Neural Networks-Based Method for Electrocardiogram Classification

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Abstract
Neural Networks are widely used for huge variety of tasks solution. Machine Learning methods are used also for signal and time series analysis, including electrocardiograms. Contemporary wearable devices, both medical and non-medical type like smart watch, allow to gather the data in real time uninterruptedly. This allows us to transfer these data for analysis or make an analysis on the device, and thus provide preliminary diagnosis, or at least fix some serious deviations. Different methods are being used for this kind of analysis, ranging from medical-oriented using distinctive features of the signal to machine learning and deep learning approaches. Here we will demonstrate a neural network-based approach to this task by building an ensemble of 1D CNN classifiers and a final classifier of selection using logistic regression, random forest or support vector machine, and make the conclusions of the comparison with other approaches.

Keywords:
electrocardiogram, ECG, ECG classification, one-dimensional convolutional neural networks, 1D CNN, machine learning, artificial neural networks.

1. Introduction

According to the statistics of the World Health Organization, a large percentage of human diseases are related to the cardiovascular system. A large number of problems and complications can be prevented with the help of continuous monitoring and constant analysis of the condition, in particular by capturing the signals of the human body and processing them in time. One of these methods is the analysis of cardiac activity in real time by reading the electrocardiogram (ECG) [1].

Many methods have been proposed for ECG classification [2-7]. They differ in approaches, accuracy, processing speed and other performance indicators.

This study uses the PhysioNet / Computing in Cardiology Challenge 2017 dataset [2,8], widely known for research and development of ECG analysis algorithms. Several approaches are reviewed and a combined analysis method based on 1D Convolutional Neural Networks (CNN) and classifiers for decision making is proposed. The proposed method makes a conclusion about the cardiogram regarding its deviations, namely, the presence of arrhythmia. Too noisy cardiograms and other types of arrhythmias are also separated (without division).

A comparison with other methods [3] is given at the end of the article. The results obtained by the authors are adequate and have a high value of the main metric of quality analysis of such methods - F_1. This makes the method suitable for further implementation and use in connection with a mobile cardiograph, further research and application.

2. Input Data

A set of cardiograms from the PhysioNet / Computing in Cardiology Challenge-2017 dataset was used to develop and test the algorithms [2]. The dataset contains 8528 unipolar ECG signals recorded using the AlivCor device at a frequency of 300 Hz. Each recording was labeled by an expert into one of four classes: normal sinus rhythm, atrial fibrillation, other type of rhythm, or noisy cardiogram, denoted as "N", "AF", "O" and "~", respectively. The percentage ratio of each class and examples of ECG are shown in Table 1 and Fig. 1.

Table 1. Ratio of cardiograms of different classes in the PhysioNet / Computing in Cardiology Challenge 2017 data set [2]

Class	N (Normal)	AF (Atrial Fibrillation)	O (Other)	~ (Noise)
Count	5076	758	2415	279
%	59.5%	8.9%	28.3%	3.3%

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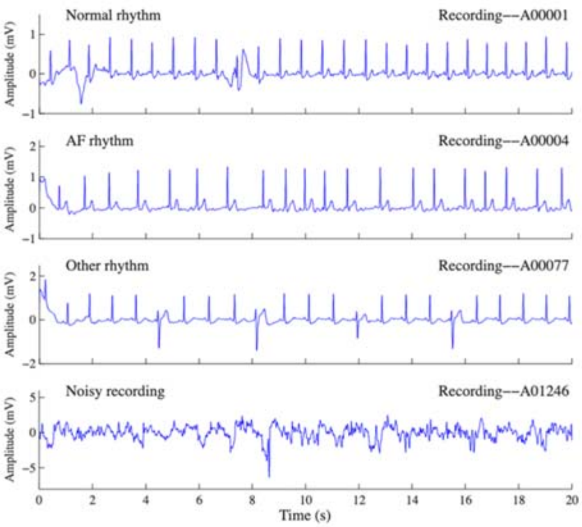

