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Detecting Cardiac Arrhythmias through Electrocardiography: Current Advancement and Future Direction from the Standpoint of Deep Learning

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Abstract

Cardiac arrhythmia remains a leading cause of mortality worldwide and is a significant risk factor for the development of various cardiovascular diseases. Electrocardiography (ECG) is a widely utilized diagnostic tool for the early detection of cardiac arrhythmias, and recent advancements in deep learning (DL) have demonstrated notable success in automating and enhancing this process. Despite the growing body of research, there remains a lack of a focused and comprehensive literature review dedicated specifically to the application of deep learning techniques in ECG-based arrhythmia detection. Addressing this gap, the present study systematically reviews recent contributions that apply deep learning algorithms to ECG data for the identification and classification of cardiac arrhythmias. The review categorizes relevant studies based on architectural approaches, datasets used, performance metrics, and clinical relevance. A novel taxonomy is proposed to classify the domains of deep learning applications in ECG, including supervised, unsupervised, and hybrid learning models, as well as real-time and offline diagnostic systems. The review also identifies current limitations in model generalizability, data quality, and interpretability. Based on these insights, future research directions are proposed to guide the development of more robust, transparent, and clinically applicable deep learning systems for cardiac arrhythmia detection. This review serves as a foundational reference for researchers and practitioners seeking to advance the intersection of artificial intelligence and cardiovascular diagnostics.

Keywords: Cardiac Arrhythmia; Electrocardiography (ECG); Deep Learning; Cardiovascular Diagnostics; Automated Detection

Introduction

The World Health Organization reports cardiovascular diseases as the primary cause of death, claiming 17.3 million lives annually. ECG, a tool for diagnosing and managing these diseases, has proven valuable (Koppad, 2021). ECG aids in arrhythmia detection, prognosis, technical quality assurance, measurement quantification, and pattern identification, providing a direct, non-invasive evaluation of heart electrical function disruptions (Shen et al., 2021). ECG devices offer real-time data on heart parameters, making them suitable for machine learning analysis. However, hand-crafted features require extensive domain knowledge, making the process time-consuming. Despite this, numerous machine learning solutions exist for ECG data classification (Wang et al 2019). Additionally, machine learning models often encounter significant issues with vanishing gradients and overfitting, which negatively impact the performance of the training model (Chen et al, 2018).

Deep learning algorithms address shallow machine learning limitations by automatically learning features from a dataset, relying on their learning process during the training phase (Asif et al., 2020). Deep learning algorithms excel in large datasets, particularly when addressing the vanishing gradient problem, enabling the uncovering of clinically relevant health data for treatment, decision-making, and disease prevention (Taha et al. 2019).

Deep leaning has shown remarkable success in various applications, including computer vision (Voulodimos et al. 2018), object recognition, detection, and segmentation (Wang 2016), face recognition(Shepley 2019), speech recognition (Azzeh et al. 2019), image classification and localization(Pak and Kim 2017), natural language processing (Cambria et al. 2018), robotics (Gashler and Pierson 2017), medical imaging (Junet al. 2017) and more, surpassing traditional machine methods and feature engineering. The application of deep learning for detecting ECG cardiac arrhythmia is attracting significant interest from the research community.

This paper provides a comprehensive systematic review of the literature on the use of deep learning in detecting cardiac arrhythmias in ECG data, despite growing interest in this field. The review is divided into three perspectives: (1) a technical overview of deep learning techniques used to identify cardiac arrhythmias in ECG, (2) an examination of how algorithms are applied in ECG analysis, and (3) Synthesis and evaluation of existing literature. This systematic review provides a roadmap for novice researchers and updates experts on developing new solutions and applications for detecting cardiac arrhythmia using ECG.

The lists of contributions of the survey article are summarized as follows:

- This summary outlines the primary deep learning algorithms used in various projects to address complex ECG cardiac arrhythmia detection issues. From a technical standpoint, the basic functions and widespread use of these algorithms are categorized, resulting in a taxonomy that include Convolutional Neural Network (CNN) Recurrent Neural Networks (RNN), Deep Neural Network, Deep Belief Network, Graph Convolutional Network and hybrid models that combine CNNs with long Short-Term Memory (LSTM) networks.
- A thorough review of the literature on the use of deep learning algorithms to address issues in ECG cardiac arrhythmia detection is presented
- A taxonomy on the application of deep learning algorithms in ECG cardiac arrhythmia detection in healthcare has been developed
- The publications trend up to 2024, the popularity of different deep learning variants in ECG arrhythmia detection, and the data sources are outlined.
- The study addresses research challenges in implementing deep learning in ECG cardiac arrhythmia detection, offering new perspectives and theoretical guidance for practical implementation.

Methodology

This section outlines the systematic literature review process for analyzing deep learning applications in ECG cardiac arrhythmia detection, covering search keywords, techniques, data sources, databases, and inclusion/exclusion criteria. The systematic literature review follows the procedure outlined in (Weidt, F., & Silva, 2016) for systematic literature review in computer science. The methodology from (Falkner et al., 2019) is also used to conduct our systematic literature review.

1. Keywords

The review objective was established, and keywords were carefully chosen to retrieve relevant articles. Key keywords included "Deep Learning (DL) and Electrocardiogram (ECG)," "Convolutional Neural Network (CNN) and Electrocardiogram (ECG)," "Recurrent Neural Network (RNN) and Electrocardiogram (ECG)," "Long Short-Term Memory (LSTM) and Electrocardiogram (ECG)," "Deep Neural Network (DNN) and Electrocardiogram (ECG)," "Deep Belief Network (DBN) and Electrocardiogram (ECG)," and "Graph Convolutional Network (GCN) and Electrocardiogram (ECG).

