





Arrhythmia detection using deep convolutional neural network with long duration ECG signals

Özal Yildirim^a  , Paweł Pławiak^b, Ru-San Tan^{c d}, U. Rajendra Acharya^{e f g}

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Highlights

- New approach based on long-duration (10 s) ECG signal fragments based on one lead is proposed.
- Involves 17 ECG classes (normal sinus rhythm, 15 cardiac arrhythmias, pacemaker rhythm).
- 1D-CNN is employed.
- Obtained overall accuracy of 91.33%.
- Can be used in tele-medicine especially in mobile devices and cloud computing due to its low computational complexity.

Abstract

This article presents a new deep learning approach for cardiac arrhythmia (17 classes) detection based on long-duration electrocardiography (ECG) signal analysis. Cardiovascular disease prevention is one of the most important tasks of any health care system as about 50 million people are at risk of heart disease in the world. Although automatic analysis of ECG signal is very popular, current methods are not satisfactory. The goal of our research was to design a new method based on deep learning to efficiently and quickly classify cardiac arrhythmias. Described research are based on 1000 ECG signal fragments from the MIT - BIH Arrhythmia database for one lead (MLII) from 45 persons. Approach based on the analysis of 10-s ECG signal fragments (not a single QRS complex) is applied (on average, 13 times less classifications/analysis). A complete end-to-end structure was designed instead of the hand-crafted feature

extraction and selection used in traditional methods. Our main contribution is to design a new 1D-Convolutional Neural Network model (1D-CNN). The proposed method is 1) efficient, 2) fast (real-time classification) 3) non-complex and 4) simple to use (combined feature extraction and selection, and classification in one stage). Deep 1D-CNN achieved a recognition overall accuracy of 17 cardiac arrhythmia disorders (classes) at a level of 91.33% and classification time per single sample of 0.015 s. Compared to the current research, our results are one of the best results to date, and our solution can be implemented in mobile devices and cloud computing.

Introduction

Electrocardiography (ECG) is the most basic and accessible method of diagnosing cardiac arrhythmia (or heart rhythm disorders), as it is a non-invasive and easy to use method that can provide useful information on heart health and pathology. Cardiac arrhythmia is an important manifestation of cardiovascular disease. The latter is a serious societal problem due to 1) its high prevalence and incidence, 2) associated high mortality (every year, 17.3 million persons die from cardiovascular disease, accounting for 37% of all deaths globally [[66], [67], [68]]), and 3) resultant high cost of treatment (the usual chronic course of the disease necessitates long-term and frequently expensive therapies [69,70]). The above issues will intensify with the expected progressive aging of populations worldwide and hence may increase number of deaths from 17 million in 2016 to 24 million in 2030 [[66], [67], [68],71]).

Existing algorithms for automated ECG recognition of cardiac arrhythmia are based on the assessment of morphological features of single or few QRS complexes or beats. In the scientific literature, analysis of QRS complexes is substantially more popular than the analysis of long-duration ECG signal fragments [45]. Current methods can be error-prone and may not achieve satisfactory diagnostic performance due to high beat-to-beat variability of these features among individuals [29,43]. This motivated us to conduct research on a new solution of diagnosing heart disease using long-duration continuous ECG beat signals, which we hypothesise as more accurate than conventional algorithms. An important design consideration is our intention to reduce the computational complexity of our developed algorithms, so as to facilitate implementation of our solution in mobile devices and cloud computing to monitor patients' health in real time.

Deep learning [4,7,8,10,16,26,54] is a type of machine learning technique that is characterized by a hierarchical architecture comprising multiple layers in which subsequent stages of information processing take place. The input layers are used to extract features, based on which the output layers perform the analysis and classification of patterns. Deep learning methods can be divided into various subtypes based on the training methods: (i) deep discriminatory models, e.g. deep neural networks (DNNs) [54], recurrent neural networks (RNNs) [15] and convolutional neural networks (CNNs) [26]; and (ii) unsupervised/generative models, e.g. restricted Boltzmann machines (RBMs) [17], deep belief networks (DBNs) [10], deep Boltzmann machines (DBMs) [51] and regularized autoencoders [7].

CNNs are most often used for processing two-dimensional data, including images [16,80,81,87]. CNN consists of at least one hidden (convolutional) layer completely connected to the upper layer (same as in typical neural networks) and also contains weights. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers. The CNN network architecture is suitable for the processing of 2D data. Compared to other deep learning architectures, CNN achieves better results for image processing and speech recognition [80,82,85,87]. CNN networks can be trained by a standard error backpropagation algorithm. It is easier to train than other regular, deep, unidirectional neural networks because CNN has much less parameters to optimize, which makes this architecture very attractive to use.

Deep learning has become very popular recently [13,84], and has been applied successfully for the classification of heart disease and arrhythmia using CNN [1,2,23,88,89] DNN [48], long-short term memory network (LSTM) [47,62,72,90].

Section snippets

Related works

The ECG signal, although simple to acquire, contains rich features that can be mined for computational analysis. Its potential and popularity for research are reflected in the growing numbers of publications in subjects concerning ECG: (i) classification or detection of ECG beat [5,32,33,56,63]; (ii) deep learning [3,23,48]; (iii) principal component analysis [12,21,22,32,34,35,49,58]; (iv) higher order statistics [[36], [37], [38]]; (v) feature selection/dimensionality reduction [11,24,28,31,39...

Material and methods

In this study, CNNs were used to classify long-duration fragments of ECG signal (10-s). The designed classifier system has a complete end-to-end structure with neither hand-crafted feature extraction of the signals nor feature selection at any stage [16,80,86,87]. For this purpose, a 16-layer deep network structure including standard CNN layers was designed. The input of this network structure comprised 3600 samples of long-duration raw ECG signals. At the classifier network output, prediction...

Results

For automatic classification of the ECG fragments, the ECG dataset containing 1000 signal fragments (each containing 3600 samples) was used for performance evaluation of the optimized 1D-CNN network. Because of sparse sample numbers in some of the ECG classes in this dataset, two other sub-datasets were created comprising 15 and 13 classes in addition to the original 17-class dataset [45,46]. 70%, 15% and 15% of the data in each sub-datasets were used for training, validation and test phases,...

Discussion

Table 4 summarizes the various published ECG diagnostic algorithms, their respective signal analysis methods and the achieved highest overall accuracies obtained using the same database (MIT-BIH Arrhythmia). The results of our proposed model (in bold) were comparable with best obtained performance, thus confirming the effectiveness of the new 1D-CNN model in classifying the cardiac arrhythmia using long-duration ECG signals.

In the scientific literature, most of the works focuses on recognition...

Conclusion

The goal of the study was to design a deep learning 1D-CNN that is able to classify cardiac arrhythmia (17 diagnostic classes encompassing “normal sinus rhythm”, “pacemaker rhythm” and 15 other rhythm disorders) effectively from analysis of long-duration (10-s) ECG signal fragments.

The proposed method is: (i) efficient; (ii) fast (real-time classification); (iii) universal; (iv) simple to use; and (v) highly accurate.

1D-CNN model achieved an overall classification accuracy of 91.33% for 17...

Conflicts of interest

There is no conflict of interest in this work....

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