Fig. 1. ECG examples from the PhysioNet data set / Computing in Cardiology Challenge 2017 [2]

3. Method Overview

A model designed to classify ECG into four classes was developed: normal rhythm, atrial fibrillation, other diseases, noisy ECG (“Normal”, “Atrial Fibrillation”, “Other”, “Noisy” [2]). The model is based on 5 one-dimensional convolutional neural networks (CNN). Before submitting the data to the neural network, preliminary processing of the ECG is performed, namely: filtering, localization of R peaks (Fig. 2), "cutting" the ECG into smaller parts and oversampling. After classifying the "cut" parts separately, the results are combined and a final class is selected for the entire ECG. Different options for selecting the final class were investigated, namely: weighted maximum likelihood using logistic regression, random trees, and the support vector method.

At the first step, we separate noisy ECGs from others. Based on the conducted experiments, this class is less amenable to classification, so we first separate such cardiograms from the rest. For this, the ECG is "cut" into parts of three seconds each and each part is classified using CNN separately (the structure of the network is presented below). ECG slicing is necessary for faster neural network training, because the gap (amount of data) becomes smaller, and the amount of data to train on a limited sample is larger. The complexity of the classification lies in the fact that some ECGs can combine several types (classes of the final classification) at the same time. For example, one part of the ECG is normal, and the other part is noisy.

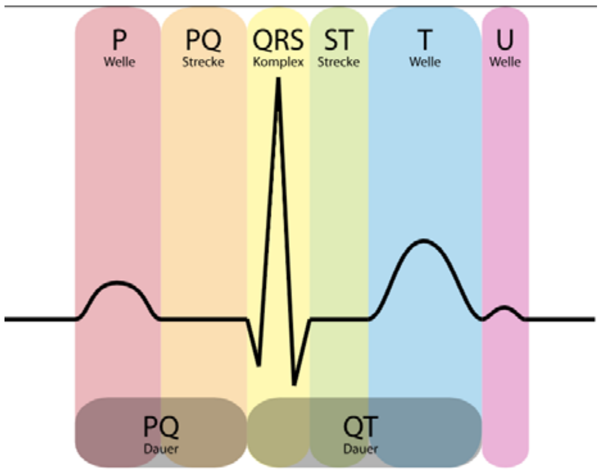

Fig. 2. The structure of the ECG cycle and R peaks

The next step is ECG filtering, where we apply the moving average and the Butterworth filter [11]. Next, we apply the algorithm for finding R peaks. In the last step, we "cut" the ECG into parts, each of which has several RR cycles, classify each part using CNN, and combine the results for the whole ECG.

4. Data Preprocessing

Before the data enters the input of the neural network, it undergoes preprocessing and primary analysis. When analyzing the ECG, researchers are interested in the periodic PQRST complex (Fig. 2). To filter out low frequencies, we use a moving average, which is subtracted from the result. To clean the signal from noise, we use a low-pass Butterworth filter [11]. In fig. 3 shows the result of applying the constructed Butterworth filter on a very noisy ECG.

To improve the accuracy of the neural network, we align the data by R-R cycles. To do this, it is necessary to localize the QRS complex in automatic mode. The authors propose an algorithm for finding R peaks, which consists of the following steps (Fig. 4):

1) Signal transformation according to formulas (1), (2), (3) below. This step helps to highlight sharp changes in amplitude, characteristic only of the QRS complex. Also, at this step, the R-peaks directed downwards are flipped upwards.

2) Isolation of potential R peaks. At this step, a moving window is used, in which the points higher than the 97th quantile are highlighted.