2. Searching the articles

The search process involved reviewing articles matching keywords, identifying relevant papers through citations, and was conducted from August 12-30, September 20- October 10, and November-December 2024.

3. Academic databases

The study gathered literature from reputable peer-reviewed journals, edited books, and conference proceedings indexed in academic databases. Searches were refined to include publications from 2015 onwards, as most relevant articles were from 2017 to the present.

Table 1: Academic databases used and their links

Academics Database	Link
Google scholar	https://scholar.google.com/
PubMed	https://pumed.ncbi.nlm.nih.gov/
Scopus	https://www.scopus.com/
IEE Explore	http://ieeexplore.ieee.org/
DBLP	http://dblp.uni-trier.de/
Science Direct	http://www.sciencedirect.com/
ACM Digital Library	http://dl.acm.org/

Springer Link	http://www.link.springer.com/
ISI Web of Science	https://apps.webofknowledge.com/

4. Article Inclusion/Exclusion Criteria

The review used specific criteria to select relevant articles, assessing titles, abstracts, conclusions, and full content, as detailed in Table 2.

Table 2: Inclusion and exclusion criteria

S/N	Inclusion	Exclusion
1	The review focuses on only deep learning architecture	Articles on traditional machine learning were not considered
2	Articles with the application of deep learning in ECG for cardiac arrhythmia detection were considered	Articles with shallow algorithms were excluded
3	Articles published in reputable peer-reviewed journals, conference proceedings, and edited books were considered.	Articles published as part of textbooks, abstracts, editorials, and keynote speecheswere excluded.
4	Only articles written in the English languagewere considered for the review.	Articles written in other languages were notconsidered for review.

5. Eligibility

The eligibility of the selected articles was determined by applying the established criteria to those retrieved from academic databases. Initially, 6,435 papers were obtained from all databases. After removing duplicates and excluding articles based on their titles, 4,213 papers were discarded. In the second stage, abstracts and conclusions were reviewed, resulting in the rejection of 2,222 additional articles. At the final stage, a full-content review was conducted, leaving only 54 papers, which were ultimately included in the review.

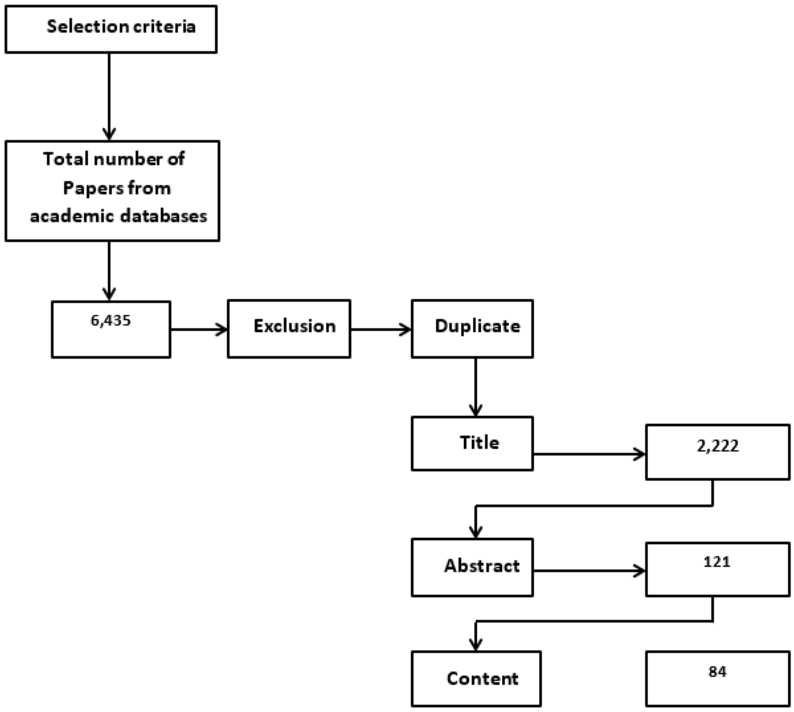

Figure 1: Articles exclusion processes

Deep Learning

Deep learning, a subset of machine learning, has garnered significant attention across various fields due to its exceptional power and accuracy in processing large datasets (Saduf et al., 2020). It is a type of artificial neural network composed of multiple layers, often numbering in the tens or even hundreds, each layer capturing increasingly detailed representations of the input (Wani et al., 2020). This layered approach allows models to uncover the hierarchical structure of data by learning both localized and interconnected patterns (Haque and Neubert, 2020). In ECG analysis, deep learning is particularly effective because of its ability to extract complex features directly from raw input data. It has also been applied to challenging areas in machine learning, such as image classification, voice recognition, handwriting transcription, natural language processing, autonomous vehicles, and more. Figure 2 illustrates the taxonomy of deep learning architectures.

