collaboration, the top three are China (29), England (24), and USA (23)

(Tables 3, 4, 5, 6, 7, 8, 9 and 10). Given the reliance solely on published data, ethical approval was unnecessary for this study.

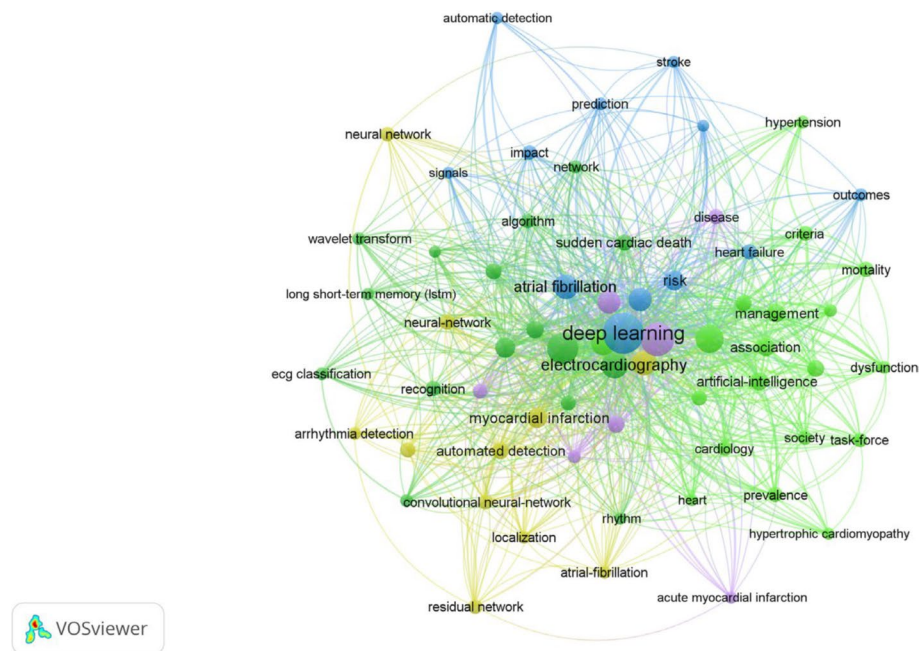


Fig. 6 Keywords of studies. The top three occurrences are deep learning (96), electrocardiogram (58), and classification (50), while the top three in Total link strength (TLS) are deep learning (415), electrocardiogram (249), and classification (215)

Table 1 Ranking of major countries and regions in the study

Ranking	C/R	AC	C/R	CC	C/R	ACP	C/R	TLS
1	China	59	USA	1237	Malaysia	158.75	China	29
2	USA	33	China	1071	Singapore	121.33	England	24
3	Taiwan	30	Singapore	728	Denmark	71.67	USA	23
4	South Korea	20	Japan	719	Japan	65.36	Taiwan	18
5	England	16	Malaysia	635	Austria	38.5	Singapore	13
6	India	15	South Korea	358	USA	37.48	India	12
7	Japan	11	Taiwan	312	Canada	32.38	Saudi Arabia	12
8	Canada	8	Canada	259	Egypt	28.67	Sweden	12
9	Saudi Arabia	7	Denmark	215	China	18.15	Japan	11
10	Sweden	7	England	202	Germany	18	Australia	10

Country/region = C/R; article count = AC; citation count = CC; average citations per article = ACP; total link strength = TLS

Results

In this study, the 198 articles discussing the application of DL to ECG for cardiovascular disease (CVD) diagnosis were chronologically organized, reflecting a notable increase in annual publications starting from 2018 (Fig. 2). This surge could be linked to the advancement of AI technology, widespread adoption of smart devices, and intensified interdisciplinary medical research. The articles were categorized based on eight CVD types, with arrhythmology, blood pressure, and CAD and ACS accounting for the lion’s share due to their prevalence, readily accessible public datasets, and the utility of DL with wearable devices (Fig. 3). In Fig. 4, public databases, particularly ARRDB[29, 30], AFDB[25, 31], and competition datasets[26, 27, 32, 33], played

Table 2 Ranking of key research keywords

Ranking	Keyword	Occurrences	Keyword	TLS
1	Deep learning	96	Deep learning	415
2	Electrocardiogram	58	Electrocardiogram	249
3	Classification	50	Classification	215
4	Artificial intelligence	37	Artificial intelligence	188
5	Electrocardiography	32	Electrocardiography	166
7	ECG	29	Diagnosis	139
6	Atrial fibrillation	29	ECG	135
8	Diagnosis	27	Atrial fibrillation	105
9	Convolutional neural network	24	Convolutional neural network	99
10	Machine learning	24	Electrocardiogram (ECG)	95

Total link strength = TLS

a crucial role in model development, especially for arrhythmology, blood pressure, and CAD/ACS, whereas proprietary databases were more prevalent in certain disease types like HF, cardiomyopathy, and valvular disease. Using VOSviewer, the global contributions were mapped, revealing China, USA, and China Taiwan as leading producers by article count, while USA topped the list for citation count (Fig. 5 and Table 1). Keyword analysis highlighted ‘deep learning’, ‘electrocardiogram’, and ‘classification’ as the most frequently occurring and interconnected terms (Fig. 6 and Table 2). Hybrid databases had less utilization. To evaluate the effectiveness of DL models, various performance metrics were employed, including area under the receiver operating characteristic curve (AUROC), accuracy (Acc), sensitivity (Sen), specificity (Spe), positive predictive value (PPV), negative predictive value (NPV), recall (Rec), precision (Pre), and false positives. This systematic approach elucidates the evolving landscape of DL applications in ECG-CVD research, identifies critical research areas, and underscores the importance of international collaboration and public dataset availability.

CAD and ACS

Studies based on PTB-ECG DB

The Physikalisch Technische Bundesanstalt Electrocardiogram Database (PTB-ECG DB) [34] is a large-scale database containing ECG recordings from subjects of varying ages and genders, encompassing health and diverse disease conditions. With its high sampling rate and precise resolution, this database serves as a foundation for numerous CAD and ACS studies.

Diagnosis of acute myocardial infarction (AMI) is crucial in clinical settings, prompting substantial research efforts in AMI detection. In 2017, Acharya et al. [35] achieved high accuracy using a CNN model on both denoised and noisy ECGs. Liu et al. [36] diagnosed extensive anterior wall MI with an Acc of 96.00% via multi-lead ECG. The model of various investigators[37–39] has excellent performance in MI diagnosis. Regarding MI localization, He et al.’s [40] MB-DenseNet-STSM model automatically labels valuable unlabelled samples, achieving an Acc of 96.09% in MI localization. The models established by several research groups [41–47] achieve nearly 100% accuracy in both diagnosis and localization, showcasing exceptional performance.

Table 3 CAD and ACS

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2017 [35]	Acharya et al.	Information Sciences	PTB-ECG DB	Make a novel approach to automatically detect the MI using ECG signals	1-Lead ECG(II)	CNN	MI	With/without noise Acc = 93.53%/95.22%
2018 [36]	Liu et al.	IEEE Journal of Biomedical and Health Informatics	PTB-ECG DB	The CNN model was used to diagnose extensive anterior wall myocardial infarction by ECG	Leads (V2, V3/V5,avL)	CNN	MI,AMI,ALMI,ASMI	Acc = 96.00%
2018 [42]	Liu et al.	Biomedical Signal Processing and Control	PTB-ECG DB	An MFB-CNN model detects and locates MI via a 12-lead ECG	12 leads ECG	MFB-CNN	MI,AMI,ALMI,ASMI,IMI,ILMI	Whether/location MI Acc = 99.95%/99.81%
2019 [43]	Zhang et al.	IEEE Access	PTB-ECG DB	An ML-BIGRU model locates different parts of MI through the eight leads of the ECG	8leads(III,V1,V2, V3/V4/V5/V6)	ML-BIGRU	MI,AMI,ALMI,ASMI,IMI,ILMI	Acc = 99.84%
2019 [39]	Strodthoff et al.	Physiological Measurement	PTB-ECG DB	A CNN model detects and locates MI using a 12-lead ECG	12 leads ECG	CNN	MI	Diagnosis MI/AMI/IMI J-Stat = 0.827/0.877/0.789
2020 [48]	Cho et al.	Scientific Reports	Proprietary DB	A DLA was developed to detect MI using 12-lead and 6-lead ECG	12 leads ECG	CNN	MI	Internal/external validation AUROC = 0.902/0.901
2020 [38]	Alghamdi et al.	Multimedia Tools and Applications	PTB-ECG DB	A VGG-MI2 model diagnoses MI with a single-lead ECG	1-Lead ECG(II)	CNN	MI	None/have noise Acc = 99.22%/97.24%
2020 [44]	Fu et al.	Sensors	PTB-ECG DB	The framework of MLA-CNN-BIGRU was designed to detect and locate MI by 12-lead ECG	12 leads ECG	MLA-CNN-BIGRU	MI,AMI,ALMI,ASMI,IMI,ILMI	Intra/inter-patient Acc = 99.93%/96.50%
2020 [70]	Eern et al.	Applied Sciences-Basel	Proprietary DB	A CNN-based model assessed coronary calcium scores by 12-lead ECG	12 leads ECG	CNN-Adam	Coronary artery calcium	12 leads ECG AUC/Acc CACS ≥ 4000.890/80.6
2021 [53]	Liu et al.	EuroIntervention	Proprietary DB	A CNN-based model for the diagnosis of STEM/INSTEMI via 12-lead ECG	12 leads ECG	CNN	MI	AUC = 0.997

Table 3 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2021 [54]	Liu et al.	Journal of Personalized Medicine	Proprietary DB	AI-S, a DL-based (active) alert strategy for diagnosing STEMI/NSTEMI	12 leads ECG	CNN	STEMI, NSTEMI	Detection STEMI/NSTEMI F1 = 0.932/0.701
2021 [57]	Chen et al.	Frontiers in Cardiovascular Medicine	PTB-XL DB, Proprietary DB	A ResNet model is used to diagnose and locate MI via a 12-lead ECG	12 leads ECG	ResNet	MI	Validation/testing set Pre = 0.789/0.830
2021 [50]	Han et al.	Journal of Medical Internet Research	Proprietary DB	A residual-based network model for MI detection by asynchronous ECG	12 leads ECG	ResNet	MI	12/4-lead AUROC = 0.880/0.858
2021 [47]	Jahmunah et al.	Computers in Biology and Medicine	PTB-ECG DB	The CNN-based model recognizes CAD, MI, and CHF by single-lead ECG	1-Lead ECG(II)	CNN and GaborCNN	MI, CAD, CHF	CNN/GaborCNN Acc = 99.55%/98.74%
2021 [62]	Tadesse et al.	Artificial Intelligence in Medicine	Proprietary DB	An end-to-end DL model identifies the time of MI occurrence with a 12-lead ECG	12 leads ECG	Dense-LSTM	MI	Acute/recent /Old MI AUC = 82.9%/ 68.6%/73.8%
2021 [45]	Karhade et al.	Applied Sciences-Basel	PTB-ECG DB	A CNN-based model identifies and locates MI through vector cardiogram	VCG signal	MMD-CNN	MI,AMI,ALMI,ASMI,IMI,ILMI	MI diagnosis/ location Acc = 99.58%/98.37%
2021 [64]	Bigler et al.	PLoS ONE	Proprietary DB	The CNN model assesses coronary ischemia by intracoronary ECG	icECG	GoogLeNet, ResNet	Coronary ischemia	AUC = 92.4% F1 = 0.918
2022 [55]	Kavak et al.	IEEE Access	Proprietary DB	A 2D-CNN model was proposed to detect STEMI by 12-lead ECG	12 leads ECG	2D-CNN	MI	Acc = 96.3% AUC = 0.962
2022 [52]	Hammad et al.	Sensors	PTB-XL DB	A CNN-SVM model for detection of MI and conduction disorders by 12-lead ECG	12 leads ECG	CNN-SVM	MI • CD	Acc = 99.20% F1 = 98.58%
2022 [58]	Wu et al.	Frontiers in Cardiovascular Medicine	Proprietary datasets	The CNN model was used for STEMI detection and localization using ECG	12 leads ECG	CNN-LSTM	MI	Detection/localization AUC = 0.999/0.958

