Detection and Classification of Cardiac Arrhythmias by Machine Learning: a Systematic Review

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Abstract

Machine learning (ML) techniques can perform as better as humans at key healthcare tasks. Recent advances make it possible to perform, using ML, automatic high-level feature extraction and classification of cardiac arrhythmia. In this work, we aimed through a systematic literature review to identify the principal methods, databases, and contributions of ML on cardiac arrhythmias classification. Electronic database including PubMed, Science Direct, IEEE, Scielo, Scopus, and Web of Science were searched, from 2014 to 2019, by combining the following keywords "ECG", "heart signals", "arrhythmia", "classification" and "machine learning". 28 studies were selected as eligible. Classifications classes ranged from 2 to 17, with prevalence of 2 classes (71.4% of the studies). The most frequent applied methods were Artificial Neural Network (13 articles), followed by Support Vector Machines and Mixed techniques (5 articles respectively). MIT-BIH Arrhythmia Database was used in 15 studies (54%), whereas 8 (28.5%) utilized their own data. The approach basis for evaluating the results is the confusion matrix, where up to 82% of the studies used accuracy, 67.8% precision, and 46% sensitivity/specificity. Classification of cardiac arrhythmias through ECG is of increasing interest from the research groups, and ML classification is showing rising levels of performance. It would benefit both patients and clinicians.

1. Introduction

Cardiovascular diseases are the leading cause of death worldwide, representing 31% of all global deaths [1]. Among these diseases, cardiac arrhythmias are one of the most important for maintaining this scenario. Factors such as genetics, aging, poor eating habits, physical inactivity and excessive use of alcohol imply changes in the anatomy and physiology of the heart, favoring the development of cardiac arrhythmias, being important diagnostic at early stage [2].

The electrocardiogram (ECG) is the most well-known and applied worldwide exam [3]. This method is of low-cost, non-invasive, and quickly accessible with excellent reproducibility [3, 4]. However, its limited spatial resolution (i.e. a restricted number of electrodes) makes it difficult to assure accurately diagnose for certain heart diseases, favoring the "silent" progression of the disease [4]. Systems known as Body Surface Potential Mapping (BSPM) have up to 300 electrodes distributed over the entire length of the torso for ECGs acquisition, and the voltages are represented through the 3D torso maps [5] . This technology has shown to assist clinicians prior invasive procedures [4].

Due to the importance of the treatment of heart diseases, there is an emerging need to study a wide range of cutting-edge techniques for their analysis and diagnosis. With the advances in data processing and storage capacity and its consequent lower cost, machine learning (ML) methods have been transforming processes in medicine, including cardiology. Recent advances make it possible to perform, using ML, automatic high-level feature extraction and classification of cardiac arrhythmias. Furthermore, reviewing the ML methods applied to the diagnosis of cardiac arrhythmias becomes important in order to facilitate the development of future or ongoing research related to the topic. The aim of this work is to identify the contributions of ML in cardiology for the purpose of detecting arrhythmias, through a bibliographic literature review.

2. Methods

The review was performed using the PRISMA statement [6]. It consists of analyzing the following items: review questions, sources of information, research strategy, and selection criteria [6]. Through the papers search, the following four questions were considered:

1. What were the applied algorithms?
2. What were the system inputs and outputs?
3. What was the database used?

4. What were the statistical metrics used to assess classification efficiency?

The selection of the articles was based on the four readings method: exploratory, selective, analytical, and interpretive [7]. The exploratory reading aims to verify whether the researched work is of interest to the research. It is done by examining the summary, introduction, conclusion, and bibliography. After the exploratory reading, the materials that are of interest to the research are selected, thus following the selective reading. The next step is the analytical reading, which is a critical reading, where the purpose is to order and summarize the studies outcomes. Interpretive reading is the last step in the process of reading materials for the bibliographic review. In the interpretative reading, we try to give a broader meaning to the results obtained with the analytical reading.

The keywords ”ECG”, ”heart signals”, ”arrhythmia”, ”classification” and ”machine learning” were used in this bibliographic review to search the articles through the StArt software (State of the Art through Systematic Review, v. 3.0.3)[8]. The papers were searched between 2014 and 2019 in the following databases: PubMed, Science Direct, IEEE, Scielo, Scopus, and Web of Science. A score generated by the StArt software was evaluated, based on the recurrence of keywords in their content combined with the location in the text. The excluding criteria were review articles and abstracts published in conferences.

3. Results

A total of 532 articles were initially selected. From those, 63 were excluded (duplicated) resulting in 469 papers. 441 papers were excluded by not being related to the bibliographic review topic. A total of 28 articles were selected, where 26 studies used ECG signals for arrhythmias classification and 2 body surface potential mapping signals.

Table 1 summarizes the main characteristics of the selected articles. Around 47% of the studies (N = 13) used Artificial Neural Network (NN) technique for arrhythmias classification. Among the reaming articles, k-Nearest Neighbors (kNN), Naive Bayes (NB) and Support Vector Machines (SVM) were applied respectively in 5 articles each.