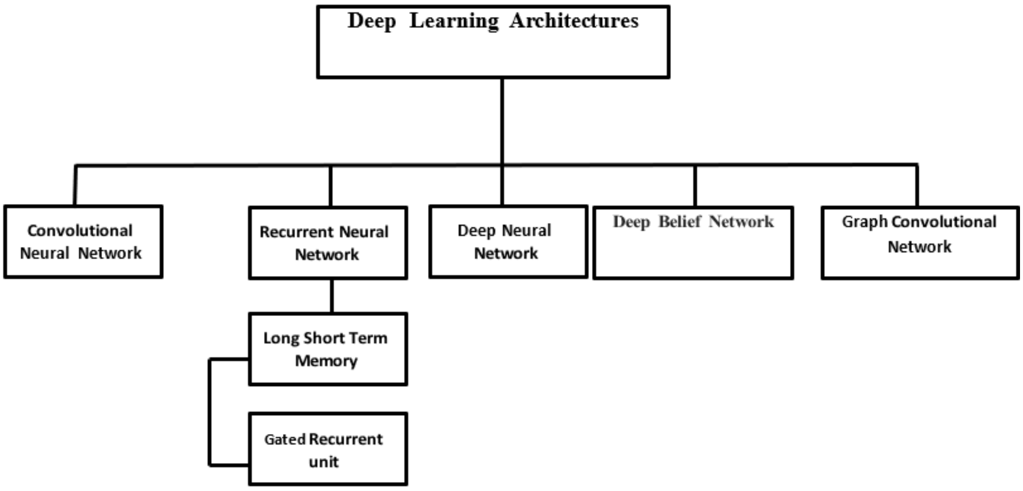

Figure 2: Taxonomy of Deep Learning Architectures

This study examines deep learning architectures used in electrocardiography (ECG) for cardiac arrhythmia detection, focusing on models specifically developed for this purpose.

1. Convolutional Neural Network (CNN)

CNNs are deep learning models used for signal analysis, image recognition, pixel data processing, and natural language understanding, detecting spatial hierarchies and patterns through trainable filters called kernels (Zhou et al., 2020). CNNs are effective in extracting local details from ECG data, aiding in diagnosing arrhythmias, and have shown strong performance in handling text and audio data types. CNNs consist of various layers, each performing different functions:

- **Convolution Layer:** The CNN core layer uses convolution operations to identify features in localized input regions, producing feature maps through each filter moving over sub-regions.
- **Activation Function Layer:** After the convolution layer, this layer applies an activation function (such as the Rectified Linear Unit, or ReLU) to introduce non-linearity, speeding up training. ReLU is mathematically defined as: f(x)=max(0,x)f(x) = max(0, x)f(x)=max(0,x)
- **Pooling Layer:** This layer reduces the input's size by summarizing feature maps and discarding non-essential data, while preserving key features.

- **Fully Connected Layer:** Used for classification, this layer connects every neuron in one layer to every neuron in the next. It processes the extracted features to make a classification decision.
- **Dropout Layer:** Helps to prevent overfitting by randomly disabling a fraction of neurons during training.

2. Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNNs) (Elman, 1990) are well-suited for handling sequential data, making them ideal for tasks involving speech, video, and text. RNNs excel at retaining temporal information, which is crucial for analyzing time-dependent data like ECG signals, where detecting abnormalities in cardiac rhythms requires sequential analysis (Khan & Kim, 2021). RNNs process sequences by utilizing both recent and past inputs to generate new outputs, effectively storing temporal information across time steps. The depth of an RNN can extend as far as the length of the input sequence (Deng, 2014). RNNs are effective in predicting words or characters in series, but face challenges like the "vanishing gradient" problem, where gradients diminish over time (Deng, 2014).

Long Short-Term Memory (LSTM)

LSTM is a variant of RNN developed to address the vanishing gradient problem inherent in standard RNNs (Brakel et al., 2016). LSTMs consist of three primary layers: the input layer, recurrent hidden layer, and output layer (Ma, Tao, Wang, Yu, & Wang, 2015). LSTM architectures consist of memory blocks with shared input and output gates, which regulate error flow and resolve weight conflicts within the memory cell (Hochreiter & Schmidhuber, 1997). The constant error carousel (CEC) is a crucial memory cell component that maintains the cell's state through multiplicative input and output gates, addressing the vanishing gradient issue (Ma et al., 2015). The memory block also includes a **forget gate**, designed to reset outdated information and prevent unlimited growth of internal cell values, especially in continuous time-series data (Tao et al., 2015).

3. Deep Neural Network (DNN)

A Deep Neural Network (DNN) is a type of deep learning architecture commonly used for solving both regression and classification tasks (Masci et al., 2017). DNNs are structured hierarchically, with each layer consisting of multiple neurons. As input data passes through successive layers, the network progressively learns more complex patterns (Farman et al., 2019). Deep Neural Networks (DNNs) use feed-forward networks for handling non-sequential data and can be trained using supervised and unsupervised learning techniques. Supervised learning uses labeled data for weight adjustments, while unsupervised learning uses feature extraction, clustering, and dimensionality reduction (Rav et al., 2017). DNNs, despite their broad applications in healthcare, robotics, gaming, and autonomous vehicles, face limitations due to the need for large datasets and computational resources.

4. Deep Belief Network (DBN)

A Deep Belief Network (DBN) (Hinton & Salakhutdinov, 2006) is a generative neural network composed of multiple layers. In DBNs, each layer contains visible units connected to hidden units, but the units within each layer are not interconnected (Khan et al., 2020). DBNs are typically constructed by stacking Restricted Boltzmann Machines (RBMs) or auto-encoders, with the hidden variables from one layer serving as the visible variables for the next layer. DBNs utilize probabilistic models to identify intricate data patterns, making them ideal for high-level abstraction applications like detecting hidden arrhythmia patterns in ECG signals (Taji et al., 2017). DBNs model ECG data to detect abnormal heartbeats and arrhythmias, but rely on large labeled datasets, challenging due to scarcity. They can be trained unsupervised (Wani et al., 2020).

5. Graph Convolutional Network (GCN)

Graph Convolutional Networks (GCNs) are popular graph networks that enhance filter performance by integrating the Fourier transform and Taylor expansion formula, learning features from neighboring nodes (Liang et al., 2021). The primary objective of GCNs is to classify graphs, nodes, or connections (Wu et al., 2020). GCNs can be categorized into two key types of algorithms: Spectral Graph Convolutional Networks (SGCNs) and Spatial Graph Convolutional Networks (SGCNs).

