1-D Convolutional Neural Network for ECG Arrhythmia Classification

(Article begins on next page)

1-D Convolutional Neural Network for ECG Arrhythmia Classification

Jacopo Ferretti[1,2], Vincenzo Randazzo[2], Giansalvo Cirrincione[3,4], and Eros Pasero[2]

[1] Universitá degli Studi di Torino, Dipartimento di Scienze Chirurgiche, Turin, Italy, jacopo.ferretti@unito.it,
[2] Politecnico di Torino, DET, Turin, Italy, {jacopo.ferretti, vincenzo.randazzo, eros.pasero}@polito.it
[3] University of Picardie Jules Verne, Lab. LTI, Amiens, France, exin@u-picardie.fr
[4] University of South Pacific, SEP, Suva, Fiji Islands, giansalvo.cirrincione@usp.ac.fj

Abstract. Automated electrocardiogram analysis and classification is nowadays a fundamental tool for monitoring patient heart activity and, consequently, his state of health. Indeed, the main interest is detecting the arise of cardiac pathologies such as arrhythmia.
This paper presents a novel approach for automatic arrhythmia classification based on a 1D convolutional neural network. The input is given by the combination of several databases from Physionet and is composed of two leads, LEAD1 and LEAD2. Data are not preprocessed, and no feature extraction has been performed, except for the medical evaluation in order to label it. Several 1D network configurations are tested and compared in order to determine the best one w.r.t. heart-beat classification. The test accuracy of the proposed neural approach is very high (up to 95%). However, the goal of this work is also the interpretation not only of the results, but also of the behavior of the neural network, by means of confusion matrix analysis w.r.t. the different arrhythmia classes.

Keywords: Arrhythmia classification, 1D CNN, Convolutional neural networks, Confusion matrix, ECG, EKG

1 Introduction

Electrocardiogram (ECG) is the electrical signal produced by heart contraction, which is recorded by physicians to monitor the heart state of health and, consequently, the person it belongs. The standard procedure uses an electrocardiograph with ten electrodes placed on specific points of a human body, which acquire up to twelve different signals, called *LEADS*. As explained in [1] , an healthy ECG, shown in Fig. 1, presents six fiducial points (P, Q, R, S, T, U) which are correlated to the four principal stages of activity of a cardiac cycle: isovolumic relaxation, inflow, isovolumic contraction, ejection. This path should

repeat itself constantly over the time; otherwise, a person suffers from arrhythmia. Cardiac arrhythmia is one of the most common disease people are killed by, therefore normal and abnormal ECG signal automatic classification is raising more and more interest in the scientific community.
Several approaches have been already proposed in literature. The most famous algorithm for automatic QRS-complex detection within an ECG signal is described in [2], while [3] uses Support Vector Machines at the same purpose. In [4] and [5] fuzzy and artificial neural networks are used, respectively, for ECG analysis. Cardiac arrhythmia is studied using hidden Markov models in [6]. Wavelet transformation and artificial neural network for arrhythmia detection is presented in [7]. [8] and [9] show two possible approaches for atrial fibrillation recognition.

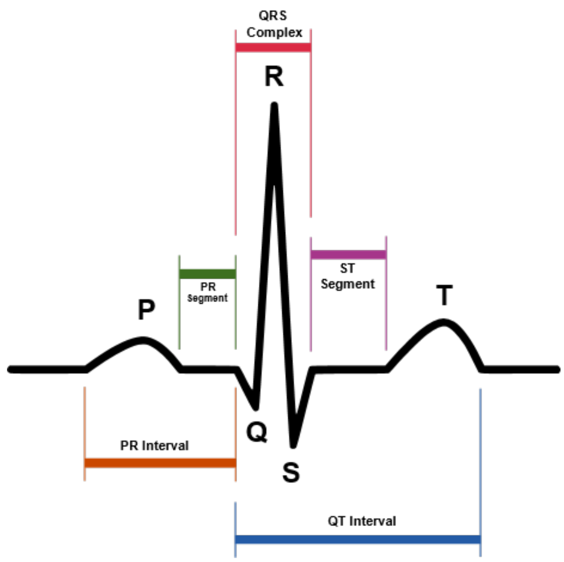

Fig. 1. Example of an healthy ECG.