Table 3 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2022 [46]	Cao et al.	Frontiers in Physiology	PTB-ECG DB	A ResNet-SENet model diagnoses and locates MI via a 12-lead ECG	12 leads ECG	ResNet-SENet	MI,AMI,ALMI,ASMI,IMI,...	Diagnosing/location MI Acc = 99.98%/99.79%
2022 [49]	Gustafsson et al.	Scientific Reports	Proprietary DB, PTB-XL	A DNN-based model was developed to identify STEMI and NSTEMI by ECG	12 leads ECG	DNN	MI	AUC = 0.985
2022 [59]	Jin et al.	Journal of the American Medical Informatics Association	Proprietary DB	A transfer learning based model is used to identify myocardial damage by ECG	12 leads ECG, 1-Lead ECG(I)	DNN	Myocardial injury	AUROC = 0.760 AUPRC = 0.321
2022 [40]	He et al.	Information Sciences	PTB-ECG DB	A MB-DenseNet-STSM model was developed for MI localization by ECG	12 leads ECG	MB-DenseNet-STSM	MI,AMI,ASMI,ALMI,IMI,ILMI	Acc = 96.09% F1 = 95.85%
2022 [37]	Li et al.	Information Sciences	PTB-ECG DB	A SLC-GAN model was proposed to diagnose MI by 1-lead ECG	1-Lead ECG(I)	SLC-GAN	MI	Acc = 99.06% F1 = 99.24%
2022 [63]	Han et al.	Expert Systems with Applications	Proprietary DB, PTB-ECG DB	A DenseNet model based ECG method for MI diagnosis, location and severity of infarction	12 leads ECG	DenseNet	IMI,AMI,ASMI,EAMI,ILMI,APMI	Detection/localization: Acc = 98.88%/94.13%
2022 [69]	Bhattacharya et al.	Physiological Measurement	Mayo Health Clinic Systems	DL model based on ECG and electronic medical record to predict prognosis after PCI	12 leads ECG	CNN	MACEs	All-cause mortality/HF/stroke AUC = 0.897/0.863/0.786
2023 [60]	Chaudhari et al.	Scientific Reports	Proprietary DB	A CNN-based model was developed to predict serum troponin I levels by ECG	12 leads ECG	CNN	myocardial injury • TnI	AUC = 0.810
2023 [56]	Tseng et al.	IEEE Journal of Translational Engineering in Health and Medicine	Proprietary DB	STEMI target vessels were diagnosed by 12-lead ECG based on CNN-STFT and CNN-CWT models	12 leads ECG	CNN-STFT CNN-CWT	MI	CNN-STFT/CNN-CWT Acc = 79.31%/83.69%

Table 3 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2023 [51]	Xiao et al.	Physiological measurement	PTB-XL DB	A composite model based on xResNet was developed to diagnose MI	12 leads ECG	xResNet	MI	AUROC = 92.1%
2023 [61]	Liu et al.	Applied Intelligence	Proprietary DB	A 12-lead ECG based on the EfficientNet model identifies ACS	12 leads ECG	EfficientNet	ACS	Acc = 73.3% Pre = 0.761
2023 [65]	Choi et al.	BMC Cardiovascular Disorders	Proprietary DB	A Resnet-based model screens for obstructive coronary artery disease via ECG	12 leads ECG	ResNet	ObCAD	MI/ObCAD detection AUC = 0.923/0.693
2023 [67]	Lee et al.	Atherosclerosis	Proprietary DB	A DL model that diagnoses CAD through a model based on ECG and information	12 leads ECG	DL + EN	CVD	AUC = 0.72 F1 = 0.72
2023 [66]	Lee et al.	Scientific Reports	Proprietary DB	An integrated DL model based on ECG and other information to diagnose ObCAD	12 leads ECG	ResNet	ObCAD	AUC = 0.767 F1 = 0.696
2023 [41]	Li et al.	Tsinghua Science and Technology	NSRDB, INCART, PTBDB, BIDMC	A CResFormer model was proposed to distinguish CAD, MI and CHF by ECG	12 leads ECG	CResFormer-ResNet-CNN	CVD/MI/CHF	Acc = 99.84%/97.48% F1 = 99.69%/94.87%
2023 [68]	Tang et al.	Aging	Proprietary datasets	A SeResNet-50 model diagnoses CAD with ECG	8 leads (I, II, V1–V6), 1 lead	SeResNet-50	CVD	AUC = 0.75 Acc = 70.0%

Studies based on other databases

Cho et al. [48] developed a DL model using Korean ECG data, achieving an AUROC of 0.902 in AMI diagnosis. Numerous scholars [49–55] continue to promote model innovation to diagnose MI. It is noteworthy that Liu et al. [54] proposed the AI-S strategy, reducing median ECG-to-catheterization-lab activation time from 6.0 min to 4.0 min ($p < 0.01$) and median door-to-balloon time from 69 to 61 min ($p = 0.037$); this is worth encouraging due to its clinical benefit. The collaborative research from many researchers [56–58] demonstrates remarkable proficiency in pinpointing the location of myocardial infarction and in the precise localization of the culprit vessels. Jin et al. [59] and Chaudhari et al. [60] constructed models assessing myocardial injury, with AUROC exceeding 0.760. Liu et al. [61] EfficientNet model accurately classified T-wave changes, ST-T segment changes, and pathological Q-waves. Tadesse et al. [62] proposed an end-to-end DL model incorporating transfer learning, demonstrating good performance in distinguishing MI at different stages. Han et al. [63] combined clinical doctors' diagnostic logic with a DenseNet network, establishing a model with an Acc and F1 of 93.65% and 94.27% in MI staging. The models constructed by many researchers [64–68] exhibits outstanding capability in discriminating CAD, obstructive coronary artery disease (obCAD) and evaluating coronary ischemia. Bhattacharya et al. [69] developed a dual-branch DL model integrating ECG and electronic medical records, showing good performance in predicting all-cause mortality and HF/stroke incidence. Eem et al. [70] assessed coronary artery calcium scores using a CNN model, achieving AUC and Acc of 0.890 and 80.6%, respectively. AMI and CAD are among the most common conditions in cardiology, with ECG serving as the fundamental diagnostic tool for these diseases. It is hoped that more research will be dedicated to their study, eventually enabling DL to diagnose MI and CAD efficiently, promptly, and accurately (refer to Table 3 for details).

Cardiac insufficiency/HF

Diagnosis of cardiac insufficiency often relies on laboratory tests such as BNP and echocardiography. However, ECG can now also serve as an auxiliary diagnostic tool. In 2018, Li et al. [71] used a CNN-RNN model to identify HF stages with an AUC and Acc of 0.851 and 97.6%, respectively. Vaid et al. [72] and Chen et al. [73] have developed models capable of accurately detecting different stages of HF and predicting adverse cardiovascular events. Sbröllini et al. [74], Chen et al. [4], and Botros et al. [75] have proposed models that demonstrate commendable performance in the diagnosis of heart HF. Raghu et al. [76] HFNet model, incorporating 12-lead ECG, age, and gender, identified HF patients with mPCWP > 18 mmHg with an AUROC of 0.81. The models conceived by Acharya [77] and fellow researchers [78–80] demonstrate noteworthy effectiveness in diagnosing congestive heart failure and forecasting episodes of acute decompensated heart failure. Attia et al. [81–83] CNN model performed excellently in diagnosing asymptomatic left ventricular dysfunction (ALVD) and left ventricular systolic dysfunction (LVSD), with AUCs of 0.93 and 0.82, respectively. Multiple independent investigators [84–89] have likewise augmented the precision in diagnosing LVSD by employing DL algorithms in their studies. In addition, Bachtiger et al. [90] CNN model diagnosed HFrEF through a specialized stethoscope with an AUROC and F1 of 0.85 and 0.369,

respectively. Chen et al. [91] CNN model effectively recognized increased left ventricular end-diastolic diameter and predicted future cardiovascular risk. Liu et al. [92] CNN model judged abnormal BNP levels, with a model diagnostic AUC of 0.8934 for $\text{BNP} \geq 1000$ pg/mL. It is expected that more research in the future will facilitate rapid and efficient diagnosis of cardiac insufficiency (refer to Table 4 for details).

Valvular heart disease

Echocardiography has traditionally been the primary means of detecting valvular heart disease. However, researchers now use ECG to diagnose these conditions as well. In 2020, Kwon et al. [93, 94] employed a CNN model to detect moderate-to-severe mitral regurgitation (MR) and developed an MLP-CNN combination model to diagnose moderate-to-severe aortic stenosis (AS), both achieving good AUCs and accuracies in internal and external validation sets. Elias et al. [95] employed ValveNet model accurately detected moderate-to-severe AS, MR, and aortic regurgitation (AR) through 12-lead ECG, with comparable diagnostic performance in white and black patients. Sawano et al. [96] employed 2D-CNN and FC-DNN combination model diagnosed moderate-to-severe AR with an AUROC and Acc of 0.802 and 82.3%, respectively. Additionally, Vaid et al. [97] employed MLP-CNN model achieved ideal results in diagnosing moderate-to-severe MR and AS, with AUROCs approaching 0.9. These studies further substantiate the potential of deep learning in diagnosing valvular heart diseases (refer to Table 5 for details).