Overview of ECG: background, component, and clinical significance

Electrocardiogram (ECG) is a widely utilized tool in clinical medicine for the evaluation of heart health due to its low cost, simplicity, and non-invasive nature, making it a preferred method for diagnosing a variety of cardiac disorders, including arrhythmias (Dilaveris et al., 1998; Elgendi et al., 2014). The ECG waveform, consisting of key components reflecting cardiac cycles, is crucial for analyzing and diagnosing cardiac conditions, detecting arrhythmias, and enhancing heart electrical activity. Figure 3 illustrates the primary components of ECG waveforms recorded by an ECG machine:

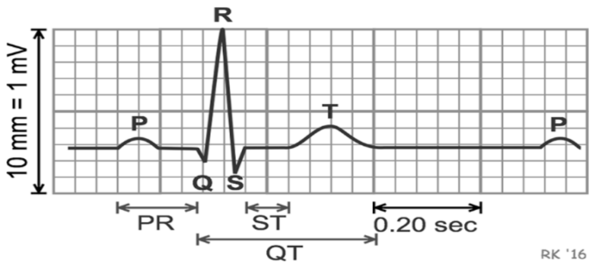

Figure 3: The ECG signal components

- **P Wave**: Represents atrial depolarization, the process by which the atria contract and pump blood into the ventricles.
- **QRS Complex**: Indicates ventricular depolarization, during which the ventricles contract and pump blood to the lungs and the rest of the body. It is typically the most prominent feature of the ECG waveform.
- **T Wave**: Reflects ventricular repolarization, the period when the ventricles recover from the contraction phase and prepare for the next heartbeat.

ECG provides clinical information for diagnosing heart conditions, including electrical conduction and heart muscle workload. It measures the duration of impulses and indicates overworked or enlarged heart muscle parts.

Deep learning algorithms applied in ECG for detecting cardiac arrhythmia

In this section, we present different projects where researchers applied deep learning algorithms to solve problems in ECG for detecting cardiac arrhythmia. Figure 4 is the taxonomy of the application of deep learning in ECG for detecting cardiac arrhythmia. The taxonomy indicates the deep learning algorithm in the relevant ECG.

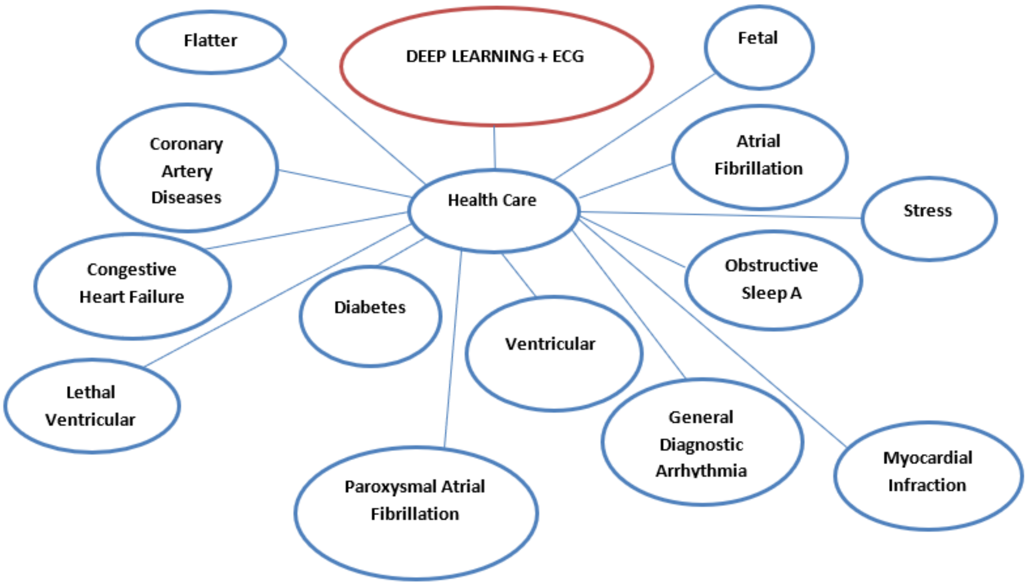

Figure 4: Taxonomy of the application of deep learning in Electrocardiogram

1. Convolutional Neural Networks (CNNs)

Various projects have employed Convolutional Neural Networks (CNNs) for analyzing ECG signals to address a range of issues. Table 4 provides an overview of these applications. Here, we summarize the uses of CNNs in ECG analysis:

CNNs in ECG Analysis

This section examines the application of CNNs to ECG-related problems.

Table 3 shows the summary of the Convolutional Neural Network applications in ECG.

Table 3: Summary of the Convolutional Neural Network applications in ECG

Reference	Proposed algorithm	Database	Results	Limitation
Li et al. (2017)	ID-CNN	MITDB (48 records)	Acc = 97.5%	J. Takes a lot of training time K. It will require new training when the model is changed L. More leads should be investigated
Acharya et al. (2017)	CNN	PTBDB (200 subjects)	Acc = 93.53% Sen = 93.71% Spe = 92.83% (with noise), Acc = 95.22% Sen = 95.49%Spe = 94.19% (without noise)	• Takes too much time during training. • Requires huge data.
Xiong et al. (2017)	CNN, RNN, Spectrogram + GoogleNet	Physionet/CinC Challenge 2017 (8,528 records)	F1 scores: 0.82 (CNN), 0.72(RNN)	• Limited dataset for training. • Imbalance ECG data problem and varying signal lengths. • Propose data augmentation