Recently, a novel class of techniques based on Convolutional Neural Networks (CNN) is gathering the attention of the scientific community thanks to its capability in automatically learning the intrinsic patterns from the data; indeed, this approach can avoid the need of manual feature engineering and it can also infer hidden intrinsic patterns more effectively. Inspired by the human mind visual cortex, CNN consists of multiple layers, each of which owns a small subset of neurons to process portions of the input data. These subsets are tiled to introduce region overlap, and the process is repeated layer by layer to achieve a high level abstraction of the original dataset as shown in Fig. 2. An application to arrhythmia detection can be found in [10]. Advanced machine learning techniques like CNNs have already been extensively used in biomedical field with various application -such as in the classification of EEG recordings in dementia [11,12]- with very promising results. A particular, quite interesting, class of convolutional neural network is the 1D-CNN, which takes as input data a single stream (i.e signal), e.g. ECG, and slides a kernel along it in search of particular patterns, as shown in Fig. 3. Applications to heart disease classification and biometric identification are presented in [15] and [16], respectively. In this paper different 1D-CNNs are applied to the MIT-BIH database [19] in order to test which configuration yields the best performances in ECG classification of arrhythmia. However, the goal of this work is also the interpretation not only of the results, but also of the behavior of the neural network, by means of confusion matrix analysis w.r.t. the different arrhythmia classes. Moreover, in this study all of the available classes of arrhythmia are used for the classification whereas in other similar studies - such as [13,14] - only the most common ones are present.

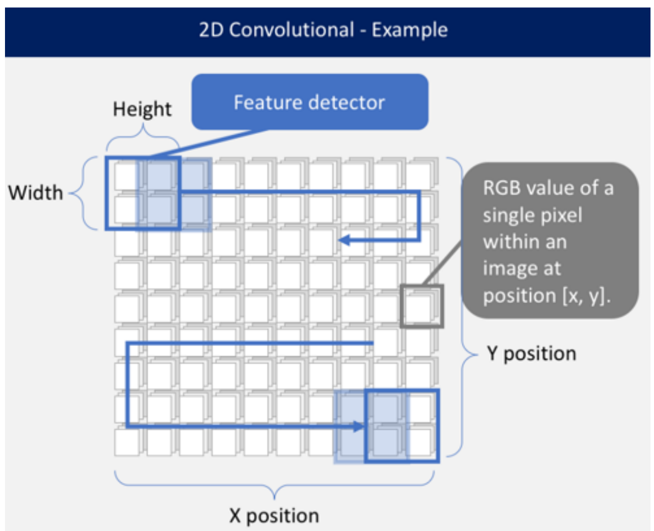

Fig. 2. 2D Convolution Neural Network.

2 Methodology

2.1 Dataset

The MIT-BIH database is considered the gold standard when comparing ECG classification techniques. Indeed, it is widespread used in research [1], [17], [18] and it covers a wide range of diseases. Each QRS complex within each record is labeled; hence, a supervised learning approach is quite straightforward. Also, the entire dataset is very well documented. The chosen dataset [20] contains data

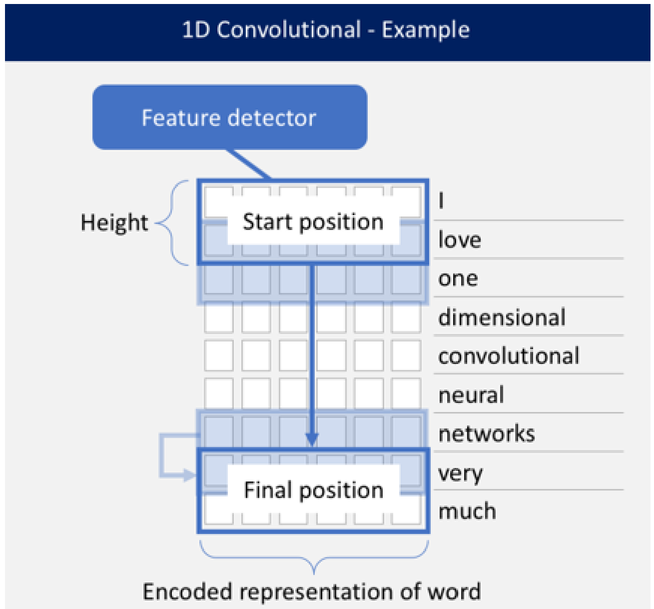

Fig. 3. 1D Convolution Neural Network.

from 48 different patients in the form of two lead ECG recording of 30 minutes. Its approximate 109000 heart-beats are distributed in 16 different classes (showed in Table 1) and each of them has been labeled by two professional cardiologists.

