Arrhythmia Classification Using Deep Learning: A Review

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Abstract: In most hospitals, the diagnosis of medical disorders involves the traditional approach of doctors manually analyzing the medical reports of the patient. This method is not only time consuming and strenuous, but is also highly prone to human error. With the advent of deep learning technology, an efficient autonomous diagnosis method holds the possibility of replacing the existing tedious approach. This in turn results in the reduction of human error which is of major concern in the medical industry today. Through this paper, we aim to put forth an articulate review of the different deep learning methodologies, observed in the past four years, to classify arrhythmia using electrocardiogram (ECG) signals.

Keywords: Deep Learning, electrocardiogram signals, arrhythmia, CNN, RNN

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1. Introduction

Heart is a muscular organ located in the center of a human's chest, between the lungs. It consists of four chambers, the two upper chambers called the atria and the two lower chambers called the ventricles. Along with the help of the different blood vessels, the heart is responsible for pumping blood throughout the body and forms the center of the circulatory system.

According to the World Health Organisation (2017), the number one cause of death globally is cardiovascular diseases. This necessitates the need to monitor the heart in order to detect the heart ailments before they could become critical or life threatening. One such widely accepted approach for monitoring the heart is through recording the electrocardiogram (ECG) signal. ECG signals are the electrical representation of the heart's activity, which serve the purpose to monitor the rate and rhythm of the heart beat. Any disruption to this sinus rhythm results in the dysfunctionality of the heart. Arrhythmias are a type of cardiovascular diseases which occur when there is an irregularity in the normal sinus rhythm. There are multiple kinds of arrhythmia depending on the fluctuations of the ECG waveform, such as atrial fibrillation, premature contraction, ventricular fibrillation, and tachycardia bradycardia. While few of them are benign, some can get life-threatening when not treated.

The rest of the paper is organized as follows: section-2 provides the background knowledge on electrocardiogram, the structure of the heart and the most commonly found arrhythmias in cardiac patients. The database and deep learning architectures most widely used by researchers are also discussed in section-2. The review of the 25 papers on arrhythmia detection using various deep learning approaches is covered in section-3. Section-4 includes the discussion on the various deep learning algorithms used for arrhythmia classification. Finally the paper is concluded in section-5.