				to solve the class imbalance and the problem.
Zhang et al. (2017)	2D-CNN	SADB (10 subjects)	ID rate = 98.4%	• Require a large dataset for training to improve performance. • The acquired data werenoisier and weaker than the standard chest-ECG.
Pyakillya et al. (2017)	ID-CNN	PhysioNet/CinC Challenge 2017 (Not stated)	Acc = 86%	• Imbalance data problem, which can be solved using GAN networks. • Unsatisfactory comparison to other DL solutions in terms of computational complexity, proposed architecture, and optimization methods.
Hagiwara, et al., (2017)	CNN	CUDB, AFDB, MITDB (21,709 segments of 2s (Net A), 8683 segmentsof 5s (Net B)	Net A: Acc = 92.50% Sen = 98.09% Spe = 93.13% Net B: Acc = 94.90% Sen = 99.13% Spe = 81.44%	(i) Require more data for training (ii) Long convergence time (iii) Data augmentation and bagging algorithm should beconsidered **M.**
Xia et al. (2018)	STFT-DCNN, SWT-DCNN	AFDB (23 records)	STFT-DCNN Sen= 98.34%, Spe = 98.24%Acc = 98.29% SWT-DCNN: Sen = 98.79%, Spe = 97.87% Acc = 98.63%	• Small number of datasetswas used
Amrani et al. (2018)	Very deep CNN and MCCA Fusion + QG-MSVM, Very deep CNN without Fusion QG-MSVM	MITDB, AFDB, SVDB (111,901 ECG segments)	Acc = 94.74% (without fusion techniques) Acc = 97.37% (applying MCCA)	• The fusion technique may increase computational time
Kachuee et al. (2018)	Deep residual CNN	MITDB (47 subjects), PTBDB (290 subjects)	Heartbeat classification: Acc = 93.4% MI classification (PTBDB): Acc: 95.9% Precision: 95.2% Recall: 95.1%	• Require more data for training to improve performance
Dey et al. (2018)	CNN	Apnoea-ECG dataset from Physionet (35subjects)	Acc: 98.91%, Sen: 97.82%, Spe: 99.20%	• Takes too much time duringtraining • Mostly expert observation is an off-line process • The model can be applied on EEG, EOG, EMG for same purpose

Z. Yao & Chen, (2018)	MCNN	MITDB (48 records), private dataset HEDB (22 records)	Over all Acc = 0.8866,Acc = 0.9600 (SVEB) Acc = 0.9250 (VEB)	• Propose to use land mark information of rhythm to improve performance
Deshmane & Madhe (2018)	1D-CNN	MITDB, Fantasia database, NSRDB and QT (210 subjects	Acc = 81.33% (MITDB), 96.95% (Fantasia database), 94.73% (NSRDB), 92.85% (QT)	1. Need for more dataset for training and testing model
TaherIsadr et al. (2018)	MFSC + DCNN, TF + DCNN	Naturalistic setting where subjects drove a real car (Ford Escape 2015) (10 subjects)	Acc around 95.51%	• Small population is used in the study
(Diker and Engin 2019)	CNN + ELM	PTBDB (294 subjects)	Acc= 88.33%, Sen = 89.47% Sp = 87.80%	• DL architectures will be investigated for classification to improve performance
(Hao et al. 2019)	WT and STFT + Multi-channel dense CNNs	Dataset from Biofourmis for training (more than 10,000 ECG records), MITDB for testing (44 subjects)	Sen = N (97.0) L (98.9) R(91.4) V (95.0) S (90.4) PPV= N (97.7) L (92.2) R(90.2) V (94.5) S (91.5)	• Limited dataset was used
(Pandey and Janghel 2019)	CNN + SMOTE	MITDB (47 subjects)	Acc = 98.30% Pre = 86.06% Recall: 95.51% FI-Score = 89.87%	• Larger dataset is required for training to improve generalization ability • Require implementation using real dataset
(Kaouter et al.2019)	CNN	MITDB (47 subjects), NSRDB (18 subjects), BIDMC congestive heart failure database (15 subjects)	Acc = 93.75%	• Require more data for training model • Other parameters of patients other than ECG signals can improve the diagnostic value of the proposed model
(Ahmed et al. 2019)	CNN-ACO	UCI-ML Repository (43,401 people's records)	accuracy = 95.78%	• Consumes memory • MapReduce to reduce memory consumption
(Baloglu et al.2019)	Deep CNN	PTBDB (200 subjects)	Acc = 99.78%, Sen = 99.80%	• Time computational cost • The MI location in ECG signals was not considered
(Dokur and Ölmez 2020)	CNN without FCNN	MITDB (47 subjects)	Acc = 99.45% (ID ECG signals),98.7% (2D ECG images)	• Limited in detecting arr ythmis • The proposed model can be deployed on mobile phones
(Ribeiro et al.2020)	ResNet	Private dataset having 2,322,513 ECG records from 1,676,384 different patients	F1- score > 80%Spe > 99%	• It was not convincing that the proposed model is better than the medical residents and students, with statistical significance on the