Cardiomyopathy

While echocardiography and cardiac MRI have traditionally been the mainstay for diagnosing cardiomyopathies, researchers can now effectively diagnose these conditions using ECGs. Kokubo et al.'s [98] ENN model accurately diagnosed left ventricular dilatation (LVD) and left ventricular hypertrophy (LVH) through 12-lead ECG, with AUROCs of 0.810 and 0.784, respectively. Following continuous endeavors by investigators [99–103], the AUROC for the diagnosis of LVH using the developed model ascended to a notable peak of 0.98, indicating exceptional discriminatory capacity. Hypertrophic cardiomyopathy (HCM) is a commonly encountered cardiomyopathy in clinical settings. Ko et al. [104] used a CNN model, leveraging a large amount of HCM data from the Mayo Clinic digital [105], to efficiently diagnose HCM, achieving an AUC and Acc of 0.96. Maanja et al. [106] and Siontis et al. [107] have lowered the false positive rate in their models' diagnosis of HCM to 13.5%, while concurrently increasing the AUC to 0.98. Chen et al. [108] employed the VGG-16 model for genotyping patients with HCM, achieving AUC of 0.89 for diagnosing G+ individuals, which outperforms the Toronto score [109] (AUC=0.69). Lee et al. [110] focused on peripartum cardiomyopathy (PPCM) and achieved promising results. Mutations in the Phospholamban (PLN) gene can lead to arrhythmogenic cardiomyopathy (ACM) and dilated cardiomyopathy, among other diseases [111]. Bleijendaal et al. [112], together with Lopes et al. [113], and others, have developed various DL models for diagnosing PLN p. Arg14del-related cardiomyopathy, with the best-performing model achieving an AUC of 0.96, demonstrating overall superiority over

Table 4 Cardiac insufficiency/HF

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2019 [71]	Li et al.	Biomedical Signal Processing and Control	Proprietary DB	A CNN-RNN model was developed to identify different stages of heart failure by single-lead ECG	II	CNN-RNN	HF(NYHA I~IV)	2 s/5 s AUC = 0.851/0.827
2019 [77]	Acharya et al.	Applied Intelligence	BIDMC, Fantasia, NSRDB	A model for diagnosing CHF by ECG based on CNN is proposed	ECG	CNN	CHF(NYHA III/IV)	Acc = 98.97%
2019 [82]	Attia et al.	Nature Medicine	Proprietary DB	A CNN-based model for diagnosis of ALVD by 12-lead ECG was developed	12 leads ECG	CNN	ALVD(LVEF ≤ 35%)	AUC = 0.93 Acc = 85.7%
2019 [83]	Attia et al.	Journal of Cardiovascular Electro-physiology	Proprietary DB	A CNN-based model was developed to predict ALVD by 12-lead ECG	12 leads ECG	CNN	ALVD(LVEF ≤ 35%)	AUC = 0.918 Acc = 86.5%
2021 [84]	Sun et al.	Journal of Cardiovascular Electro-physiology	Proprietary DB	A model based on LeNet-5 framework for screening LVEF ≤ 50% by 12-lead ECG	12 leads ECG	LeNet-5	HF(LVEF ≤ 50%)	AUC = 0.713 Acc = 73.9%
2021 [88]	Cho et al.	ASAIO Journal	Proprietary DB	A TensorFlow-CNN model can diagnose HFrEF with 12-lead or single-lead ECG	12 leads ECG	TensorFlow-CNN	HF(HFrEF(LVEF ≤ 40%))	Internal/external validation AUC = 0.913/0.961
2021 [4]	Chen et al.	Journal of Healthcare Engineering	Physio-Bank, MIMIC-III	A CBAM-CNN model can diagnose HF by ECG	ECG	CBAM-CNN	HF	Segmented by R peak/time Acc = 97.6%/97.5%
2021 [81]	Attia et al.	International Journal of Cardiology	Proprietary DB	A study to detect ALVD in an external population	12 leads ECG	CNN	LVSD(LVEF ≤ 35%)	AUC = 0.82 Acc = 97.0%
2021 [87]	Katsushika et al.	International Heart Journal	Proprietary DB	A CNN model identifies LVSD with a 12-lead ECG	12 leads ECG	CNN	LVSD(LVEF < 40%)	AUROC = 0.945 AUPRC = 0.740
2022 [91]	Chen et al.	Frontiers in Medicine	Proprietary DB	LV-D, LV-S and prognostic correlation were investigated by 12-lead ECG based on CNN model	12 leads ECG	CNN	LV-D and Adverse event	LV-D mild/severe increased AUC = 0.8297/0.9295

Table 4 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2022 [73]	Chen et al.	Journal of Personalized Medicine	Proprietary DB	An ECG 12Net model estimates LVEF levels and determines MACEs events from a 12-lead ECG	12 leads ECG	CNN	HF(LVEF < 35%/50%) and MACEs	ECG-LVEF < 35%/50% AUC = 0.9472/0.8845
2022 [89]	Lee et al.	Digital Health	Proprietary DB	A CNN model examines LVD and predicts future LVD risk using 12-lead ECG detection	12 leads ECG	CNN	LVD(LVEF < 40%)	Internal/external sets AUC = 0.9759/0.9653
2022 [98]	Kokubo et al.	International Heart Journal	Proprietary DB	An ENN model was developed to detect LVD and LVH using a 12-lead ECG	12 leads ECG	ENN(CNN + DNN)	LVD and LVH	LVD/LVH AUROC = 0.810/0.784
2022 [75]	Botros et al.	Sensors	MIT-BIH NSRDB, BIDMC CHFDB	A CNN-SVM model detects HF by ECG	ECG	CNN-SVM	HF	Acc = 99.17%
2022 [85]	Honarvar et al.	Cardiovascular Digital Health Journal	Proprietary DB	A new subwaveform represents enhanced CNN for LVD detection by 8ECG	I ∖ II ∖ V1 ~6	DNN	LVD(LVEF < 35%)	AUROC = 0.926 AUPRC = 0.578
2022 [86]	Golany et al.	Journal of Clinical Medicine	Proprietary DB	A CNN-ResNet model is used to detect LVSD by 12-lead ECG	12 leads ECG	CNN-ResNet	LVSD(LVEF < 50%;LVEF < 35%)	EF < 35%/50% AUC = 0.88/0.85;
2022 [90]	Bachtiger et al.	Lancet Digital Health	Proprietary DB	A CNN-based model screens for HFref by single-lead ECG signals via a special stethoscope	Single lead	CNN	HFref(LVEF ≤ 40%)	AUROC = 0.85 F1 = 0.439
2022 [72]	Vaid et al.	JACC-Cardiovascular Imaging	Proprietary DB	A CNN-based model evaluated left and right ventricular dysfunction with an 8-lead ECG	I ∖ II ∖ V1 ~6	CNN-Efficientnet47	LVD and RVD	LVEF ≤ 40% Internal/external AUROC = 0.94/0.94

Table 4 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2023 [92]	Liu et al.	Diagnostics	Proprietary DB	A CNN-based model was developed to predict BNP/pBNP levels and assess prognosis by ECG	12 leads ECG	ECG 12 Net	BNP ∨ pBNP	Internal/external AUC = 0.8934/0.8527
2023 [74]	Sbrollini et al.	Biomedical Signal Processing and Control	Proprietary DB	A repetitive structuring and Learning Process model is used to diagnose HF with a 12-lead ECG	12 leads ECG	RS&LP-ANN	HF	AUC = 0.86 Acc = 75%
2023 [79]	Prabhakararao et al.	IEEE Transactions on Systems Man Cybernetics-Systems	BIDMC-CHF,PTBDB,MIT-BIH NSRDB	A DA-DRRNet model is used to diagnose CHF with a 12-lead ECG	ECG	DA-DRRNet	HF	Beat/5 min excerpt-lever AUC = 0.98/0.99
2023 [78]	Pan et al.	Artificial Intelligence In Medicine	Proprietary DB	An ECGX-Net model predicts acute decompensated heart failure using a wearable ECG and transthoracic bioimpedance	Single lead, TBI	ECGX-Net	ADHF	AUC = 0.9249 F1 = 0.85
2023 [76]	Raghu et al.	Scientific Reports	Proprietary DB	A HFNet model identifies HF patients with mPCWP > 18 mmHg by 12-lead ECG, age, and sex	12 leads ECG, mPCWP	HFNet	HF	Internal/external datasets AUROC = 0.82/0.81
2023 [80]	Nahak et al.	Biomedical Signal Processing and Control	BIDMC-CHF,MIT-BIH NSRDB, ARRDB	An AlexNet combination model is used to diagnose arrhythmias and CHF via II and V1 lead ECGs	II ∨ V1	AlexNet	Arrhythmia and CHF	Acc = 99.06% F1 = 98.85%

Table 5 Valvular heart disease

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2020 [94]	Kwon et al.	Journal of Electro-cardiology	Proprietary DB	A CNN-based model can detect moderate-to-severe mitral regurgitation by 12-lead or single-lead ECG	12 leads, single lead	CNN	MR	Internal/external validation AUROC = 0.816/0.877
2020 [93]	Kwon et al.	Journal of the American Heart Association	Proprietary DB	A combined MLP-CNN based model for detection of moderate-to-severe aortic stenosis (AS) by ECG	12 leads, single lead	MLP-CNN	AS	Internal/external validation AUROC = 0.884/0.861
2022 [95]	Elias et al.	Journal of the American College of Cardiology	Proprietary DB	A Valvetnet-based model can detect moderate-to-severe AS, MR, and AR with a 12-lead ECG	12 leads, single lead	ValveNet	AS/AR/MR	Internal/external validation AUROC = 0.84/0.751
2022 [96]	Sawano et al.	Journal of Cardiology	Proprietary DB	A combined 2D-CNN and FC-DNN model can detect moderate-to-severe AR with ECG	12 leads, single lead	2D-CNN + FC-DNN	AR	AUROC = 0.802 Acc = 82.3%
2023 [97]	Vaid et al.	Communications Medicine	Proprietary DB	A MLP-CNN model can detect moderate-to-severe AS and MR Using an 8-lead ECG	8 leads(I,II,V1~6)	MLP-CNN	AS and MR	External testing-MR/AS AUROC = 0.81/0.86

Table 6 Cardiomyopathy

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2020 [100]	Wu et al.	Journal of Ambient Intelligence and Humanized Computing	Proprietary DB	A DNN-based model for diagnosis of left ventricular hypertrophy by 12-lead ECG	12 leads	DNN	Left ventricular hypertrophy	Acc = 73.6%
2020 [104]	Ko et al.	Journal of The American College of Cardiology	Mayo Clinic digital DB	A CNN model for diagnosis of HCM based on 12-lead ECG was established	12 leads, single lead(I)	CNN	HCM	Auc = 0.96 Ppv = 31%
2021 [112]	Bleijendaal et al.	Heart Rhythm	Proprietary DB	The DL model was used to diagnose PLN p.AGAR 14del cardiomyopathy by 12-lead ECG	12 leads	CNN + LSTM	Phospholamban p.Arg14del mutation	Internal/external datasets AUC = 0.83/0.70
2021 [113]	Lopes et al.	Computers in Biology and Medicine	Proprietary DB	The CNN model of transfer learning was used to diagnose PLN p.AGg14del cardiomyopathy using an 8-lead ECG	8 leads (I,II,VI ~ 6)	CNN	Phospholamban p.Arg14del mutation	Balanced/unbalanced dataset AUROC = 0.87/0.90
2021 [114]	Gumpfer et al.	Biological Chemistry	Proprietary DB	A combined model based on the CNN algorithm and other clinical parameters predicts MS	12 leads	CNN	Myocardial scar	AUC = 0.89 Acc = 78.0%
2021 [107]	Siontis et al.	International Journal of Cardiology	Mayo Clinic digital DB	A CNN model based on 12-lead ECG for the detection of HCM in minors	12 leads	CNN	HCM	AUC = 0.98 F1 = 0.35
2022 [106]	Maanija et al.	Cardiovascular Digital Health Journal	Mayo Clinic DB, Mayo Clinic digital DB	An HCM-Detect score helps the CNN-ECG model diagnose HCM with ECG and reduce its false positive rate	12 leads	CNN	HCM	False-positive: 13.5%
2022 [110]	Lee et al.	International Journal of Cardiology	Proprietary DB	A CNN-based model for the diagnosis of perinatal cardiomyopathy (PPCM) by 12-lead ECG	12 leads	CNN	Peripartum cardiomyopathy (LVEF ≤ 45%)	Internal/external datasets AUC = 0.896/0.877