2. Background Knowledge

2.1. Structure of the heart and Electrocardiogram

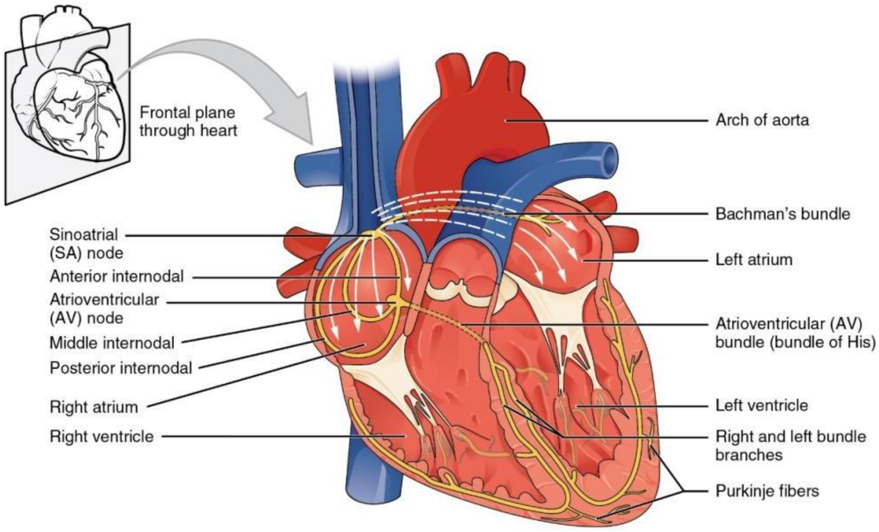

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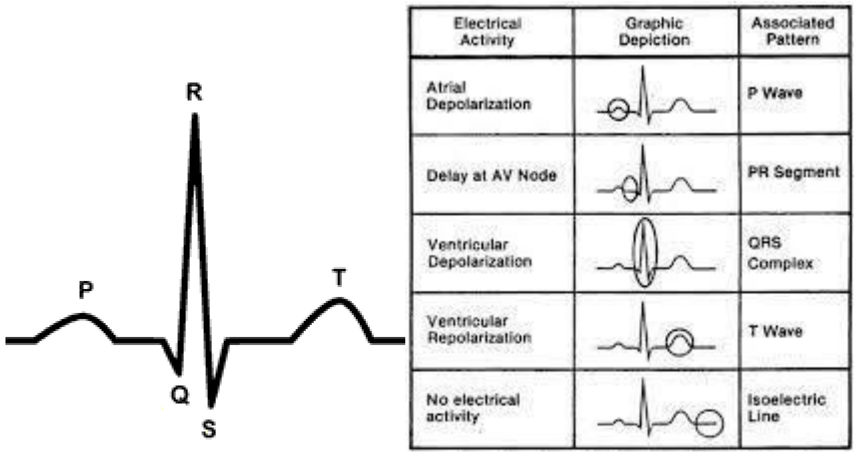
Figure 2.1.1: Conduction system of the heart



Electrical Activity	Graphic Depiction	Associated Pattern
Atrial Depolarization		P Wave
Delay at AV Node		PR Segment
Ventricular Depolarization		QRS Complex
Ventricular Repolarization		T Wave
No electrical activity		Isoelectric Line

Figure 2.1.2: Cardiac Cycle represented through an ECG waveform and its interpretation

Electrocardiogram or ECG denotes the heart's electrical activity. An absence of any significant electrical activity is represented through an isoelectric line. The Sino Atrial node (SA node) located in the right atrium is responsible for starting the cardiac cycle (Figure 2.1.1). A normal sinus rhythm starts with the P wave representing the atrial myocardium depolarization as illustrated in Figure 2.1.2. In other words, it represents the atrial contraction. After the P wave there is the QRS complex, representing the ventricular myocardium depolarization or ventricular contraction. The T-

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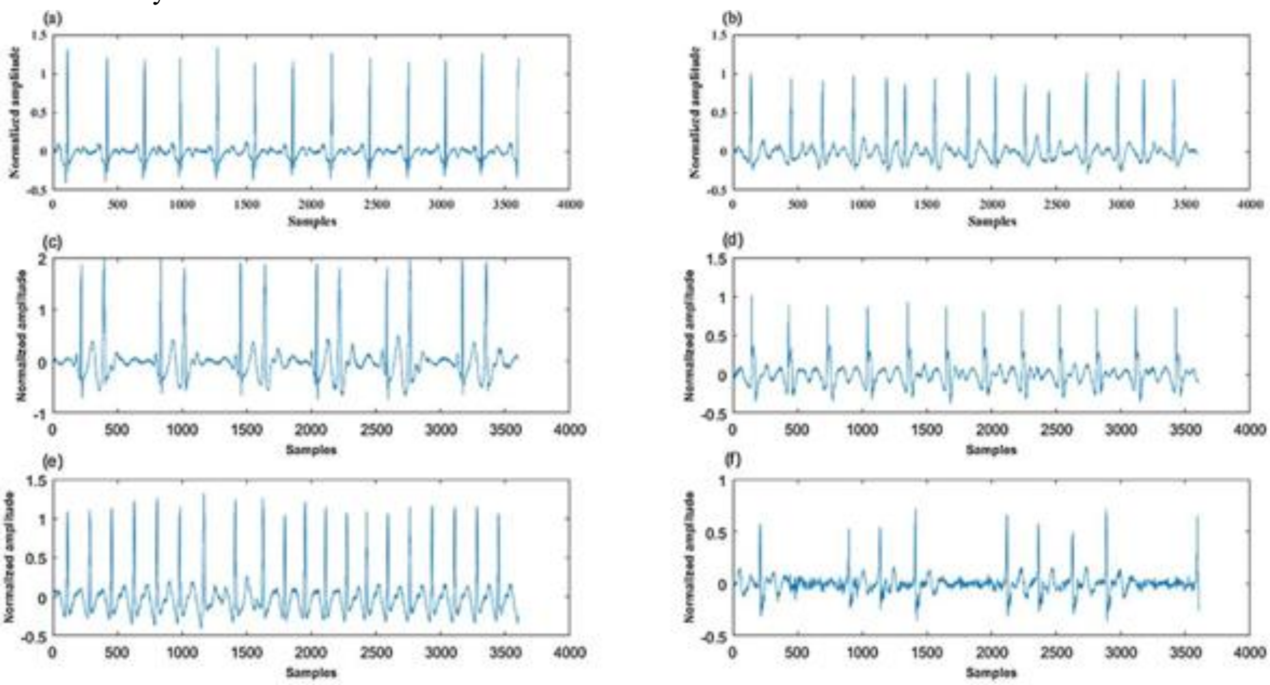
wave is observed next which represents the repolarization of the ventricular myocardium. It is also worthwhile to note that the atrial myocardium repolarization wave is hidden within the dominant QRS complex, hence not visible through an ECG recording. In a normal sinus rhythm, the waves (P Q R S and T) are to be in the right order and fairly regular with a heart rate between 60 and 100 bpm.