		of 811 counties in the state of Minas Gerais/ Brazil, from the TNMG		McNemar statistical test and bootstrapping • The proposed model can be applied to myocardial infarction, cardiac chamber enlargement
(Shaker et al.2020)	Deep-CNN and Two-stage deep-CNN	MITDB (48 records)	Acc > 98.0%, Pre > 90.0%, Spe > 97.4%, Sen > 97.7%	• Need to apply post-processing using a smoothing filter to enhance the quality of heartbeats • Outlier removal should be applied to enhance the precision of results • another variant of GAN should be investigated with different deep network architectures
(Byeon et al.2020)	Ensemble of Xception, ResNet, and DenseNet	PTBDB (290 subjects)	The best accuracy of the ensemble by time frequency representation is Xception of 99.05% using an average of scores from log spectrogram to spectrogram. The best accuracy of the ensemble by the open CNN model = MFCC of 99.04% using an average of scores from Xception to DenseNet	• More robust ensemble methods will be studied
(M.-G. Kim et al.2020)	Parallel ensemble CNN	MITDB (47 subjects) and acquired ECG signals for 89 adults in different states	Acc = 98.5%	• A small population was used • Only one device was used to acquire ECG signals • Wearable devices should be used to acquire ECG data for real applications
(Y. Li et al. 2020)	(F-CNN + M CNN)	FANTASIA (40 subjects), CEB-SDB (20 subjects), NSRDB (18 subjects), STDB (28 subjects), AFDB (23 subjects)	Acc = 94.3% (3s, 18-40 subjects), 97.1% (7s with the 5 datasets)	• Intra-subject factors problem • Proposed to capture more robust characteristics by eliminating the effect of different states should be investigated
(Essa et al. 2021)	CNN	MIT-BIH standard database	Acc = 95.81%	• It causes over-fitting, exploding gradient, and class imbalance. • It does not immediately corrode
(Cui, J et al. 2021)	1D-CNN	MIT-BIH database's	Acc = 98.35%	• It has inherited noise. • It ignores some essential features.

(Hassan et al. 2022)	CNN-BiLSTM	MIT-BIH dataset	Acc = 0.98	• It causes over-fitting, exploding gradient,and class imbalance.
(Yuanlu et al. 2022)	CNN	MIT-BIH database's	Acc = 98.65%	• It has an overfitting problem. • It has an exploding gradient
(Shadhon et al. 2022)	2D-CNN	MIT-BIH database's	Acc = 98.85%	• Performance depends upon input data. • It's a very sensitive network to noise data
(Huang et al. 2022)	CNN	MIT-BIH database's	Acc = 99%	• It has smaller time frames that cause the leakage issue
Ojha et al. (2022)	CNN-SVM	MIT-BIH	Acc = 99.53%	• Need for extra individually annotated beats. • class unbalances.
Midani et al. (2023)	CNN + BiLSTM	MIT-BIH	Acc = 97.63%	• small database for training and testing, and used R peak segmentation based on dataset annotation

2. Recurrent Neural Network – Long Short-Term Memory in ECG

Table 4 presents a summary of the applications of LSTM in ECG. The application of LSTM in solving different ECG problems has been found in many research studies (See Table 4).

Table 4: Summary of the Recurrent Neural Network – Long Short-Term Memory applications in ECG

Reference	Proposed algorithm	Database	Results	Limitation
(Cheng et al. 2017)	LSTM	Apnea-ECG database (70 ECGrecords)	Acc = 97.80%	• CNN should be explored
(Sujadeviet al. 2017)	RNN, LSTM,GRU	AFDB (25 signals), NSRDB(25 signals)	Acc: 0.95(RNN),1.00(LSTM),1.00(GRU) Pre: 1.00(RNN), 1.00(LSTM), 1.000(GRU) Recall: 0.889(RNN), 1.00(LSTM). 1.00(GRU) F-score: 0.941(RNN), 1.00(LSTM), 1.00(GRU)	• Only binary classification was performed. • The model lacks showing the inner mechanics of the deep models, this can be solved by transforming the non-linearity to a linearized form
(Shenfield, et al. 2018)	bi-LSTM	AFDB (23 subjects)	**Cross validation**: Acc = 98.51%,Sen = 98.32%, Spe = 98.67%,Ppr = 98.39%. **Blind fold validation**: Acc = 99.77%,Sen = 99.87%, Spe = 99.61%, Ppr = 99.72%	• Small number of population (data) used • Training speed during the design phase was too slow • Only the AF type is studied

(Singh et al. 2018)	RNN, GRU, LSTM	MITDB (47 subjects)	Acc = 85.4% (RNN), 82.5% (GRU), 88.1% (LSTM) Sen: 80.6% (RNN), 78.9% (GRU), 92.4%(LSTM) Spe: 85.7% (RNN), 81.5%(GRU), 83.35% (LSTM)	• Only binary classification is Performed. • Manual features were used. • Not clear if the proposed features will perform well onnew diseases
(Yildirim 2018)	DBLSTM-WS	MITDB (47 subjects)	Acc = 99.39%	• Not all heartbeats from MITDB were used due to the limitations of the hardware • Training cost problem
(Saadatnejad et al. 2019)	RR features and wave-let features + LSTM	MITDB(47subjects)	VEB Acc = 99.2 Sen = 93.0 Spe = 99.8 Ppr = 98.2 F1-score = 95.5SVEB Acc = 98.3 Sen = 66.9 Spe = 99.8 Ppr = 95.7 F1-score = 78.8	**N.** Limited dataset for training
(Darmawahyuni et al. 2019)	RNN, LSTM,GRN	PTBDB (290 subjects)	LSTM resultssen,98.49% spe,97.97% precision, 95.67%, F1-score, 96.32%, BACC, 97.56%, and MCC 95.32% (best performance)	• Initial performance wasaffected due to minimal preprocessing
(Darmawa-hyuni and Nurmaini 2019)	LSTM	PTBDB (290 subjects)	Pre = 0.91, Sen = 0.91, F1 score = 0.90, BAcc = 0.83, and MCC = 0.75	• The proposed model is simple and standard • Performance was not good enough due to minimal preprocessing
(Sharma et al. 2020)	FB expansion + LSMT	MITDB (2880 segments), PhysioNet/ CinC Challenge 2017 dataset (8528 segments)and privatedataset (301 segments)	Acc & F1 score = 90.07% (MIT-BIH dataset) Acc = 89.04% Sen = 75.68% Spe = 93.39% F1-score = 85.01% (private dataset)	• Only two classes, normal and arrhythmic, were detected. • Signal quality assessment was not applied before classification. • More ECG signals are needed to improve arrhythmia identification accuracy. • Limited to rhyme-based analysis, wherein morphologicalfeatures were difficult to detect
(Chang et al.2020)	LSTM	Dataset from China Medical University Hospital (CMUH) recorded by a GE Marquette MAC 5500 (38,899 subjects)	Acc ≥ 0.982 (range: 0.982–1.0) precisionranged from 0.692 to 1, recall ranged from 0.625 to 1 F1-score of ≥0.777 (range: 0.777–1.0).	2. The model did not detect ST-T change, but only predictedthe 12 rhythm classes. ST-T change is important for diagnosing acute myocardial infarction. 3. ECG noise may affect the performance of the proposed modelnegatively 4. More data is required for testing and training. The imbalance data problem 5. Increased computational costdue to QRS detection