Table 6 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2022 [101]	Zhao et al.	Frontiers in Cardiovascular Medicine	Proprietary DB	A CNN-LSTM model was used to diagnose LVH by 12-lead ECG	12 leads	CNN-LSTM	LVH	Test set/Cornell/Sokolow-Lyon AUC = 0.622/0.567/0.507
2022 [102]	Liu et al.	Circulation-Cardiovascular Quality and Outcomes	Proprietary DB	A CNN-based model detects LVH and explores prognosis by 12-lead ECG	12 leads ECG	CNN	LVH	Internal/external(1)/external(2) AUC = 0.89/0.86/0.83
2023 [103]	Ryu et al.	Plos ONE	Proprietary DB	A Coar-Mix & Resnet-CBAM model diagnosed LVH by 12-lead ECG, demographics, and ECG characteristics	12 leads	CoAt-Mixer&ResNet-CBAM	LVH	AUC = 0.836 F1 = 46.85%
2023 [108]	Chen et al.	Annals of Medicine	Proprietary DB	A VGG-16 based model predicts the genotype of HCM patients by 12-lead ECG	12 leads	VGG-16	HCM	AUC = 0.89
2023 [99]	Dwivedi et al.	Journal of Electrocardiology	Proprietary DB	A DNN-based model identifies LVH from a 6-lead ECG	6 leads(I,II,III,AVL,AVR,AVF)	DNN	LVH	AUC = 0.92

Table 7 Arrhythmology

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2018 [135]	Pourbabaei et al.	IEEE Transactions on Systems Man Cybernetics-Systems	PAF prediction challenge database	CNN-based model for Identification of paroxysmal atrial Fibrillation (PAF) by ECG signals	ECG signal	CNN	PAF	Rec = 0.9020
2018 [136]	Fan et al.	IEEE Journal of Biomedical and Health Informatics	GinC 2017	A MS-CNN model confirms AF with a single-lead ECG	1-Lead ECG	MS-CNN	AF	AUC = 98.13% Pre = 91.78%
2019 [115]	Andersen et al.	Expert Systems with Applications	AFDB,ARRDB,NSROB	A combined CNN-RNN model is used to diagnose AF by ECG	ECG	CNN-RNN	AF	AUC = 0.997
2019 [116]	Wu et al.	2019 41 St (Embc)	MIT-BIH DB, Long-Term AF Database	CWT-CNN models were developed to detect AF by single-lead ECG	1-Lead ECG	CWT-CNN	AF	AUC = 0.9983 Acc = 97.56% Sen = 99.40%
2019 [118]	Mousavi et al.	2019 IEEE Embs (Bih)	MIT-BIH AFD8	A two-channel CNN model diagnoses AF with 5-s ECG segments	5-s ECG segments	RCNN-LSTM	AF	Sen = 99.53%
2019 [25]	Lai et al.	2019 41 St (Embc)	MIT-BIH AFD8	A CNN model is used to diagnose AF by single-lead ECG	1-Lead ECG	CNN	AF	Acc = 97.3%
2020 [150]	Lai et al.	IEEE Journal of Biomedical and Health Informatics	Proprietary DB, MIT-BIH AFD8	A CNN model is used to diagnose AF by ECG analysis of an electrode patch at a specific location	1-Lead ECG	CNN	AF	Acc = 93.1%
2020 [166]	Missel et al.	Computers in Biology and Medicine	Proprietary DB	A combined VESP-CNN model was developed to map the VT origin site using a 12-lead ECG	12 leads	CNN-VAE	VT	Localizing exact pading/ origin Acc = 52.6%/65.6%
2020 [125]	Dang et al.	IEEE Access	MIT-BIH ARRDB	A MSF-CNN B model is used to diagnose multiple heart rhythms with II and V5 lead ECG	2-Lead(MLII + VT)	MSF-CNN	NSR, fusionbeat, supraventricular...	Acc = 98.00%
2020 [119]	Wang et al.	Future Generation Computer Systems-The International Journal of Esience	MIT-BIH AFD8	A CNN-MENN model is used to diagnose AF by ECG	ECG	CNN	AF	AUC = 0.991 Acc = 97.4% Sen = 97.9%

Table 7 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2020 [137]	Gao et al.	Biomedical Signal Processing and Control	CinC 2017	An LSTM-RNN model confirms AF with a single-lead ECG	1-Lead ECG	LSTM-RNN	AF	Acc = 82.949% F1 = 0.810
2020 [157]	Cai et al.	Computers in Biology and Medicine	Proprietary DB	A DDNN-based model was developed to diagnose AF by 12-lead ECG	12 leads	DDNN	AF	AUC = 0.994 Acc = 97.74%
2020 [31]	Ma et al.	Discrete Dynamics in Nature and Society	MIT-BIH AFDB	A CNN-LSTM model is used to diagnose AF by ECG	ECG	CNN-LSTM	AF	AUC = 0.97 Acc = 97.21%
2020 [142]	Hsieh et al.	Sensors	CinC 2017	A 1D CNN model confirmed AF with ECG	1-Lead ECG(I)	1D CNN	AF	F1 = 78.2%
2020 [141]	Liaquat et al.	Information	MIT-BIH AFDB • CinC 2017	LSTM and CNN models have better performance in diagnosing ECG AF by ECG	1-Lead ECG	LSTM • CNN	AF	CNN/LSTM (MIT-BIH AFDB) Acc = 0.812/0.829
2020 [132]	Yu et al.	Electronics	MIT-BIH ARRDB	A CNN model is used to diagnose PVC by ECG	ECG	CNN	PVC	Acc = 99.64% ~ 100%
2020 [161]	Zhang et al.	Cardiovascular Diagnosis and Therapy	Proprietary DB	A CNN model is used to diagnose multiple arrhythmias by 12-lead ECG	12 leads	CNN	Multiple rhythm	Acc = 98.27% Pre = 60.93%
2021 [170]	Baek et al.	Scientific Reports	Proprietary DB	A RNN model based 12-lead ECG for the diagnosis of PAF with normal heart rhythm	12 leads	RNN	PAF	Internal/external datasets AUROC = 0.79/0.75
2021 [143]	Tutuko et al.	BMC Medical Informatics and Decision Making	MIT-BIH AFDB • CinC2017 • CPSC 2018...	A CNN-based AFibNet model for diagnosing AF by ECG	ECG	CNN-AFibNet	AF	Acc = 99.13%
2021 [121]	Ramesh et al.	Sensors	MIT-BIH NSR-DB • AFDB • ARRDB	A CNN model based diagnosis of AF by ECG in a wearable device	1-Lead ECG • PPG	CNN	AF	Acc = 95.10%
2021 [138]	Shi et al.	Computational and Mathematical Methods in Medicine	CinC 2017	A DCAA-based model confirms AF with a single-lead ECG	1-Lead ECG	ResNet-GRNN	AF	Acc = 91.7% F1 = 88.3%
2021 [29]	Yu et al.	Biosensors-Basel	MIT-BIH ARRDB	A KNN-based model identifies PVC by ECG	ECG	KNN	PVC	Acc = 99.7%
2021 [127]	Ullah et al.	Computational Intelligence and Neuroscience	MIT-BIH ARRDB • PTB Diagnostic ECG-DB	Different heart rhythms are distinguished by ECG based on three CNN-based models	ECG	CNN	Multiple rhythm	CNN + LSTM + Attention Model Acc = Pre = Rec = F1 = 99.29%

Table 7 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2021 [30]	Cinar et al.	Computer Methods in Biomechanics and Biomedical Engineering	MIT-BIH ARRD8	An Alexnet-SVM model differentiates NSR, ARR and CHF by ECGECG	ECGECG	Alexnet-SVM	NSR , ARR , CHF	Acc = 96.77%
2021 [74]	Raghunath et al.	Circulation	Gelsinger's clinical MUSE database	A DNNECG-AS model can predict new AF from a 12-lead ECG	12 leads	DNNECG-AS	AF	New-onset AF within 1 year AUROC = 0.85
2021 [152]	Jo et al.	International Journal of Cardiology	EGDB8...	A CNN-based model is used to diagnose AF by ECG	12 leads , 6 leads , 1 lead	CNN	AF	AUC of 12 leads: 0.997–0.999
2021 [62]	Jo et al.	Journal of Electrocardiology	MSH DB , SGH DB , ECGDB8...	An NBET-XDM model classifies different types of arrhythmias by ECG	ECG	NBET-XDM	Multiple rhythm	Internal/external validation AUC = 0.976/0.966
2021 [122]	Seo et al.	Scientific Reports	MIT-BIH AFD8; ARRD8,LTAFD8	A RNN-based model identifies AF by ECG	ECG	RNN	AF	Acc = 98.53%
2021 [140]	Zhang et al.	Computers in Biology and Medicine	CPSC 2018	A GH-MS-CNN model for the diagnosis of AF by single-lead ECG	1-Lead ECG(II)	GH-MS-CNN	AF	AUC = 0.9984 Pre = 0.9989
2021 [130]	Zhang et al.	Journal of Mechanics in Medicine and Biology	PhysioNet 2017	Classification of A/NRT and AVRT by ECG based on BAM-ResNet model	ECG	BAM-ResNet	SVT	AVNRT/AVRT Pre = 98.95%/87.47%
2022 [164]	Chang et al.	Journal of Personalized Medicine	Proprietary DB	The origin of PVC is determined by 12-lead ECG based on CNN model	CNN 12 leads	CNN	PVC	AUROC = 0.963 (left/right) AUROC = 0.998 (LV summit)
2022 [163]	Hong et al.	Applied Soft Computing	Proprietary DB	A CNN-LSTM model determines A/PVC and PAC by ECG	ECG	CNN-LSTM	AF , PVC , PAC	Determines AF/PVC/PAC AUC = 0.93/0.96/0.87
2022 [124]	Wang et al.	Applied Soft Computing	MIT-BIH AFD8 , ARRD8	CNN-ECA-BiLSTM and CNN-ECA-BiGRU models identify AF and AFL by ECG	ECG	CNN+ECA-BiLSTM/ ECA-BiGRU	AF , AFL	BiLSTM/BiGRU Acc = 99.2%/99.3% (in AFD8)
2022 [128]	Mohebbanaaz et al.	Signal Image and Video Processing	MIT-BIH ARRD8	AlexNet, Resnet 18 and GoogleNet models were used to distinguish ECG arrhythmias	ECG	AlexNet , Resnet 18 , GoogleNet	Multiple rhythm	AlexNet/Resnet 18/GoogleNet: Acc = 99.09%/99.56%/98.98%
2022 [120]	Subramanian et al.	Knowledge-Based Systems	MIT-BIH AFD8	A CNN-RNN + MVAR model is used to determine AF by ECG	ECG	CNN-RNN + MVAR	AF	AUROC = 0.9987 Acc = 99.16%
2022 [144]	Zhang et al.	Algorithms	CinC 2017 , SPSC 2018	A MCNN-BiLSTM model is used to diagnose AF by single-lead ECG	1-Lead ECG	MCNN-BiLSTM	AF	In CinC 2017/CPSC 2018 Acc = 85.76%/87.50%