The first step to prepare the dataset used in this work was dividing the over 31 *million* samples in smaller segments to feed the neural network. In order to be sure to include at least one heart-beat in each segment the size was chosen to be between 1 and 2 *seconds*. Since the frequency of the whole database is 360 $samples/s$ a segment size of 500 *samples* was selected. Furthermore an overlapping factor of 10% was chosen in order to increase the final number of segments (data augmentation).

Each segment was then normalized in a range of [-1,+1], and the appropriate label was assigned to the segment. Finally, the dataset was randomly divided in training dataset and validation dataset with a ratio of 90%/10%, respectively.

2.2 1D-CNN

A Convolutional Neural Network (CNN) is a class of neural network where a filter - commonly called kernel - is passed (convoluted) along data in order to learn particular patterns. These pattern extracted grow in complexity along with the depth of the network. Namely, deeper networks extracts more elaborate features.

In Fig. 4 there is an example of the most commonly used 2D-CNN where a kernel of width and height $3x3$ is passed across an image, or a generic numerical

Table 1. Heart-beat labels and their meaning.

Label	Meaning	Label	Meaning
/	Paced beat	R	Right bundle branch block beat
A	Atrial premature beat	S	Supraventricular premature beat
E	Ventricular escape beat	V	Premature ventricular contraction
F	Fusion of ventricular and normal beat	!	Ventricular flutter wave
J	Nodal premature beat	a	Aberrated atrial premature beat
L	Left bundle branch block beat	e	Atrial escape beat
N	Normal beat	f	Fusion of paced and normal beat
Q	Unclassifiable beat	j	Nodal escape beat

matrix, producing an output filtered image. The convolution starts by superimposing the kernel with part of the image; then, the corresponding elements are multiplied and summed with each other and the results is the new element of the output matrix. Finally, the kernel is moved and the process is repeated for all the elements of the input matrix. It is important to note that because of how the convolution works, the output matrix is smaller than the input one depending on the size of the kernel.

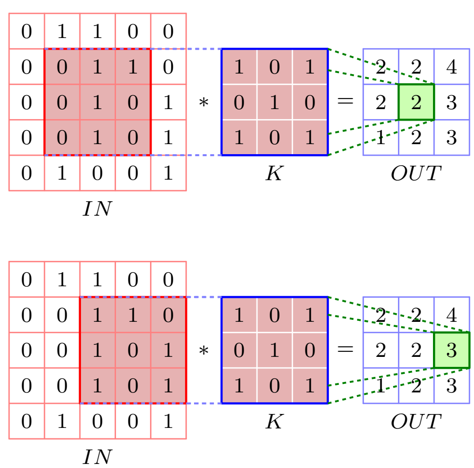

Fig. 4. Example of two passages of a 2D CNN.

In 1D-CNN the procedure is analogous. The only difference is that filters and signals are mono-dimensional, and thus the kernel can only slide in one direction.

2.3 Google Colab

Albeit this work didn't needed to elaborate vasts amount of data, the training of a deep CNN can require a tremendous amount of time if performed on a low end machine. For this reason, all the experiments were performed on Google Colab, where it was available a virtual server with a resourceful GPU (Nvidia Tesla k80), which greatly helped in speeding up the training process.

3 Experiments

To assess the classification quality of a 1D-CNN on the MIT-BIH dataset, several configurations of the network have been tested and compared. The number of layers, the size and the number of the filters, the dropout rate, together with the activation function have been varied to determine the best architecture. Among the different possibilities, only the 4 most representative examples, w.r.t. the classification performances, are reported together with their topology. Table 2 resumes the results of the selected experiments.

Table 2. Accuracy values for the four most representative network architectures

	Training Accuracy	Test Accuracy	Total Parameters
Net 1	92 %	91 %	65,056
Net 2	96 %	94 %	257,104
Net 3	96 %	94 %	533,072
Net 4	98 %	95 %	1,266,768

To begin, a simple configuration, say Net1, with around $65K$ parameters has been tested. It was made of a first convolutional layer of 16 filters with a kernel size of 32, followed by a max pooling layer and a softmax classifier. Net1 has reported a training and testing accuracy equal to 92% and 91%, respectively.