3. Deep Neural Networks (DNN) for ECG Analysis

This section reviews various DNN models proposed by researchers to address problems in ECG analysis. Table 5 provides a summary of DNN applications in ECG research.

Table 5: Summary of the Deep Neural Networks applications in ECG

Reference	Proposed algorithm	Database	Accuracy	Limitations
Xu et al. (2017)	FDR + DNN	UCI cardiac arrhythmia dataset (245 normal, 206 abnormal)	Acc = 82.96%	• Small dataset, imbalanced data
Assodiky et al. (2017)	GA + DL, PSO + DL	UCI-ML Repository (452 samples)	PSO: Acc = 76.51%, GA: 74.44%	• Data imbalance, normal class is larger
Xu et al. (2018)	DNN	MITDB (47 subjects)	S-class: Sen = 66.2%, Spe = 98.6%	• Insufficient data, need a larger dataset for training
Sannino & De Pietro (2018)	Temporal feature extraction + DNN	MITDB (47 subjects)	Acc = 99.68%, Sen = 99.48%, Spe = 99.83%	• Heavy expert involvement, binary classification
Singh et al. (2019)	DNN	MIT-BIH	99%	• The best size of the hidden layer is obtained by GSA. • It has dice loss.
Hanbay et al. (2019)	DNN	MIT-BIH	96.40%	• Time-consuming feature learning phase • The effect of temporal waveform patterns on feature extraction.
Cho et al. (2019)	DNN	Driving data, Mental Arithmetic Data (31 subjects)	Acc = 90.19%	• Require a larger dataset, explore anxiety detection
Vullings et al. (2019)	DNN	Private dataset (266 healthy, 120 CHD subjects)	Acc = 76%	• Limited dataset, need for the larger sample population
Cai et al. (2020)	DDNN	China PLA General Hospital, CPS 2018 (11,994 subjects)	Acc = 99.35%, F1 = 90.7%	• Only AF detected, insufficient data for other classes, wearable devices

4. Deep Belief Network in ECG

The DBN has been used in diverse ECGs to solve various problems. In this section, different works involving DBN and a summary of the projects are presented in Table 6.

Table 6: Summary of the Deep Belief Network applications in ECG

Reference	Proposed algorithm	Database	Result	Limitation
Mostafa et al. 2017	DBN	St. Vincent's University Hospital/University College Dublin Sleep Apnea Database (8 subjects), PhysioNet Apnea ECG Database (25 subjects)	UCD database: 85.26%, Apnea ECGDB: 97.64%	• Issues with imbalanced data; hidden layers were optimized only for the UCD database; fixed DBN structure; small sample size.
Altan et al. 2018	Morphological Features, HOS, WPD, DFT + DBN	MITDB (48 subjects)	Accuracy: 94.15' Sensitivity: 92.64 Selectivity: 93.38	• Difficulty in comparisons due to varying heartbeat numbers across subjects; need for more training data.
Mathews et al. 2018	RBM-DBN	MITDB (48 records)	SVEB: 93.78%, VEB: 96.94% (a 360 Hz); SVEB: 93.63%, VEB: 95.57% (at 114 l	• Suggested future work on integrating RBM with ensemble/Bagging methods for developing multiple classifiers.

5. Graph Convolutional Network (GCN)

This section discusses a paper that applied a GCN-based model for ECG signal analysis. Table 5 summarizes the GCN application.

Table 7: Summary of the Graph Convolutional Network applications in ECG

Reference	Proposed algorithm	Database	Result	Limitation
Bahare et al. (2024)	GCN-WMI	chapman	Accuracy: 99.82%,	• requires strong systems

The domain of deep learning applications in ECG cardiac arrhythmia detection

Deep learning has been applied in various domains such as healthcare, driving, and biometric security to detect ECG cardiac arrhythmias. In driving, deep learning algorithms are used to detect distractions, drowsiness, stress, fatigue, and work load. In healthcare, deep learning is used to detect atrial fibrillation, coronary artery disease, stress, and more. In biometric security, researchers work on anomaly identification and authentication. As research continues, more domains and subdomains will be explored, highlighting the significance of deep learning in ECG cardiac arrhythmia detection. Figure 5 shows the taxonomy of the domains of DLA in ECG.