Table 7 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2022 [123]	Prabhakara- rao et al.	IEEE Journal of Biomedical and Health Informatics	MIT-BIH AFD,NSRDB, LTNSRDB,ITAFDB	An MT-DCNN model was developed to diagnose AF and predict AF load by ECG	ECG	MT-DCNN	AF	Internal/external validation Acc=0.971/0.983
2022 [151]	Rodrigo et al.	Computers in Biology and Medicine	COMPARE registry	The CNN and RNN models use EGM to classify AF and AT	EGM	CNN&RNN	AF&AT	CNN/RNN AUC=0.97/0.95
2022 [158]	Yang et al.	Computers in Biology and Medicine	Shaoxing DB	CAT models were used to diagnose AF by single-lead and 12-lead ECG	1-Lead ECG • 12 leads ECG	CAT-Transformer	AF	Single lead(I/II)/12 leads AUC=0.9767/0.9823
2022 [32]	Pandey et al.	Journal of Sensors	CinC 2017	ResNet-BLSTM and ResNet-RBF were used to diagnose AF by ECG	ECG	ResNet-BLSTM, ResNet-RBF	AF	ResNet-BLSTM F1=80.08% ResNet-RBF F1=80.20%
2022 [131]	De Marco et al.	Plos ONE	MIT-BIH ARRD	The MobileNerv2 model was used to diagnose PVC by ECG	ECG	MobileNerv2	PVC	AUC=0.9963/0.9909 Acc=0.9990/0.9909
2022 [33]	Yu et al.	IEEE Journal of Biomedical and Health Informatics	CinC 2017	A DDCNN model was developed to diagnose AF by single-lead ECG	1-Lead ECG	DDCNN	AF	Acc=0.931 F1=0.833
2022 [175]	Wang et al.	Computational and Mathematical Methods in Medicine	Proprietary DB	A ResNet-based model for diagnosis of radiofrequency ablation by 12-lead ECG	12 leads ECG	ResNet	Efficacy of radiofre- quency ablation	AUROC=0.798 Acc=86.81%
2022 [117]	Kumar et al.	Computer Methods and Programs in Biomedicine	CACHET CAD, NSRDB,MIT- BIH AFD, ARRD, NSRDB,QTDB	A DeepAware model is used to diagnose AF by ECG	ECG	CNN-BLSTM	AF	Acc=98.06% Sen=97.94% Spe=98.39%
2022 [24]	Li et al.	International Journal of Advanced Computer Science and Applica- tions	INCART DB	An SE-ResNet model was developed to diagnose PVC by 12-lead ECG	12 leads ECG	SE-ResNet	PVC	Acc=98.71%
2022 [26]	Xiong et al.	Computers in Biology and Medicine	CinC 2017	A CRN model was developed to diagnose AF by single-lead ECG	1-Lead ECG	CRN	AF	Acc=93.79% F1=96.4%

Table 7 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2022 [153]	Lee et al.	Computers in Biology and Medicine	KMUHDB	A CRNN+PBLSTM model for the diagnosis of AF and atrial enlargement by ECG	II、VI	CRNN+PBLSTM	AF	Acc=74.81% F1=55.98%
2022 [173]	Tang et al.	Circulation-Arrhythmia and Electrophysiology	ProprietaryDB	A CNN-CatBoost model predicts AF recurrence 1 year after ablation by EGM, ECG, and clinical features	ECG、EGM	CNN-CatBoost	AF prognosis	AUROC=0.859 Acc=0.866
2022 [139]	Alsalem et al.	Bioengineering-Basel	CnC 2017	A ResNet model for diagnosing AF by ECG	ECG	ResNet	AF	Acc=98.37% F1=98.54%
2022 [133]	Sarshar et al.	Journal of Healthcare Engineering	MIT-BIH ARRD8	A CNN-based model for diagnosing PVC by ECG	ECG	CNN	PVC	Ppv=98.6% F1=99.2%
2022 [171]	Gregoire et al.	Archives of Cardiovascular Diseases	ProprietaryDB	A DNN-based model predicts the likelihood of paroxysmal AF attacks by ECG	Holter	DNN	PAF	AUC=0.74 Acc=66.5%
2022 [156]	Zhang et al.	IEEE Journal of Biomedical and Health Informatics	ProprietaryDB、MIT-BIH AFD8	A CNN-LSTM based model for diagnosing PAF by ECG	Holter	CNN-LSTM	PAF	AUC=0.994 Acc=97.9%
2022 [147]	Tutuko et al.	Sensors	ProprietaryDB,CinC2017, CPSC2018,QTD8,LUD8	A CNNs-Bi-LSTM model identifies AF by single-lead ECG	1-Lead ECG(II)	CNNs-Bi-LSTM	AF	Acc=95.79% F1=98.96%
2022 [23]	Chen et al.	Scientific Reports	KGHDB、ChapmanDB	A Confident learning-CNN model identifies AF by ECG	4 leads ECG(I、II、III、VI)	Confident learning-CNN	AF	F1=0.67 Ppv=0.59
2023 [159]	Chen et al.	Intensive Care Medicine Experimental	KGHDB、ChapmanDB	A Confident learning-CNN model identifies AF by ECG	4 leads ECG(I、II、III、VI)	Confident learning-CNN	AF	AUROC=0.935 PPV=0.548
2023 [154]	Hsieh et al.	Technology and Health Care	ProprietaryDB	A CNN-based model identifies AF by ECG	12 leads ECG	CNN	AF	Acc=92.7%
2023 [155]	Aldughayfiq et al.	Diagnostics	MIMIC PERFORM	A combined 1D CNN-BiLSTM model recognizes AF by ECG and PPG	ECG、PPG	1D CNN-BiLSTM	AF	AUROC=0.85 Acc=0.95
2023 [134]	Ullah et al.	Diagnostics	MIT-BIH ARRD8、INCART	A transfer learning model based on ResNet-18 identifies PVC by ECG	ECG	ResNet-18	PVC	Acc:99.74%~99.93%
2023 [129]	Zhuang et al.	Neural Computing & Applications	MIT-BIH ARRD8	DL and ML models identify arrhythmias in adolescent martial arts athletes by ECG	ECG	CNNGAN、ANN	Multiple rhythm	GNV/ANN AUC=98.30%/97.85%

Table 7 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2023 [149]	Dhyani et al.	Biomedical Signal Processing and Control	CPSC 2018	A ResRNN-based model identifies multiple arrhythmia disorders by 12-lead ECG	12 leads ECG	ResRNN	Multiple rhythm	Acc = 0.91 F1 = 0.91
2023 [160]	Wang et al.	Annals of Noninvasive Electrocardiology	Proprietary DB	A variety of DL models have been developed to identify latent bypasses by 12-lead ECG	12 leads ECG	MobileNetV3_large,DenseNet	AP	Densenet 69 (R) AUC = 0.941 MobileNetV3_large(P) AUC = 0.957
2023 [126]	Midani et al.	Biomedical Signal Processing and Control	MIT-BIH ARRRBD	A model called DeepArr diagnoses arrhythmias using ECG	ECG	1DCNN-BiLSTM	RBBB、LBBB、PVC、APB	Acc = 99.46% F1 = 97.63%
2023 [145]	Hu et al.	Journal of Personalized Medicine	CPSC2021, Cinc2017, LTAF	A Residual blocks and Transformer based model is used to diagnose AF and PAF by ECG	ECG	Residual blocks、transformer	AF	Acc = 98.67% F1 = 0.9008
2023 [146]	Li et al.	Computer Methods and Programs in Biomedicine	MIT-BIH AFDDB、Cinc 2017、CPSC 2018、SPH DB	A SC-CNN model is used to diagnose AF by ECG	ECG	SC-CNN	AF	AFDB/Cinc 2017/CPSC 2018 Acc = 99.79%/95.51%/98.80%
2023 [165]	Zhang et al.	IEEE Transactions on Biomedical Engineering	Proprietary DB	An ECGNet model diagnoses the origin site of PVC using a 12-lead ECG	12 leads ECG	CNN	PVC	AUC = 0.93 Acc = 91.74%
2023 [167]	Monaci et al.	Europace	Proprietary DB	A CNN-LSTM model used ECG and EGM to locate VT sites after myocardial infarction	ECG、EGM	CNN-LSTM	VT	Torso models mean LE ECG = 9.61 ± 2.61 mm Minimum LE in test = 1.5 ± 1.3 mm
2023 [168]	Pilia et al.	Artificial Intelligence in Medicine	Proprietary DB	Two CNN-based models locate VT through BSPM	BSPM	CNN	VT	
2023 [169]	Kim et al.	Diagnostics	Proprietary DB	Three DL models based on Heartbeat and ECG predict arrhythmia occurrence	12 leads ECG	ResNet-18,LSTM,transformer	Multiple rhythm	Predict AF/other arrhythmias AUC = 0.9523/0.9196
2023 [27]	Ganeshkumar et al.	IEEE Transactions on Engineering Management	CPSC 2018	A CNN-based model identifies multiple arrhythmia disorders by ECG	3-leads ECG(AVF、V5、V6)	CNN	Multiple rhythm	Acc = 96.2% F1 = 0.967

expert cardiologists (AUC=0.91). Gumpfer et al. [114] combined a CNN algorithm with clinical information to develop a composite model for diagnosing myocardial scar (MS), with the model diagnosing MS with an AUC and Acc of 0.89 and 78.0%, respectively. These studies not only enrich the technical arsenal for diagnosing cardiomyopathies, but also provide strong support for clinical decision-making (refer to Table 6 for details).

Arrhythmology

Based on MIT-BIH database

The MIT-BIH database, encompasses over 4,000 long-term ambulatory ECG recordings. Comprising databases such as AFDB, ARRDB, and NSRDB, it includes data on various arrhythmias like NSR, AF, SVT, CAVB, AVB, PVC, providing valuable resources for related research. Andersen et al. [115] utilized a CNN-RNN combination model to diagnose AF based on RR interval segments, achieving an AUC and Acc of 0.947 and 87.40%, Wu et al. [116] achieved improvements up to 0.9983 and 97.56% with Morlet-CWT-CNN model. Thereafter, the models developed by numerous researchers [25, 31, 117–124] have demonstrated substantial improvements in the diagnostic performance for AF, with accuracies approaching nearly 100%. Dang et al. [125] introduced the MSF-CNN B model, efficiently diagnosing multiple arrhythmias through single-lead ECGs, with mean Acc, Sen, and Spe of 98.00%, 96.17%, and 96.38%, respectively. Successive multiple studies [30, 126–129] have incrementally improved the classification performance across various types of cardiac rhythms, with accuracies nearing 100%, accompanied by a marked increase in computational speed. It is worth mentioning that Zhang et al. [130] designed a BAM-ResNet model that achieved a Pre of 98.95% in categorizing atrioventricular nodal reentry tachycardia (AVNRT) and atrioventricular reentrant tachycardia (AVRT). Marco et al. [131] introduced a MobileNetv2 model, which displayed outstanding diagnostic performance in an imbalanced dataset for premature ventricular contractions (PVCs), Acc of 0.9990 and AUC of 0.9963. Additionally, CNN model [132] and KNN model [29] by Yu et al., as well as the CNN model from Sarshar et al. [133], and the ResNet-18 model developed by Ullah et al. [134], have all demonstrated commendable performance.