2.2. Arrhythmia

There are three normal heart rhythms - normal sinus rhythm, sinus bradycardia and sinus tachycardia. As mentioned above in section-2.1, normal sinus rhythm (NSR) is observed when the P Q R S and T are in order and fairly regular with a heart rate between 60 and 100 bpm. However, when the P Q R S and T are in order and regular but the heart rate is slower than 60 bpm it is sinus bradycardia (SBR). On the other hand, sinus tachycardia (STR) is when the P Q R S and T are in order and regular but the heart rate is faster than 100 bpm. SBR and STR can be considered normal or a clinical condition depending on the underlying cause. To elucidate with an example, SBR may be thought of as normal during sleep and STR is thought of as normal during a physical activity.



Source: [1]

Figure 2.2.1: ECG Waveform for Arrhythmias: (a) NSR, (b) AFIB (c) B, (d) P, (e) AFL, (f) SBR

A common method to classify arrhythmias is based on the location of its origin. This categorizes them into supraventricular and ventricular arrhythmias. Supraventricular as the name suggests originate from the upper two chambers, the atrium. These are characterized by narrow QRS complexes. Ventricular arrhythmias on the other hand origin below the AV node or within the two ventricles. Atrial flutter, atrial fibrillation and paroxysmal supraventricular tachycardia fall under supraventricular arrhythmia. Ventricular tachycardia and ventricular fibrillation are subcategories of ventricular arrhythmias. Out of the two main categories, ventricular arrhythmias are known to be more life threatening.

2.3. Database

Majority of the research papers mentioned in this review utilize the most widely available open source arrhythmia database provided by Boston's Beth Israel Deaconess Medical Center (previously known as Beth Israel Hospital (BIH)) and MIT. Hence, we will discuss this database here. The MIT-BIH arrhythmia database [28-29] consists of six classes of ECG signals – normal N sinus rhythm segments, atrial fibrillation AFIB, ventricular bigeminy B, pacing rhythm P, atrial flutter AFL, and sinus brady-cardia SBR. The Database consists of 48 ECG recordings from two- channels of 47 subjects. The recordings are collected from 1975 and 1979 by the BIH Arrhythmia Laboratory. Out of the 48 subjects, 25 were men and 22 women. Age range of the men varies from 32 and 89 and the women from 23 and 89 [28-29]. Each record is roughly about 30 minutes and sampled at 360 Hz. The database also contains annotations, which is highly beneficial for training our deep learning models.