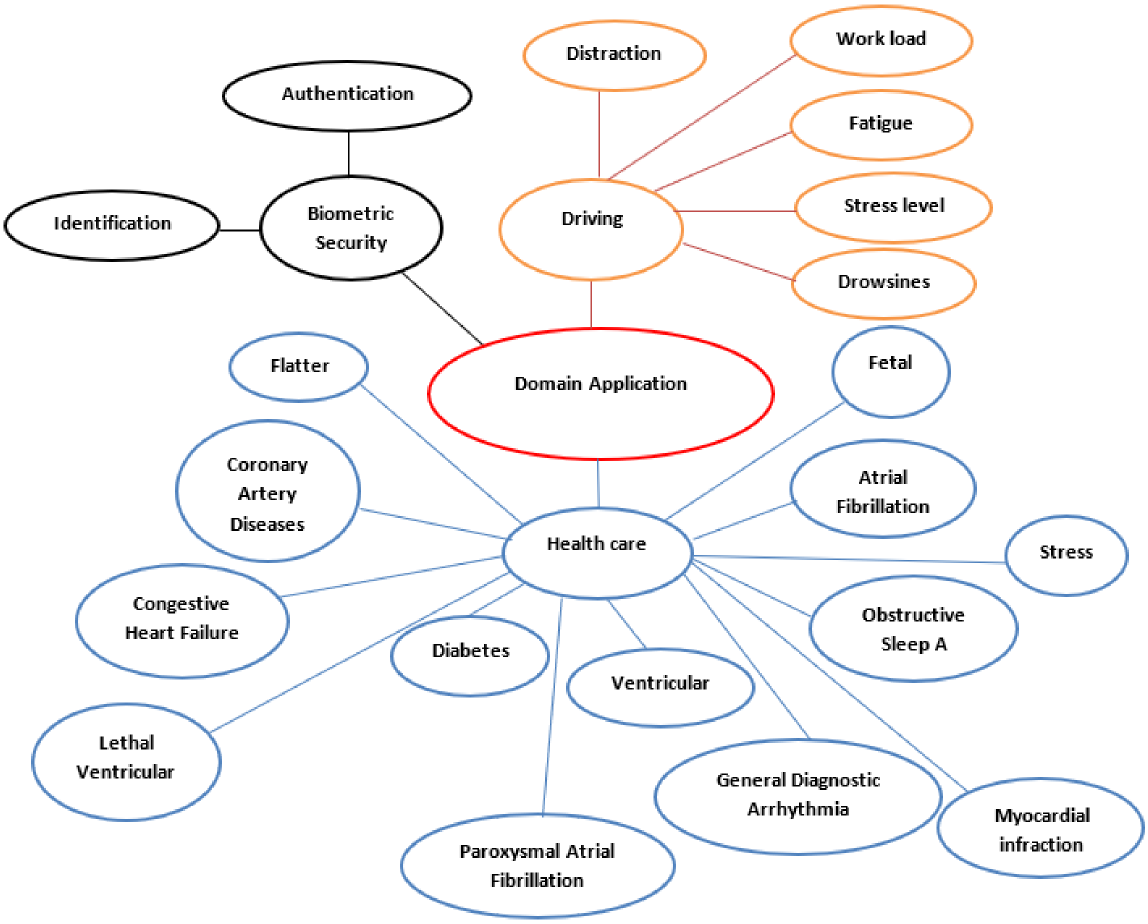

Figure 5: The taxonomy of the domains of deep learning applications in ECG cardiac arrhythmia detection

ECG cardiac arrhythmia detection datasets

This section provides sources of datasets for deep learning in ECG cardiac arrhythmia detection, aiding new researchers and expert researchers in starting research. Table 10 summarizes datasets used by different researchers, providing links for easy access. Projects that revealed the source of the dataset are included in Table 6, while those that didn't are not included.

Table 6: Summary of standard databases for cardiac arrhythmia detection

Database	Link
The Creighton University Ventricular Tachyarrhythmia Database (CUDB)	https://archive.physionet.org/physiobank/database/cudb/
MIT-BIH Noise Stress Test Database (NSTDB)	https://physionet.org/content/nstdb/1.0.0/

St Petersburg INCART 12-lead Arrhythmia Database (INCARTDB)	https://physionet.org/content/incartdb/1.0.0/
Long-Term AF Database (LTAFDB)	https://physionet.org/content/ltafdb/1.0.0/
MIT-BIH Supraventricular Arrhythmia Database (SVDB)	https://physionet.org/content/svdb/1.0.0/
Sudden Cardiac Death Holter Database (SCDDB)	https://physionet.org/content/sddb/1.0.0/
Normal Sinus Rhythm RR Interval Database (NSRDB)	https://physionet.org/content/nsr2db/1.0.0/
Georgia 12-Lead ECG Challenge Database (GA12ECG)	https://shorturl.at/qCN79
Apnea-ECG Database	https://physionet.org/content/apnea-ecg/1.0.0/
MIT-BIH Arrhythmia Database	https://www.physionet.org/content/mitdb/1.0.0/
PTB Diagnostic ECG Database	https://www.physionet.org/content/ptbdb/1.0.0/
European ST-T Database	https://physionet.org/content/edb/1.0.0/
The PhysioNet Computing in Cardiology Challenge 2017 (AFDB)	https://physionet.org/content/challenge-2017/1.0.0/
MITBIH Atrial Fibrillation Database	https://physionet.org/content/afdb/1.0.0/

Challenges and Future Research Directions

The integration of deep learning (DL) into electrocardiography (ECG) has delivered significant advancements. However, several unresolved challenges remain. This section discusses these challenges and outlines potential future research directions to further the field.

Benefit and challenges of deep learning for ECG cardiac arrhythmia detection

Deep learning has gained interest in automated feature extraction in ECG signal processing and diagnosis, but its predictive accuracy needs improvement. Interpretation is challenging and requires large datasets. Future research should explore hyperparameter optimization techniques, develop lightweight, clinically viable models for mobile applications, address model generalization across patient demographics, and ensure robustness against adversarial attacks.

Conclusion

This paper provides a comprehensive review of deep learning architectures applied to electrocardiography for cardiac arrhythmia detection, including both synthesis and analysis. It assesses the performance of deep learning in ECG over the past decade, highlighting its ability to achieve state-of-the-art results, often surpassing experienced cardiologists. This study serves as a benchmark for new researchers aiming to improve existing deep learning models for ECG signal analysis.

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