3) Grouping potential R peaks if they are close to each other and selecting the best candidate in the group.

$$\boldsymbol{UpPeak_k} = \left|\min_{j=k-9,k-1}(x_j) - x_k\right| + \left|\min_{j=k+1,k+9}(x_j) - x_k\right| \quad (1)$$

$$\boldsymbol{DownPeak_k} = \left|\max_{j=k-9,k-1}(x_j) - x_k\right| + \left|\max_{j=k+1,k+9}(x_j) - x_k\right| \quad (2)$$

$$\boldsymbol{Tr_k} = \max(\boldsymbol{UpPeak_k}, \boldsymbol{DownPeak_k}) \quad (3)$$

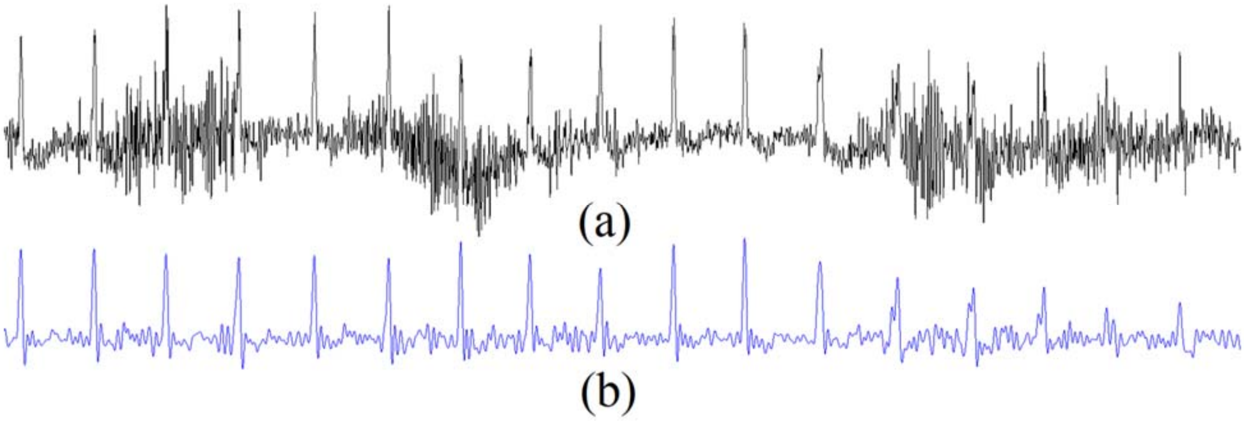

Fig. 3. Fragment of ECG 104 after high-frequency noise filtering: a – input ECG; b – filtered ECG

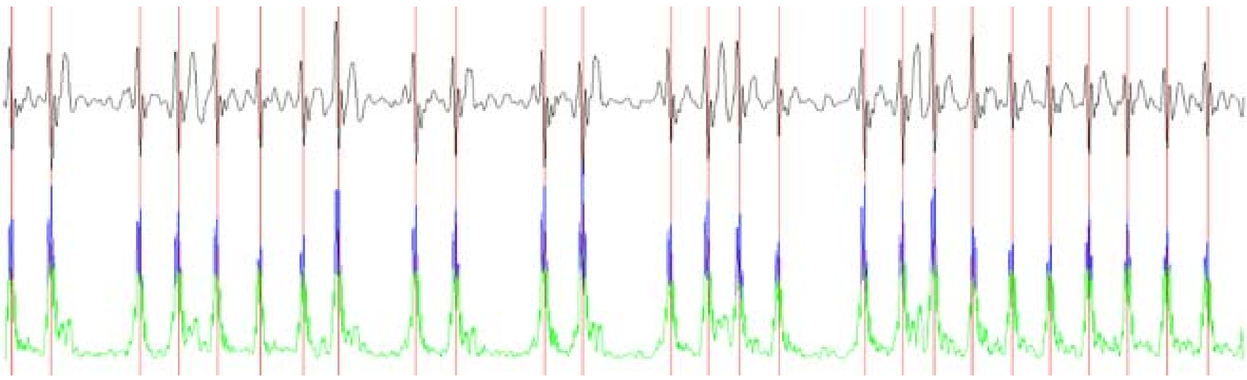

Fig. 4. Localization of R peaks (black – input ECG A00706, green – transformed, blue – potential R peaks, red – determined R peaks)

The MIT-BIH Arrhythmia Database dataset was used for algorithm testing and parameter selection [9,10]. It consists of 48 ECGs, each lasting 30 minutes. The dataset also contains labeled R-peaks and their classification. The main quality indicators of the algorithm for determining R peaks are: $\boldsymbol{T_p}$ is the number of correctly identified R peaks, $\boldsymbol{F_p}$ is the number of false positive determined R peaks, $\boldsymbol{F_n}$ is the number of false-negatively determined R peaks, and error $\boldsymbol{F_d}$.