The second experiment deals with a more complex network ($257K$ parameters), called Net2. It consisted of a first convolutional layer of 64 filters with a kernel size of 8, followed by a max pooling layer and a softmax classifier. Overall training and testing accuracy were equal to 96% and 94%, respectively, thus improving the previous classification performances.

Third experiment was conducted using a deeper architecture (Net3) made of three convolutional layers with growing number of filters - $64, 128, 256$ - and decreasing kernel size - $32, 16, 8$ - each followed by a pooling layer. The convolutional layers feed a 128 neurons fully-connected layer which finally flows into the softmax classifier. Despite the number of parameters doubled ($533K$) w.r.t. the previous experiment, the performances remained roughly the same.

In order to improve the classification, in the last experiment a much more complex configuration ($1200K$ parameters) was implemented, Net4. Fig. 5 shows the architecture detail: it is a 5-layer CNN with 2 fully connected layers and 1 fully connected softmax classifier. The latter experiment yields the best results w.r.t. classification performances; indeed, it reached 98% and 95%, training and testing accuracy, respectively.

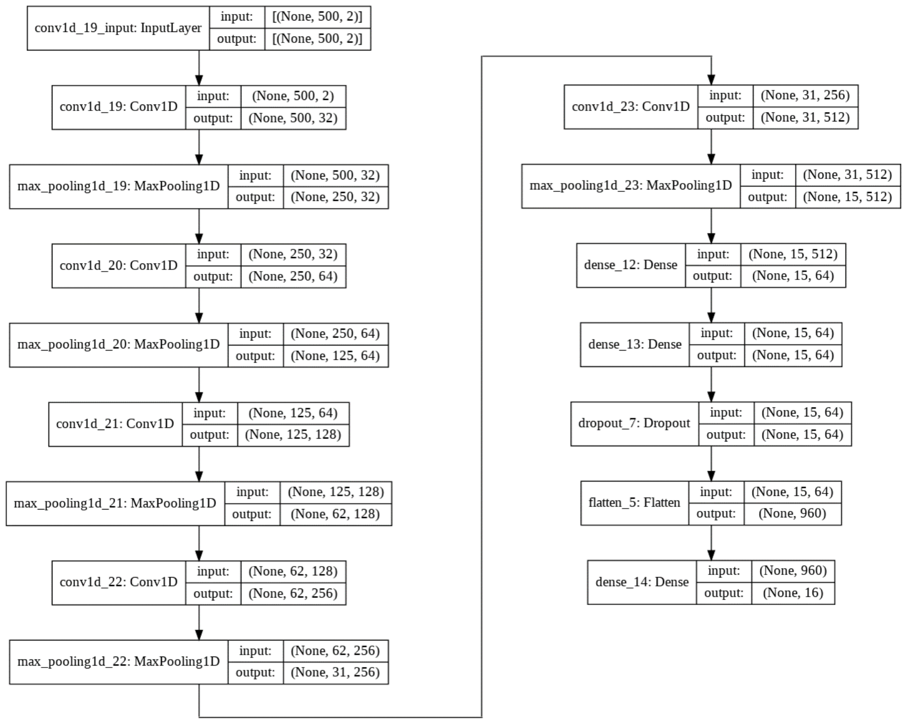

Fig. 5. Net4 architecture.

3.1 Results Analysis

Net4 is the best architecture resulting from the experiments. Despite several attempts to increase the classification rate both in training and test sets, the network did not improved its performances. Therefore, the confusion matrix of the latter experiment has been analysed in order to deepen the response of Net4 to the different classes of the input dataset.

Analyzing the confusion matrix in Fig. 6 there are a few observation to be made. First, class F, which is the fusion of ventricular and normal beat, is sometimes mistaken with class N (Normal beat) or class V (Premature ventricular contraction); F is, by definition, the fusion of the other two classes, therefore if the analyzed window is not perfectly aligned with the whole series of heartbeat, these classes are virtually unrecognizable. A possible solution could be the window expanding; unfortunately, this approach is not feasible because it would prevent the recognition of the other classes.

It can also be observed that class e (Atrial escape beat) is spread across multiple classes, but not class e itself. The main reason for this behaviour is that class e is the least represented class in the whole dataset, then Net4 could not be able to train properly on its recognition. However, since class e is very similar to class A (Atrial premature beat), the net was able to partially classify it as that.