Based on competition databases

Competition databases refer to those officially released for public competitions, offering ECG and other data resources to interdisciplinary researchers, such as Computing in Cardiology Challenge and CPSC 2018. A plethora of studies are founded on these databases. Pourbabaee et al. [135] employed a CNN model to diagnose PAF, achieving high correct classification rates and low false-negative rates on the PAF prediction challenge database. Fan et al. [136] proposed the MS-CNN model, utilizing different filter sizes in a dual-stream convolutional network to capture multi-scale features, diagnosing AF with an AUC and Pre of 98.13% and 91.78%. Subsequently, researchers have developed several models, including the LSTM-RNN model [137], DCAA model [138], ResNet-BLSTM/RBF model [32] DDCNN model [33], a ResNet-based model [139], and CNN-based models [140–143], all of which have contributed to enhancing the diagnostic performance for AF. It should be mentioned that Zhang et al.'s [140] GH-MS-CNN

model, incorporating hybrid multi-scale convolution modules, improved AF diagnostic performance, with mean Acc, Pre, and F1 of 0.9984, 0.9989, and 0.9954, respectively. To enhance model performance and ensure their robustness across various databases, numerous researchers have undertaken additional work: Zhang et al.'s [144] MCNN-BLSTM model dynamically set branches and enhanced feature information, Xiong et al.'s [26] 37-layer CRN model utilizing a transfer generator to expand sample size, Hu et al.'s [145] model based on residual blocks and transformers, and Li et al.'s [146] SC-CNN model employing a self-complementary attention mechanism, all showed superior performance in AF diagnosis. Tutuko et al.'s [147] CNNs-BiLSTM model recognized AF on QTDB and LUDB datasets [148] with Acc, Pre, and F1 of 99.79%, 99.01%, and 98.96%, respectively. In addition, Dhyani et al. [149] and Ganeshkumar et al. [27] each proposed a model classifying nine types of arrhythmia signals, with best Acc and Rec of 0.962 and 0.949.

Based on other databases

Lai et al. [150] trained a CNN model on Holter data from a Chinese hospital, diagnosing AF through II-lead data with Acc, Sen, and Spe of 93.1%, 93.1%, and 93.4%, respectively. CNN-based models [23, 151–156], DDNN-based models [157], and the CAT model proposed by Yang et al. [158] have all demonstrated commendable performance in the diagnosis of AF, with reported AUCs and Acc for detecting AF occurrence reaching up to 99.4% and 97.9%. It is worth noting that the Confident learning-CNN model proposed by Chen et al. [23] achieved an AUC of 0.935 for atrial fibrillation (AF) recognition on the KGHDB dataset [159].

Moreover, several researchers have conducted extensive studies [24, 160–164] and achieved commendable outcomes in the diagnosis of various cardiac arrhythmias, localization of PVC, and identification of Concealed Accessory Pathway (AP). Such as Wang et al.'s [160] Densenet 169 (R) model identified AP with AUC and Acc of 0.941 and 0.973. DL models have also proven instrumental in the localization of the origin sites of cardiac arrhythmias. Zhang et al.'s [165] ECGNet model has demonstrated appreciable accuracy in pinpointing the origin of PVC. Similarly, studies by Missel et al. [166], Monaci et al. [167], and Pilia et al. [168] have showcased commendable localization precision for the origins of ventricular tachycardia (VT), evidenced by robust performance in both internal and external validation tests, such as CNN-VAE model localization errors for LV pacing sites averaging just 5.3 ± 2.6 mm.

DL models have impressively demonstrated their mettle in predicting arrhythmia onset [169–171], AF risk stratification [172], and postoperative recurrence [173–175], thus substantiating the edge of deep learning. Notably, the CNN-CatBoost model by Tang et al. [173] excels in forecasting AF relapse with an AUC of 0.859, surpassing traditional AF ablation prognosis measures like the APPLE Score [176] (AUC=0.644) and the CHA2DS2-VaSC index [177] (AUC=0.650). Together, these studies poignantly highlight the expansive applicability of DL in arrhythmia prognosis and assessment across diverse clinical contexts (refer to Table 7 for details).

Table 8 Malignant arrhythmia and survival prognosis

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2019 [182]	Elola et al.	Entropy	DFW center	Two DNN-based models distinguish between pulseless electrical activity and pulsing rhythms by ECG	Defibrillation pads	DNN	PEA,PR	DNN/DNN + BGRU BAC = 93.5%/93.5%
2020 [183]	Tseng et al.	IEEE Access	CUDB • MIT-BIH NSRDB	A model based on CNN to predict the onset of VF	ECG	CNN-CWT, CNN-STFT	VF	1D-CNN setting 1/2 Acc = 60.5%/56%
2020 [185]	Raghunath et al.	Nature Medicine	Geisinger DB	A DNN-based model predicts 1-year all-cause mortality from an ECG voltage–time trajectory	12 leads ECG	DNN	Survival prognosis	AUROC = 0.876 AUPRC = 0.425
2021 [184]	Kaspal et al.	Multimedia Tools and Applications	MIT-BIH ARRDB,SCD Holter DB, Apnoea-ECG DB	A CNN-RCN hybrid model for early prediction of sudden cardiac death by ECG	ECG	CNN-RCN	Survival prognosis	ARRDB/SCD Holter /apnoea-ECG DB ACC = 93.24%/90.60%/92.13%
2021 [192]	Prifti et al.	European Heart Journal	Generepol,cLQTS, PharmacidITdP	A CNN model diagnoses long QT syndrome and predicts the risk of drug-induced arrhythmias with ECG	ECG	CNN	LQTS	AUROC = 0.98

Table 8 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2021 [198]	Dunn et al.	Artificial Intelligence in Medicine	SGH-ECG DB	A CNN-based model screens non-adaptive populations of S-ICD by ECG	Holter	CNN	T Wave over sensing	MAE=0.0545 STD=0.0926
2021 [179]	Sabut et al.	Physical and Engineering Sciences in Medicine	CUDB,VFDB	A DNN-based model identifies VF and VT by ECG	ECG	DNN	VF、VT	Acc=99.2%
2021 [180]	Lai et al.	IEEE Sensors Journal	MIT-BIH VFDB, ARRD, CUDB, AHADB	The CNN-based model identifies SHR by ECG	ECG	CNN	SHR	AUC=0.9964 Acc=98.82%
2021 [181]	Shilla et al.	Emitter-International Journal of Engineering Technology	Proprietary DB, MIT-BIH NSRDB, MVFDB, Creighton University Ventricular Tachyarrhythmia	An AlexNet-CNN model identifies SHR by ECG	ECG	AlexNet-CNN	SHR	Acc=98.7% F1=0.9867
2021 [200]	Nejadedh et al.	Biocybernetics and Biomedical Engineering	Proprietary DB	A model based on the DBSCAN algorithm predicts CRT responses from ECG and clinically relevant information	ECG, Clinical features	DBSCAN	CRT	AUC=0.957 Acc=91.85%
2022 [178]	Rajeshwari et al.	Cluster Computing The Journal of Networks Software Tools and Applications	MIT-BIH ARRD, ventricular arrhythmia DB	An integrated DNN-based model identifies routine and ventricular arrhythmias via ECG	ECG	DNN	Arrhythmia diagnosis	Arr/ventricular Arr Acc=98.11%/98.23% F1=98.89%/91.78%

Table 8 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2022 [199]	ElRefai et al.	Journal of Interventional Cardiac Electrophysiology	Proprietary DB	An attempt was made to further clarify the indication of S-ICD implantation through a CNN-based model	Holter	CNN	TWOS	-
2022 [193]	Doldi et al.	Journal of Personalized Medicine	Proprietary DB	An XceptionTime model identifies congenital and hidden LQTS using a 12-lead ECG	12 leads ECG	CNN	LQTS	AUC = 0.97 Acc = 91.8%
2022 [195]	Liu et al.	Canadian Journal of Cardiology	Proprietary DB	A CNN-BiLSTM model recognizes Brugada Type 1 from a 12-lead ECG	12 leads ECG	CNN-BiLSTM	Brugada Type 1	Internal/external AUC = 0.96/0.89
2022 [196]	Liao et al.	JACC-Clinical Electrophysiology	Proprietary DB	A Resnet-18 based model diagnoses Brugada Type 1 with a 12-lead ECG and Holter	V1 ~ 2, V1H, V2H	Resnet-18	Brugada Type 1	AUC = 0.976/0.975
2023 [194]	Diaw et al.	IEEE Transactions on Biomedical Engineering	Proprietary DB, QTDB, LUDB, PTB-XL, ECGRDVQ DB	Three DL models determine the QT interval by ECG	ECG	AttnCNN • KanResWide • U-QT Net	U-QT	Acc = 71%
2023 [197]	Dunn et al.	Annals of Operations Research	Proprietary DB	An MLP5-based model evaluates the T:R ratio with a single-lead ECG	Single lead ECG	MLP5	TWOS	Mean RMSE(MLP5) = 0.105 Mean MAE(Ensemble MLP5) = 0.0461

Table 8 (continued)

Publication year	Author	Publication title	Dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2023 [201]	Wouters et al.	European Heart Journal	Proprietary DB	A DNN-based model predicts CRT treatment outcomes from 12-lead ECG	12 leads ECG	DNN	CRT	C-statistic = 0.69
2023 [188]	de Capretz et al.	BMC Medical Informatics and Decision Making	EXPECT DB	The CNN-based model identified AML and death within 30 days by 12-lead ECG	12 leads ECG	CNN	AML ∨ death within 30 days	CNN-RAW/CNN-MB AUROC = 93.8%/93.9%
2023 [189]	Tsai et al.	Digital Health	Proprietary DB	A DNN model explores prognosis by 12-lead ECG	12 leads ECG	DNN	Survival prognosis	Internal/external validation AUC = 0.894/0.858
2023 [190]	Kondo et al.	IEEE Journal of Translational Engineering in Health and Medicine	Proprietary DB	The DL model determines the short-term prognosis of CCU patients by ECG	II ∨ V3 ∨ V5 ∨ aVR	CNN	Survival prognosis	AUC = 0.841 Acc = 77.3%
2023 [191]	Sun et al.	NPJ Digital Medicine	Proprietary DB	The DL model predicts future mortality from a 12-lead ECG	12 leads ECG	ResNet	Survival prognosis	30 days/1 year/5 years(%) AUROC = 85.19/82.58/82.8