2.4. Deep Learning

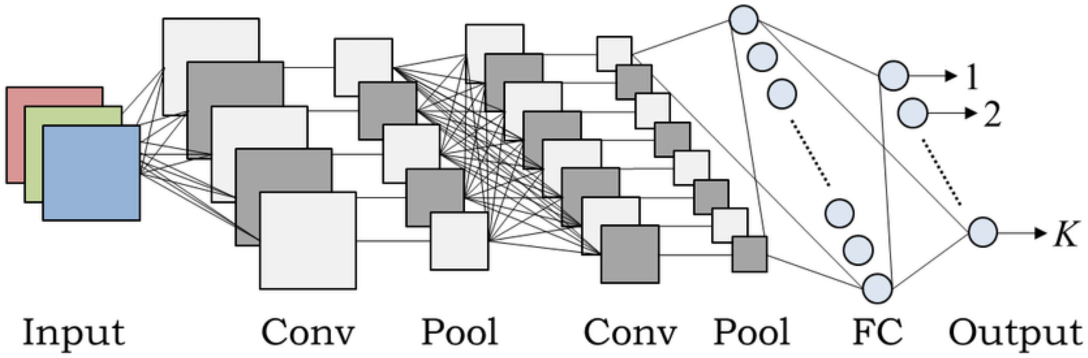
With the advent of humongous amounts of data, deep learning has gained fresh momentum since the past few years. It is widely used in various applications today, specifically, in healthcare. Be it detecting cancer cells, thermal scanning of breasts or electrocardiogram classification, deep learning has a solution today. With many hospitals now going digital, deep learning engineers are equipped with sufficient amounts of data to achieve high accuracy yielding models. Among the many deep neural network architectures used for electrocardiogram classification, convolutional neural network (CNN) and recurrent neural network (RNN) are the two most widely used architectures to classify the different types of arrhythmias. Hence, we look more in detail regarding these in the following subsections.

2.4.1 Convolutional Neural Network (CNN)

Convolutional Neural Network commonly also known as CNN, is used to extract essential features from two dimensional input data namely images. However, biomedical signals are time series one dimensional signals. Biomedical signals include ECG, electroencephalogram (EEG) etc for which a one-dimensional convolution is used to process the signal. A CNN basic unit includes input, convolution, pooling, fully connected and an output layer which is expressed as

$$Y = f\,(Wx+b)$$

Where x is input; y is output;
f is the ReLu function;
W is convolution matrix; b is bias



Source: [30]

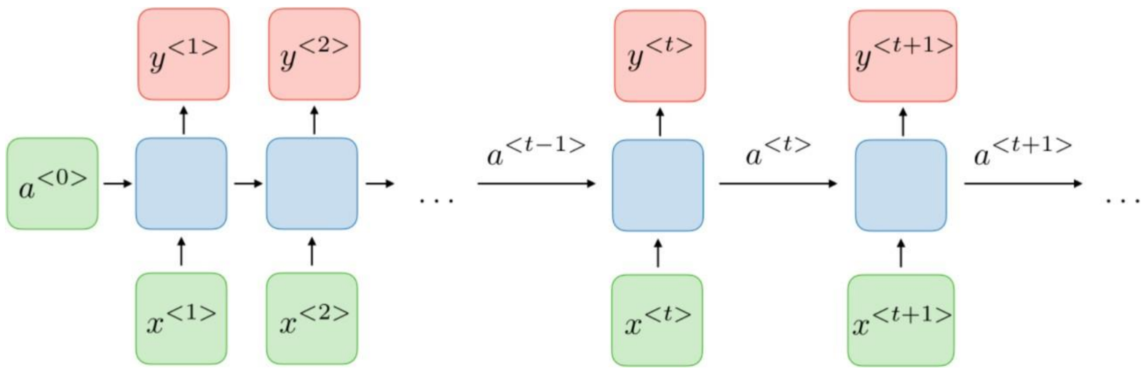
Figure 2.4.1: Architecture of a traditional CNN