Table 2 shows the results of a comparison with the method proposed in [12] (ECG Enhancement and R-Peak Detection Based on Window Variability).

Table 2. Characteristics of the accuracy of determining R-peaks in comparison with [12]

The Proposed Algorithm			**[11]**		
F_p	F_n	$\boldsymbol{F_d}$	F_p	F_n	$\boldsymbol{F_d}$
40	141	**0.2256**	244	192	**0.5759**

After determining the R peaks, we "cut" the cardiogram into several R-R cycles. Since the length of the cycles may differ, even between pairs of adjacent peaks, we resample the selected R-R cycles so that the resulting sequence has the length specified in the neural network.

5. Classification

As a result of the analysis of existing solutions, scientific articles and the authors' previous attempts at ECG classification, it was found that convolutional neural networks show some of the best results. That is why a convolutional 1D neural network (1D CNN) is used to build the model, that is, one-dimensional convolution was used. As a result, 5 different, but very similar in architecture, neural networks were obtained. From the dataset [2], ~91% of ECGs were taken for training and ~9% as test samples. The network architecture is shown in fig. 5 and fig. 6.

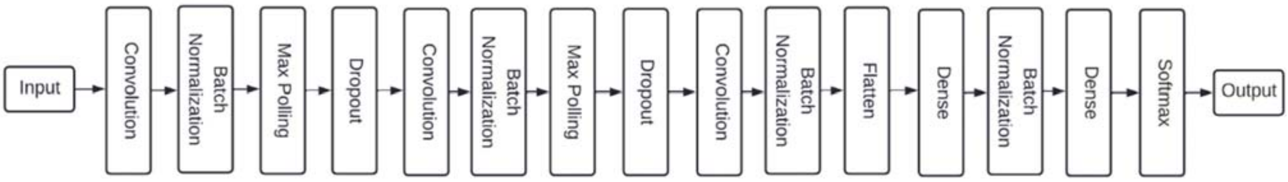

Fig. 5. Network architecture for classification into noisy and clean ECGs

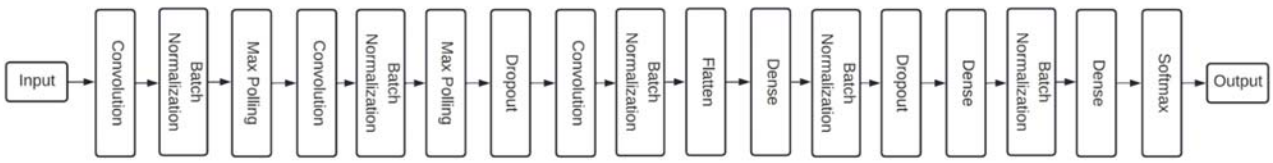

Fig. 6. Network architecture for ECG classification into “N”, “A” and “O” classes

The Adam optimizer, ReLU activation function and Softmax for the output layer were used for model training. Categorical cross-entropy is used as an error function. Also, L2 regularizer was used for all convolutional layers. The learning rate was set to 0.001 using Exponential Decay.

The first stage of classification was the definition of noisy cardiograms. For this, the ECG was divided into parts of 3 seconds each with different shifts. As a result, they are divided into the "Noisy" and "NotNoisy" classes. It was for this classification that clean data was taken without the use of filters so as not to distort the result. The obtained accuracy of the neural network is Fp = 0.6167.