Table 9 Blood pressure

Publication year	Author	Publication title	Population/dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2020 [203]	Soh et al.	Computers in Biotechnology and Medicine	MIT-BIH NSRDB, SHAREE DB	A CNN-based model for diagnosing hypertension via ECG	ECG	CNN	HPT	Acc = 99.99%
2020 [207]	Li et al.	Sensors	MIMIC II DB	An LSTM-based model evaluates blood pressure in real time via ECG and PPG	ECG, PPG	LSTM	Blood pressure	MAE(SBP/DBP) = 6.726/2.516 STD(SBP/DBP) = 14.505/6.442
2020 [205]	Miao et al.	Artificial Intelligence in Medicine	MIMIC III DB, Proprietary DB	A ResLSTM model assesses blood pressure in real time via ECG	ECG	CNN, LSTM	Blood pressure	MD(SBP/DBP) = -0.12/0.01/-0.03 STD(SBP/DBP) = 9.99/6.29/6.36
2021 [208]	Jeong et al.	Scientific Reports	MIMIC	A CNN-LSTM model evaluates blood pressure in real time via ECG and PPG	ECG, PPG	CNN-LSTM	Blood pressure	MAD(SBP/DBP) = 1.2/1.0 SD(SBP/DBP) = 1.6/1.3
2021 [209]	Esmaelpoor et al.	Physiological Measurement	MIMIC-II DB	The CNN-based model assesses blood pressure in real time via ECG and PPG	ECG, PPG	CNN	Blood pressure	MAE(SBP/DBP) = 3.28/1.75 SD(SBP/DBP) = 5.38/2.75
2021 [215]	Yang et al.	Optical and Quantum Electronics	Proprietary DB	A hybrid DL model based on CNN assesses blood pressure in real time via ECG and PPG	ECG, PPG	CNN, LSTM, Dense	Blood pressure	MAE(SBP/DBP) = 4.43/3.23 SD(SBP/DBP) = 6.09/4.75
2022 [212]	Zabihi et al.	Biomedical Signal Processing and Control	MIMIC DB	A TCN-based model evaluates blood pressure in real time via ECG and PPG	ECG, PPG	TCN	Blood pressure	MAE(SBP/DBP) = 2.59/1.33 STD(SBP/DBP) = 3.5837/1.9742
2022 [213]	Huang et al.	Biomedical Signal Processing and Control	MIMIC DB, UQVS DB	An MLP-BP model evaluates blood pressure in real time via ECG and PPG	ECG, PPG	MFMC, MLP, LSTM, gMLP	Blood pressure	MAE(SBP/DBP) = 3.52/2.13 SD(SBP/DBP) = 5.09/3.07

Table 9 (continued)

Publication year	Author	Publication title	Population/dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2022 [214]	Yen et al.	IEEE Access	MIMIC-III DB	A CNN-based model for real-time blood pressure assessment by ECG and PPG is proposed	ECG, PPG	CNN, LSTM, GRU	Blood pressure	ME(SBP/DBP) = 0.02/-0.1 SD(SBP/DBP) = 3.59/2.56
2022 [216]	Jo et al.	Plos ONE	Vital DB	The Resnet-based model predicts IOH in real time through ECG and ABP	ECG, ABP, EEG	Resnet	IOH	3 /5/10/15 min AUROC = 0.970/0.935/0.898/0.894 AUPRC = 0.943/0.882/0.819/0.808
2022 [210]	Baker et al.	Knowledge-Based Systems	MIMIC-III DB	A CNN-LSTM model evaluates blood pressure in real time via ECG and PPG	ECG, PPG	CNN-LSTM	Blood pressure	MAE(SBP/DBP) = 4.53/3.37 SD(SBP/DBP) = 6.27/4.84
2023 [206]	Long et al.	Biomedical Signal Processing and Control	MIMIC DB	A BPNet model evaluates blood pressure in real time via ECG and PPG	ECG, PPG	CNN,FPN	Blood pressure	ME(SBP/DBP) = -0.17/-0.24 STD(SBP/DBP) = 4.62/2.95
2023 [211]	Wang et al.	Frontiers in Digital Health	MIMIC III DB, VitalDB	A CNN-based model for real-time blood pressure assessment by ECG and PPG is proposed and a usable PulseDB dataset is presented	ECG, PPG	CNN	Blood pressure	SDE(SBP/DBP) = 2.76/3.09 MAE(SBP/DBP) = 2.00/2.11

Table 10 Others

Publication year	Author	Publication title	Population/ dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2019 [217]	Fan et al.	BMC Medical Informatics and Decision Making	Elderly nursing home	Two DL models predict the health status of older adults one day in the future using a single-lead ECG	TeleMedCare (single lead)	LSTM,BiLSTM	health status	BiLSTM/LSTM: AUROC = 0.9312/0.9065
2019 [219]	Attia et al.	Circulation: Arrhythmia and Electrophysiology	Mayo Clinic digital data	A CNN-based model for gender and ECG-age diagnosis via 12-lead ECG	12 leads ECG • CXR	CNN	Gender • ECG-age	ECG-age:MAE = 6.9 ± 5.6 year ECG-Gender:AUC = 0.97,Acc = 90.4%
2021 [225]	Mori et al.	Pediatric Cardiology	Proprietary DB	A CNN-LSTM model diagnoses ASD with a 12-lead ECG	12 leads ECG	CNN-LSTM	ASD	AUC = 0.95 Acc = 0.89
2021 [221]	Lima et al.	Nature Communications	CODE • ELSA-Brasil DB • SaMi-Trop DB	A DNN-based model diagnoses ECG-age with a 12-lead ECG	12 leads ECG • CXR	DNN	ECG-age	CODE/ELSA-Brasil /SaMi-Trop MAE = 8.38/8.44/10.04 SD = 7.00/6.19/7.76
2021 [218]	Butt et al.	Information	Proprietary DB	The CNN-based model identifies falls and activity classifications by ECG	ECG	CNN	Fall • Daily activities	Acc = 98.02%
2022 [226]	Lou et al.	Journal of Personalized Medicine	Proprietary DB	A CNN-based model was developed to diagnose LAE with a 12-lead ECG	12 leads ECG	CNN	LAE	AUC of Internal/external validation sets Moderate LAE = 0.8587/0.8688 Severe LAE = 0.8899/0.8990

Table 10 (continued)

Publication year	Author	Publication title	Population/ dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2022 [227]	Liu et al.	Canadian Journal of Cardiology	Proprietary DB	The DL model was used to diagnose aortic dissection by 12-lead ECG and CXR	12 leads ECG, CXR	CNN,DenseNet	AD	AUC= 0.943
2022 [228]	Liu et al.	Journal of Personalized Medicine	Proprietary DB	A DL model for diagnosis of acute pericarditis by 12-lead ECG	12 leads ECG, CXR	CNN	Acute pericarditis	AUC= 0.954
2022 [223]	Chang et al.	Frontiers in Cardiovascular Medicine	Proprietary DB,SaMi-Trop CODE-15%	An MXNet-based model predicts the relationship between human biological age and morbidity and mortality from ECG	12 leads ECG, CXR	MXNet	Heart Age, Prognosis	All-cause mortality HR= 1.61 CV-cause mortality HR= 3.49
2023 [222]	Zhang et al.	Frontiers in Cardiovascular Medicine	UK Biobank DB	A CNN-based model is used to diagnose ECG age with a 12-lead ECG	12 leads ECG, CXR	DNN	ECG age	MAE= 9.1 ± 6.6
2023 [229]	Gomes et al.	Medical & Biological Engineering & Computing	Proprietary DB	The DL model uses a 12-lead ECG to determine the effects of COVID-19 on the heart in the ECG	12 leads ECG	VGG 16	COVID-19	AUC= 1 Acc= 0.94
2023 [230]	Hassan et al.	Signal, Image and Video Processing	Proprietary DB	The DL model diagnoses Covid-19 in patients with heart disease by 12-lead ECG	12 leads ECG, CXR	VGG-19,AlexNet,ResNet-101	COVID-19	Acc= 99.1%

Table 10 (continued)

Publication year	Author	Publication title	Population/ dataset	Purpose of study	Sensors	Framework	Diseases	Performance
2023 [224]	Iakunchykova et al.	European Journal of Neurology	Tromsø 7	A CNN-based model for the diagnosis of heart-related age via 12-lead ECG	12 leads ECG	• CXR CNN	HDA	MSD = −4.63
2023 [231]	Gupta et al.	IEEE Transactions on Instrumentation and Measurement	f-ECG ARRDB	A DCM-based model identifies fetal arrhythmia by fetal electrocardiogram	Fetal-electrocardiogram	DCM	Fetal arrhythmia	AUC = 99.57% Acc = 94.18% F1 = 94.90%
2023 [220]	Baek et al.	Frontiers in Cardiovascular Medicine	Proprietary DB	A Bi-LSTM-based model estimates biological heart age by 12-lead ECG	12 leads ECG	Bi-LSTM	Biological heart age	MAE = 5.8 ± 3.9
2023 [172]	Zvuloni et al.	IEEE Transactions on Biomedical Engineering	TNMG DB	A DNN-based model for arrhythmia diagnosis, atrial fibrillation risk prediction, and age estimation via ECG	12 leads ECG	DNN	Arrhythmia diagnosis, AF risk prediction, age estimation	MAE = 6.26 ± 5.35

Malignant arrhythmia and survival prognosis

Life-threatening arrhythmias are disorders that can swiftly disrupt cardiovascular dynamics, potentially leading to hemodynamic collapse, syncope, and even sudden death upon manifestation. Hence, early detection plays a pivotal role. Multiple research teams have developed DL models [178–181] that achieve strikingly high accuracies of close to 99% in the identification of VT and VF events. Elola et al. [182] employed Bayesian-optimized DNN models to discriminate between pulseless electrical activity (PEA) and pulse-generating rhythm (PR). TSENG et al. [183] developed a CNN model capable of issuing warnings 50 and 20 s before ventricular fibrillation (VF) onset, achieving accuracies of 56% and 47.1%, respectively. Kaspal's team [184] reported a CNN-RCN model with a remarkable 93.24% accuracy in predicting sudden cardiac deaths (SCD). Raghunath et al. [185] utilized a DNN model to predict one-year all-cause mortality from ECGs, with an AUC of 0.876, outperforming the fragrance risk score (AUC = 0.648) [186] and the Charlson comorbidity index (AUC = 0.816) [187]. Capretz et al. [188] adopted a CNN model integrating ECG and baseline data to forecast 30-day acute myocardial infarction (AMI) and mortality risks in chest pain patients, achieving AUROC, Ppv, and Npv of 93.9%, 73.6%, and 99.9%, respectively. Tsai et al. [189], Kondo et al. [190] with their CNN model, and Sun et al. [191] with their ResNet-based model, all demonstrated high predictive precision in forecasting short-term or long-term outcomes for patients. Prifti et al. [192] and Doldi et al. [193] have developed DL models with remarkable diagnostic precision in identifying Long QT Syndrome (LQTS), exhibiting high accuracy. The KanResWide model by Diaw et al. [194] demonstrates a mean overall absolute error (MGAE) in assessing QT intervals of merely 11.2 ± 12.1 ms. Liu et al.'s [195] proposed CNN-BiLSTM model and Liao et al.'s [196] ResNet-18 model exhibit superior predictive accuracy in diagnosing Brugada type 1 syndrome, achieving an AUC value approximating 0.97. Dunn et al. [197, 198] and ElRefai et al. [199] harness DL models to screen out non-appropriate populations for S-ICD, utilizing the T:R ratio to predict TWOS risk with a mean absolute error (MAE) of only 0.0461. Nejadeh et al. [200] and Wouters et al. [201] forecast CRT outcomes with models demonstrating enhanced predictive performance (C-statistic = 0.69), surpassing QRSAREA [202] (C-statistic = 0.61). Collectively, these studies illuminate the potential and advantages of deep learning in recognizing and anticipating malignant arrhythmias (refer to Table 8 for details).

Blood pressure

Model performance standards in this section reference the Association for the Advancement of Medical Instrumentation (AAMI) and British Hypertension Society (BHS). AAMI requires MD of BP values < 5 mmHg and STD < 8 mmHg in cohorts with over 85 participants. BHS categorizes accuracy into A, B, and C grades based on absolute error: < 5 mmHg proportion > 60%/50%/40%, < 10 mmHg proportion > 85%/75%/65%, < 15 mmHg proportion > 95%/90%/80%, corresponding to A, B, and C grades, respectively. These criteria assess the accuracy and reliability of BP measurement models.