2.4.2 Recurrent Neural Network (RNN*)*

A recurrent neural network commonly also known as RNN, is a class of artificial neural networks which has internal memory to process variable length sequences of inputs. RNNs also allow their previous outputs to be used as inputs, while also maintaining hidden states. All RNN inputs are related to one another. Long Short-Term Memory networks are another popular choice when it comes to ECG classification, which is again a modified version of recurrent neural networks. In a given traditional RNN, for each timestep t, the activation $a^{<t>}$ and the output $y^{<t>}$ are expressed as follows:

$$a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a) \quad \text{and} \quad y^{<t>} = g_2(W_{ya}a^{<t>} + b_y)$$

Where W_{ax}, W_{aa}, W_{ya}, b_a, b_y are coefficients that are shared temporally and g_1, g_2 activation functions.



Source: Stanford.edu

Figure 2.4.2: Architecture of a traditional RNN

Approaches for ECG Classification: Review Table

No.	Author – Year	Dataset	Model	Results
1.	Chen, Chen, et al. [1] (2020)	MIT-BIH	Front end is CNN and LSTM is the back end	Acc: 99.32 %
2.	Wang Jibin [2] (2020)	MIT-BIH AF	11 layer CNN and Modified Elman NN Ten-fold cross-validation	Acc: 97.4% Se: 97.9% Sp: 97.1%
3.	Li Zhi [3] (2020)	MIT-BIH	31-layer 1D residual CNN	Accuracy, sensitivity and positivity values: 99.38%, 94.54%, 98.14% respectively
4.	Xia and Xie [4] (2019)	MIT-BIH database	1D CNN and active learning	Acc: 99.2%
5.	Karthik R [5] (2019)	MIT-BIH database	Scaled Conjugate Grading (SCG) – ML algorithm. Use of four NN - feed forward, fit, pattern and cascade forward	One input layer with 7 neurons had best results Feed Forward and fit best performance for classifying arrhythmia with long term AF, and long term AF with sleep apnea.
6.	Hanbay Kazim [6] (2019)	MIT-BIH database	DNN model created from an improved DAE reformed by eigenvalues of ECG signals.	SVEB Accuracy NB 95.7 SVM 91.0 DT 90.3 RF 89.3 Eig-DNN-entropy 99.8 VEB Accuracy NB 96.4 SVM 93.2 DT 89.4 RF 87.3 Eig-DNN-entropy 99.5
7.	Andoni Elola [7] (2019)	Subset of OHCA data collection	Two deep neural network (DNN) architectures: CNN + recurrent layer for learning temporal dependencies	Sensitivity, specificity, and balanced accuracy were 94.1%/92.9%/93.5% for the first one, and 95.5%/91.6%/93.5% for the second one

8.	Yildirim Ozal, et al. [8] (2018)	MIT-BIH	1D version of CNN model 16-layer 13- 15 and 17 classes of arrhythmia recognised	Accuracy: 13 classes 95.20% 15 classes 92.51% 17 classes 91.33%
9.	Sannino Giovanna and Giuseppe De Pietro [9] (2018)	MIT–BIH Arrhythmia Database	DNN classifier	Acc: 99.68% Se : 99.48% Sp : 99.83%
10.	Tae Joon Jun, et al. [10] (2018)	MIT-BIH arrhythmia database ECG recording.	2D-CNN classifier data augmentation, and K-fold cross-validation	AUC, acc., sp, se and + predictive value 0.989, 99.05%, 99.57% and 98.55% respectively
11.	Kachuee, et al. [11] (2018)	MIT-BIH dataset PTB Diagnostics dataset	Deep residual CNN model	Heartbeat classification Accuracy 93.4% MI classification Accuracy 95.9%
12.	Sherin Mathews [12] (2018)	MIT BIH	Demonstrates the application of RBM and DBN	Accuracy of 93.78% and 96.94% for SVEB class and VEB class respectively for sampling rate 360 Hz. Accuracy of 93.63% and 95.87% for SVEB for VEB respectively for sampling rate 114 Hz
13.	Yildirim Ozal [13] (2018)	MIT-BIH arrhythmia database.	Deep bidirectional LSTM network-based wavelet sequence	a high recognition performance of 99.39%
14.	Bahareh, et al. [14] (2018)	MIT-BIH database	CNN	Acc: 92.0%
15.	Jai Li [15] (2018)	MIT-BIH	Three CNN layers and two MLP layers	Acc: 99.0% Se : 93.9% Sp : 98.9% +P: :90.6%
16.	Tae Joon Jun [16] (2018)	MIT-BIH	Two-dimensional CNN	AUC, accuracy, specificity, sensitivity and positive predictive values 0.989, 99.05%, 99.57%, 97.85% and 98.55% respectively
17.	Fernando Andreotti [17] (2017)	Physionet	Feature-based classifier and a Convolution neural network	Feature-based classifier – 72.0% on training set. 79% on test set. CNN – 72.1% on augmented database and 83% on test set.