Not surprising, MIT-BIH Arrhythmia Database was used in 15 studies (54%), whereas 8 (28.5%) utilized their own data. The remaining used databases were from: American Heart Association (AHA) (N = 2), The European ST-T database (N = 2) and , UK Biobank database (N = 1). One of the reasons for MIT-BIH Arrhythmia Database popularity might be due the annual PhysioNet - Computing in Cardiology Challenges.

In terms of the choice of signal length, around 86% of the studies (N = 24) used signals with length varying between 8 s to 12 s. The studies divide the signals' database between training and classification tasks. The percentage of the database's signals chosen for the training task narrowed between 25% and 40%, being the preferable the 30% strategy (68% of the studies), followed by the 35% (11% of the studies). Output classifications classes varied significantly, from 2 to 17, but there is a visible prevalence of 2 classes (71.4% of the studies). The evaluation of the classification tasks were assessed by different statistics metrics, in special, accuracy (23 out of 28), precision (N = 19), sensitivity/specificity (N = 13), area under the ROC curve (12) and F-score (6). As can be observed, accuracy was the most recurrent metric used to assess the success of the algorithms (82% of the studies), with the following ranges by the applied ML techniques: NN [70.00 - 99.99], kNN [95.42 - 99.30], SVM [84.80 – 98.40] and NB [77.60 - 99.14].

Accessing the articles allowed us to observe that investigators aimed classification in a wide range of cardiac arrhythmias. Atrial fibrillation was considered in 9 of the 28 studies. It was followed by: left (7) or right (6) branch block, AV block (6), premature ventricular (5) or atrial (3) contraction, idioventricular rhythm (6), sinus tachycardia (4), atrial (2) or ventricular (2) flutter, atrioventricular nodal reentry tachycardia (2), and Wolff-Parkinson-White syndrome (1).

4. Discussion

In this work, through a bibliographic literature review, we showed the principal methods, databases, and contributions of ML in cardiac arrhythmias classification. Overall, the applied methods achieved good rates of success even for complex cardiac arrhythmias. NN and SVM outperform the other methods and public databases have contributed without precedents to the evolution of the field. But, as few authors use the same evaluation scheme for testing, it is difficult to make a fair comparison between methods.

Classification of cardiac arrhythmias through ECG is of increasing interest from the research groups, and ML classification is showing rising levels of performance. It would benefit both patients and clinicians. Public databases and scientific challenging competitions based on clinical problems (such as PhysioNet - Computing in Cardiology Challenge) have contributed without precedents to the evolution of the field.

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Table 1. Methods and metrics of each article

REF	ML	Database	Length	Training	Class	SE	SP	ACC
[9]	NN	MIT	10 s	30%	17	83.91	99.41	
[10]	NN	Own	10 s	40%	2	99.19	99.44	
[11]	NN	MIT	8 s	30%	5			99.39
[12]	kNN	Own	12 s*	30%	2			95.42
[13]	NB	Own	5 s	28%	2			77.60
[14]	NB	AHA	8 s	35%	2			98.20
[15]	SVM	Own	10 s*	35%	13			88.07
[16]	NN	Own	8 s	30%	2	97.60	96.20	
[17]	NN	ST-T	10 s	30%	17			70.00
[18]	NN	MIT	8 s	35%	2	98.70	99.90	99.75
[19]	kNN	Own	9 s	30%	2	94.41	98.45	97.50
[20]	NN	Own	10 s	30%	2			95.70
[21]	kNN	MIT	8 s	30%	3	88.00	96.00	96.00
[22]	NN	MIT	10 s	30%	2	99.99	99.99	99.99
[23]	kNN	AHA	10 s	28%	2	99.7	98.9	99.30
[24]	NN	ST-T	10 s	25%	2	98.98	98.98	
[25]	SVM	MIT	12 s	30%	2			91.10
[26]	NB	MIT	10 s	30%	2			99.14
[27]	NB	MIT	10 s	25%	2	95.63	97.81	
[28]	SVM	MIT	10 s	30%	6			96.83
[29]	NN	MIT	8 s	30%	2			98.73
[30]	SVM	MIT	10 s	30%	2	91.1	98.7	98.40
[31]	NN	MIT	8 s	30%	4			92.10
[32]	NN	MIT	9 s	30%	2			83.40
[33]	NB	Own	10 s	30%	2			98.30
[34]	NN	MIT	8 s	30%	3			97.77
[35]	kNN	MIT	8 s	28%	2	99.61	100.00	99.45
[36]	SVM	UKbank	11 s	30%	2	75.00	97.50	84.80

*Indicates that investigators did apply overlapping strategy on the signals segment for training/classification

NN: Neural Networks; kNN: k-Nearest Neighbors; NB: Naive Bayes; SVM: Support Vector Machines; SE: Sensitivity; SP: Specificity; ACC: Accuracy.

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