Soh et al. [203] deployed a CNN model to diagnose hypertension via ECG, utilizing data from MIT-BIH NSRDB and the SHAREE database [204]. Their model demonstrated outstanding performance, with Acc, Sen, Spe, and Ppv nearing 100%. Miao

et al. [205] introduced a ResLSTM model that evaluated blood pressure using single-lead ECGs, meeting the American Association for Medical Instrumentation (AAMI) standards, and achieving A-grade performance according to the British Hypertension Society (BHS) criteria for MAP and DBP measurements. Multiple DL models [206–214] assessed blood pressure through ECG and PPG signals, conforming to both BHS and AAMI standards. For instance, BPNet model proposed by Long et al. [206] integrated preprocessing, cross-modal fusion, post-feature extraction, and multitasking modules, constructing the model using CNN and Feature Pyramid Network (FPN) fusion of PPG and ECG signal features. Yang et al. [215] presented a hybrid CNN+LSTM+Dense model combining ECG, PPG, and physiological data to evaluate blood pressure, satisfying AAMI standards and achieving A and B grades according to BHS. Furthermore, DL models have been applied to predict intraoperative hypotension (IOH), defined as MAP < 65 mmHg during surgery. Jo et al. [216] devised a ResNet model that, using ECG and arterial blood pressure (ABP) data, predicted IOH 3 and 5 min prior with AUROCs of 0.970 and 0.935, and AUPRCs of 0.943 and 0.882, respectively (refer to Table 9 for details).

Others

Fan et al. [217] put forth LSTM and BiLSTM models capable of forecasting elderly health status over the following day using single-lead ECG, achieving impressive AUROC and Accuracy rates of 0.9312 and 93.21% for health status prediction, respectively. Butt et al. [218] introduced the SGDM-AlexNet-CNN model, which classifies falls and activities with a Validation Accuracy of 98.44%. Attia et al. [219] developed a CNN-based model that utilizes 12-lead ECG to determine gender with a Sex Prediction AUC of 0.97 and Accuracy of 90.4%. Several researchers [172, 220–223] constructed DL models to estimate ECG-derived age, achieving a best mean absolute error (MAE) of 5.8 ± 3.9 years; they also found that individuals with a significant discrepancy between ECG-age and actual age face a significantly elevated risk of death [220, 223]. Iakunchykova et al. [224] utilized a CNN model revealing a statistically significant correlation ($r = 0.12$, $p < 0.0001$) between heart delta age (HDA) and brain delta age (BDA). Mori et al. [225] introduced a CNN-LSTM model for diagnosing autism spectrum disorder (ASD) in minors, achieving AUC and Accuracy values of 0.95 and 0.89, respectively. Lou et al. [226] proposed a CNN model to diagnose Left Atrium Enlargement (LAE), reporting AUCs of 0.8688 and 0.8990 for moderate and severe LAE, along with C-indices of 0.688 and 0.806 for predicting Stroke and AF occurrences. Liu et al. [227] combined D-dimer, ECG, and Chest X-ray (CXR) to diagnose aortic dissection (AD) with an AUC of 0.943. Another study by Liu et al. [228] presented a DL model to diagnose Acute Pericarditis using 12-lead ECGs, attaining an AUC, Sensitivity, and Specificity of 0.954, 78.9%, and 97.7%; when coupled with the STEMI-DLM [53], specificity improved to 99.4%. Gomes et al. [229] developed a DL model proficient at classifying arrhythmic ECGs and ECGs from COVID-19 patients. Hassan et al. [230] demonstrated excellent performance of their DL model in diagnosing COVID-19 in patients with heart disease. Lastly, Gupta et al. [231] constructed a DCM model capable of identifying fetal arrhythmia (FA) through Fetal ECG, achieving an AUC, accuracy, and precision of 99.57%, 94.18%, and 95.63% for FA diagnosis (refer to Table 10 for details).

Discussion

Through a comprehensive review of existing research, the application of DL in ECG analysis has become increasingly common, with CNN and RNN serving as the core frameworks and continuously undergoing innovative improvements. However, ECG signals are characterized by high noise and complexity, posing stringent requirements for preprocessing techniques. Factors such as baseline wander and electrode position can affect signal quality and model performance. Therefore, optimizing preprocessing techniques, including noise reduction and standardization, has become a crucial breakthrough. From the aforementioned research, it is evident that datasets, as the core of DL model construction, exhibit two main characteristics in their selection and application. Firstly, in the early stages of research, scholars tend to adopt publicly available datasets, such as the MIT-BIH database, which are easily accessible and comprehensive, greatly simplifying the data collation process and providing convenience for interdisciplinary and junior researchers. Secondly, there is a focus on the application of public and proprietary datasets in disease model construction. Public datasets are commonly used for model training in diseases such as coronary artery disease (CAD) and arrhythmias, while proprietary datasets are more often seen in conditions like heart failure (HF) and cardiomyopathy. These differences stem from factors such as the difficulty of data collection, the purpose of database creation, and the openness of public datasets. Nevertheless, the inherent differences among various datasets may significantly affect model performance, necessitating a clear understanding of the specificities of each dataset. It is noteworthy that transfer learning has demonstrated significant value in addressing issues of data scarcity and heterogeneity, aiding in reducing training time and enhancing model effectiveness. However, its complex parameter tuning and limited flexibility limit its application prospects, necessitating further exploration.

Multiple studies reviewed here are based on local lead ECGs from wearable devices, particularly single-lead ECGs, which show great potential in daily health management. Nevertheless, wearable devices also face numerous challenges. For instance, static ECG models struggle to adapt to dynamic conditions, and noise and artifacts can lead to false alarms. While single-lead data offer convenience, it may also result in the loss of critical information. Additionally, the issue of protecting the privacy of health data has become prominent. Currently, most models exhibit significant limitations when faced with the complex and variable ECG diagnoses encountered in clinical practice. There is an urgent need to develop a comprehensive model with strong generalization ability and high recognition accuracy. This necessitates the establishment of large-scale, multi-center databases covering diverse disease types and geographical regions, combined with continuous optimization of model performance through advanced model structures and feedback mechanisms.

It is common knowledge that the rigor, comprehensiveness, and feasibility of experimental design directly affect the reliability of research outcomes. In early DL and ECG studies, experimental designs were relatively simplistic, and while dividing datasets for training and testing yielded good performance indicators, they did not fully demonstrate the practical application value of the models. Nowadays, experimental designs have become more sophisticated, introducing validation sets, external test sets, and multi-dimensional evaluation metrics to comprehensively assess model performance. Methods

such as tenfold cross-validation are also employed to reduce data selection biases. However, no matter how optimized, experimental designs may still conceal potential issues. For example, limited data sources may lead to selection bias, and the complexity of clinical diseases can also affect ECG interpretation. Therefore, when evaluating model performance, it is essential to consider not only numerical indicators but also the prerequisites and clinical application significance of model construction. Additionally, the standardization of electrocardiographic data represents a critical issue for future research, as there is currently a lack of standardized ECG input types and preprocessing protocols. As previously mentioned, the ECG data utilized in studies are often derived from different devices, and preprocessing protocols vary across different researches. It is important to emphasize that model performance may vary due to differences in signal acquisition and processing methods. Therefore, we cannot solely judge the performance of a model based on numerical differences; similarly, it is uncertain which form or preprocessing method can fully unleash the potential of deep learning techniques. Moreover, the heterogeneity of ECG signals demands models with robust generalization capabilities to maintain consistent performance across diverse patient populations and clinical settings. Models also require continuous updates and iterations to retain their clinical relevance. Thus, the application of deep learning in ECG requires not only continuous exploration and discovery of new model characteristics by each researcher, but also the establishment of unified standards within the industry to provide a solid platform.

Currently, some studies have successfully integrated model performance with clinical applications, such as the AI-S active alert strategy [54] in reducing diagnosis time for MI patients and successful cases in screening non-adaptive populations for S-ICD [198] and predicting VF onset [183]. These examples demonstrate the practical utility of models in clinical practice. However, questions remain regarding how to ensure the rationality of model performance improvements, their alignment with clinical logic, and their specific clinical value. It is recognized that many deep learning models are termed "black boxes", owing not only to their complex internal structures, intractable decision paths, and the uncertainty inherent in their training processes, but also to the insufficient exploration of disease-relevant information embedded within the signals during their construction. This diminishes the models' efficacy and interpretability, thereby impeding their application in clinical practice. Clinical practitioners value the reliability of evidence-based medicine; without understanding how a model arrives at specific diagnoses, there is a lack of trust in the model's decision-making process. Even though some models have been compared to the diagnostic acumen of clinical physicians, showing a slight superiority in overall diagnostic performance [86, 185], this indicates that significant improvements are needed before deep learning models can be applied in clinical settings. Additionally, the acceptance of novel assistive diagnostic devices by patients and their families is a concern, especially in remote or medically underserved hospitals. Furthermore, ECG analysis models, as medical devices, must navigate stringent regulatory approval processes, such as FDA's 510(k) clearance and the European CE marking. These approval processes can be both time-consuming and costly, limiting the models' ability to quickly enter clinical practice. Moreover, medical devices must undergo rigorous testing and evaluation to ensure their safety and efficacy. In this process, the number

of algorithms may serve as an indicator of a product's maturity and diversity. Thus, the assessment of the number of algorithms in medical devices is also a crucial step. Therefore, despite the rapid development of deep learning, there is no evidence to suggest that the role of human experts in ECG analysis will be eliminated. It should be emphasized that deep learning algorithms are designed for computer-assisted interpretation, serving as a decision support system to assist human experts, rather than replacing them. In the foreseeable future, the central role of trained cardiologists in ECG analysis remains unassailable.

In the future, we look forward to more studies that can balance the feasibility of clinical applications with the robustness of model performance, jointly advancing the field of DL and ECG to provide more accurate and efficient diagnosis and treatment solutions for patients.

Limitations

In this study, the latest research on the application of deep learning in electrocardiography has been analyzed from multiple perspectives to reveal the hot spots in this field. However, for the construction of some deep learning models, such as the process of computer development programs, design concepts, and methods, only a general outline of development has been shown, without intuitive presentation of the details, and more attention has been paid to their relevance to clinical applications. In addition, this study selected the Web of Science literature search platform under the premise of complying with the (PRISMA) guidelines, and if databases such as PubMed or Scopus are added for search, it may result in a larger sample size and reduce selection bias.

Conclusion

This article focuses on the application of deep learning and ECG in the field of cardiovascular diseases. It systematically reviews the research trajectory encompassing 198 articles, presenting them in a chronological order to closely align with clinical research practices. The application prospects of AI in the medical field are vast, but to build reliable DL models that meet clinical needs requires not only the support of a vast database but also close collaboration among clinicians, data researchers, and programmers. Additionally, we must recognize that while AI is powerful, it cannot replace the professional knowledge of doctors. Instead, it should serve as an auxiliary tool to enhance diagnostic accuracy, treatment precision, and prognostic improvement capabilities. Otherwise, when significant clinical errors occur in AI, issues of responsibility attribution become inevitable. Furthermore, the integration of AI with clinical practice may affect the doctor–patient relationship, which requires careful consideration based on the development level of AI and policy formulation. These issues are complex and challenging, necessitating our collective efforts to address and resolve them.

Author contributions

W is mainly responsible for the writing of articles and the specific work of submission. G is mainly responsible for the idea construction of the article, the revision of the article and the selection of the journal for submission.

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