Class S (Supraventricular premature beat) is completely misinterpreted as class V (Premature ventricular contraction) and requires further investigation since they are two very different patterns.

The last remark is about the class Q (Unclassifiable beat). This class is a special case because, by definition, it does not have a specific pattern. In fact, it represent an heart-beat that the cardiologists discarded or were not able to classify due to noise, uncertainties, alteration, etc. It is interesting to note how the network classified most (49%) of those heart-beats as class N (Normal heartbeat). Albeit the net clearly classified this class as a wrong heart-beat, we cannot exclude, in advance, the fact that it was responding to some specific pattern of the correctly trained classes. Therefore a further investigation is required for each of class Q heart-beats, to assert if the classification was right.

Finally, the most influential flaw of the network was the class unbalance in the dataset. Almost 40% of the whole dataset examples were of class N, while other classes were only represented by a very small amount of examples (e.g. class e only counted less than 2% of the dataset). Of course, this dis-homogeneity of class representations had a decisive impact on the results of the training.

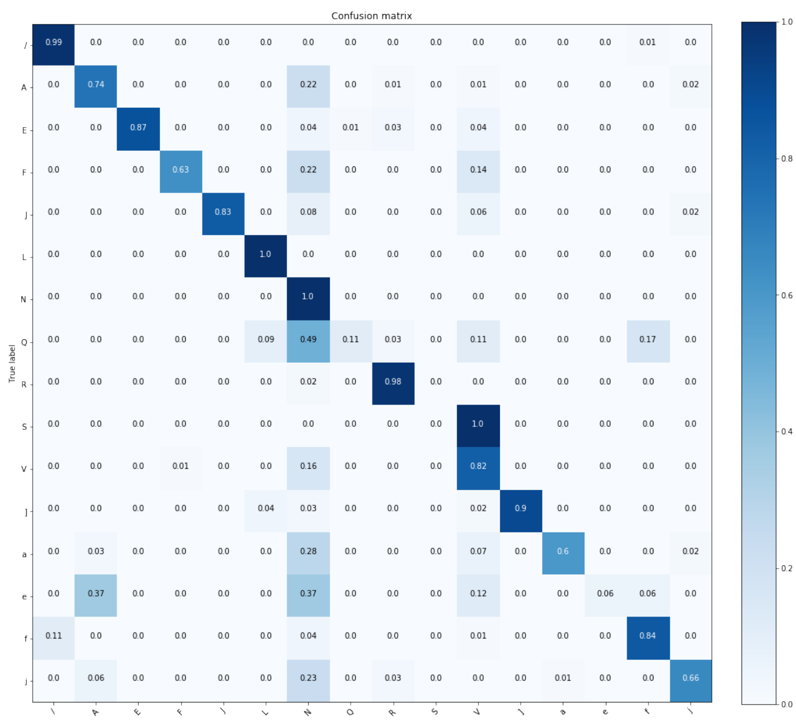

Fig. 6. Confusion matrix obtained with Net4.

4 Conclusions

Automated ECG classification represents a promising technique to improve physicians diagnostic performances on cardiac diseases. Several techniques have been already proposed in literature at this purpose. This paper presents a novel approach based on 1D-CNN. Different network architectures have been tested and compared; among these, Net4 has reached the highest accuracy both in training (98%) and test (95%) phases. The analysis of its confusion matrix has shown some misclassifications due to both data nature and class unbalancing.

Future works will tackle data dis-homogeneity either using selective class augmentation to balance the dataset or tuning learning rates depending on class rarity. Another approach worth of investigation is the hierarchical clustering to better represent the less represented classes and, consequently, improve the overall classification. Finally, a separate work will deal with the study of Net4 convolutional layers to analyse their features.