18.	Pyakillya, et.al [18] (2017)	PhysioNet/Computing in Cardiology Challenge 2017	1D CNN with 7 convolution layer + maxpooling and dropout after every layer + 3 FCN	Acc: 86%
19.	Kan Luo [19] (2017)	PhysioNet MIT-BIH database	One encoder layer of SDA (stacked denoising auto-encoder) with 1024 neurons and one softmax-formed DNN model.	Accuracy 98.8 % for SVEB Accuracy 99.1% for VEB
20.	Rajendra Acharya [20] (2017)	ECG database (Physikalisch-Technische Bundesanstalt diagnostic)	Eleven-layer deep CNN 10-fold cross-validation	Two seconds ECG signal: Acc: 92.50% Five seconds ECG signal: Acc: 94.90%
21.	Pranav Rajpurkar [21] (2017)	Dataset of 30,000 patients	34-layer CNN	Se: 82.7%
22.	Isin, Ozdalili [22] (2017)	MIT-BIH arrhythmia database	DCNN performs feature extraction and these features are fed to BPNN for final classification	CRR: 98.51% Acc : 92.00%.
23.	Rajendra Acharya [23] (2017)	Vfib from Creighton University Ventricular tachyarrhythmia, Afib and Afl from MIT-BIH Afib, Afl, and Nsr from MIT-BIH arrhythmia database.	11-layer DCNN with output layer for the Nsr, Afib, Afl, and Vfib	For 2 and 5 seconds of ECG segments: accuracy, sensitivity and specificity numbers are 92.50%, 98.09%, 93.13% and 94.90%, 99.13%, 81.44% respectively
24.	Majumdar and Ward [24] (2017)	MIT-BIH database	Dictionary learning classifiers – Nearest Neighbor and Sparse Representation based Classifier and SVM with RBF kernel to test	Acc: 97.0%
25.	Al Rahhal, et al. [25] (2016)	INCART (St.-Petersburg Institute of Cardiological Technics 12-lead arrhythmia database) MIT-BIH arrhythmia Database MIT-BIH supraventricular arrhythmia database (SVDB)	Stacked denoising autoencoders (SDAEs) with sparsity constraint - for feature learning DNN with entropy and DNN with Breaking-Ties	MIT-BIH - 99.7% INCART - 99.83% SVDB -99.58%

3. Discussions

Through this survey we review 25 papers published between 2016 to 2020, whose objective is to detect cardiac arrhythmia using deep learning models. Out of the 25 papers discussed, 16 of them use Convolutional Neural Networks as a part of their model. And 20 of the papers use the MIT- BIH database. Potential opportunities for future studies would be to evaluate the performance of different AI algorithms on the same dataset. This dataset could be from multiple sites with different equipment and different noises.

4. Conclusion

In this article, we review the different approaches to classify arrhythmia using ECG signals. The review looked into the different datasets used, the architectures employed and the various metrics used for evaluation to detect arrhythmia. Additional work in this area can be carried out in order to evaluate efficiency of the different algorithms.

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