References

1. Cirrincione, G., Randazzo, V., Pasero, E.: A Neural Based Comparative Analysis for Feature Extraction from ECG Signals. In: Esposito A., Faundez-Zanuy M., Morabito F., Pasero E. (eds) Neural Approaches to Dynamics of Signal Exchanges. Smart Innovation, Systems and Technologies, vol 151. Springer, Singapore, 2020.
2. Pan, J. P., Tompkins, W. J.: A Real-Time QRS Detection Algorithm. In: IEEE Transactions on Biomedical Engineering, vol. 32, no. 3, pp. 320-326, Mar. 1985.
3. Mehta, S. S., Lingayat, N. S.: SVM-based Algorithm for Recognition of QRS Complexes in Electrocardiogram. In: Irbm vol. 29, no. 5, pp. 310-317, Nov. 2008.
4. Shyu, L. Y., Wu, Y. H., Hu, W.: Using Wavelet Transform and Fuzzy Neural Network for VPC Detection from the Holter ECG. In: IEEE Transactions on Biomedical Engineering, vol. 51, no. 7, pp. 1269-1273, Jul. 2004.
5. Debnath, T., Hasan, M. M., Biswas, T.: Analysis of ECG Signal and Classification of Heart Abnormalities Using Artificial Neural Network. In: Proc. 9th Annual International Conf. of Electrical and Computer Engineering(ICECE), Dhaka, 2016, pp. 353-356.
6. Coast, D. A., Stern, R. M., Cano, G. G., Briller, S. A.: An approach to cardiac arrhythmia analysis using hidden markov models. In: IEEE Transactions on biomedical Engineering, 37(9):826âĂŞ836, 1990.
7. Ranaware, P. N., Deshpande, R. A.: Detection of Arrhythmia Based on Discrete Wavelet Transform Using Artificial Neural Network and Support Vector Machine. In: Proc. 11th Annual International Conf. of Communication and Signal Processing(ICCSP), Beijing, 2016, pp. 1767-1770.
8. Artis, S. G., Mark, R.G., Moody, G.B.: Detection of atrial fibrillation using artificial neural networks. In: Computers in Cardiology 1991, Proceedings., pp. 173âĂŞ176. IEEE, 1991.
9. Clifford, G.D., Liu, C.Y., Moody, B., Lehman, L., Silva, I., Li,Q., Johnson, A.E.W., Mark, R.G.: Af classification from a short single lead ecg recording: The physionet computing. In: Cardiology Challenge 2017. 2017.

10. Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., Ng, A. Y.: Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. In: Nature Medicine, 25, pp. 65âĂŞ69 (2019).
11. Cosimo Ieracitano, Nadia Mammone, Alessia Bramanti, Amir Hussain, Francesco C. Morabito, A Convolutional Neural Network approach for classification of dementia stages based on 2D-spectral representation of EEG recordings, Neurocomputing, Volume 323, 2019, Pages 96-107, ISSN 0925-2312.
12. Cosimo Ieracitano, Nadia Mammone, Amir Hussain, Francesco C. Morabito, A novel multi-modal machine learning based approach for automatic classification of EEG recordings in dementia, Neural Networks, Volume 123, 2020, Pages 176-190, ISSN 0893-6080.
13. D. Li, J. Zhang, Q. Zhang and X. Wei, "Classification of ECG signals based on 1D convolution neural network," 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom), Dalian, 2017, pp. 1-6. doi: 10.1109/HealthCom.2017.8210784.
14. Kiranyaz, Serkan & Ince, Turker & Gabbouj, Moncef. (2015). Real-Time Patient-Specific ECG Classification by 1D Convolutional Neural Networks. IEEE transactions on bio-medical engineering. 63. 10.1109/TBME.2015.2468589.
15. Karhe, R. R., Badhe, B.: Arrhythmia Detection Using One Dimensional Convolutional Neural Network. In: International Research Journal of Engineering and Technology (IRJET), 05(08), 2018.
16. Karhe, R. R., Badhe, B.: Heart Disease Classification Using One Dimensional Convolutional Neural Network. In: International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, 06(06), 2018.
17. Moody, G.B., Mark, R.G.: The impact of the MIT-BIH Arrhythmia Database. In: IEEE Engineering in Medicine and Biology 20(3), 45-50 (2001)
18. Goldberger, A.L., Amaral, L.A.N., Glass, L., Hausdorff, J.M., Ivanov, P.Ch., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.K., Stanley, H.E.: PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation, 101(23), 215-220 (2000)
19. MIT-BIH Arrhythmia Database, https://www.physionet.org/physiobank/database/mitdb/, last accessed 2019/04/19
20. MIT-BIH Arrhythmia Database Directory, https://www.physionet.org/physiobank/database/html/mitdbdir/mitdbdir.htm