The next stage of classification was the development of 3 more neural networks to detect cardiograms with normal rhythm, arrhythmia and other type of rhythm, namely for the following binary classifications: “N” - “NotN”, “AF” - “NotAF”, “O” - "NotO", as well as the development of a network for classification into 3 classes: "N", "AF", "O" ("Normal", "Atrial Fibrillation", "Other"). For this, the ECG was divided into parts of several RR cycles with different shifts.

At the output of the neural networks, the probabilities b_N,b_A,b_O for binary classifiers and t_N,t_A,t_O for the ternary classifier were obtained. To combine the results of different neural networks, weighted probabilities are introduced as follows:

$$\boldsymbol{w_N = b_N\sqrt{t_N}, b_A = b_A\sqrt{t_A}, b_O = b_O\sqrt{t_O}}\ .$$

The final class was chosen based on the highest weighted probability. Classification based on random trees, the method of support vectors and logistic regression was also carried out. For this, the SKLearn library in Python was used. All parameters, except min_samples_leaf = 100 for random trees, were chosen automatically by the classifiers.

Each of the methods was trained on tuples with 6, 9, and 21 parameters. Tuples of parameters were composed as follows:

$$(\boldsymbol{b_N, b_A, b_O, t_N, t_A, t_O})$$
$$(\boldsymbol{b_N, b_A, b_O, t_N, t_A, t_O, w_N, w_A, w_O})$$
$$(\boldsymbol{b_N, b_A, b_O, t_N, t_A, t_O, w_N, w_A, w_O, b_N^2, b_A^2, b_O^2, t_N^2, t_A^2, t_O^2, \sqrt{b_N b_A}, \sqrt{b_N b_O}, \sqrt{b_A b_O}, \sqrt{t_N t_A}, \sqrt{t_N t_O}, \sqrt{t_A t_O}})$$

6. The Results

To evaluate the performance of the entire classification model, the F_1 metric proposed in PhysioNet / Computing in Cardiology Challenge-2017 was used [2,6]:

Table 3. Cross-validation matrix

		Forecast				
		Normal	AF	Other	Noisy	Разом
Ground Truth	Normal	*Nn*	*Na*	*No*	*Np*	ΣN
	AF	*An*	*Aa*	*Ao*	*Ap*	ΣA
	Other	*On*	*Oa*	*Oo*	*Op*	ΣO
	Noisy	*Pn*	*Pa*	*Po*	*Pp*	ΣP
	Разом	Σn	Σa	Σo	Σp	

$$\boldsymbol{F_{1n} = \frac{2\,Nn}{\Sigma N+\Sigma n}} \quad \boldsymbol{F_{1a} = \frac{2\,Aa}{\Sigma A+\Sigma a}}$$
$$\boldsymbol{F_{1o} = \frac{2\,Oo}{\Sigma O+\Sigma o}} \quad \boldsymbol{F_{1p} = \frac{2\,Pp}{\Sigma P+\Sigma p}}$$
$$Final\ Score = \boldsymbol{F_1 = \frac{F_{1n}+F_{1a}+F_{1o}}{3}}$$

The calculation results are presented in Table 4.

Table 4. The value of the F_1 metric for different models of the final classifier

Method	# params	$\boldsymbol{F_{1n}}$	$\boldsymbol{F_{1a}}$	$\boldsymbol{F_{1o}}$	$\boldsymbol{F_1}$	$\boldsymbol{F_1}$ val.
Maximal $\boldsymbol{w_x}$	6	0.8975	0.8531	0.7485	0.8330	0.8243
Logistic regression	6	0.9031	0.8676	0.7672	0.8460	0.8194
Logistic regression	9	0.9028	0.8709	0.7674	0.8470	0.8219
Logistic regression	21	0.9042	0.8715	0.7733	**0.8497**	0.8195
Random forest	6	0.9037	0.8728	0.7674	0.8480	0.8246
Random forest	9	**0.9050**	0.8686	0.7718	0.8485	0.8225
Random forest	21	**0.9050**	0.8690	**0.7740**	0.8493	0.8173
SVM	6	0.9048	**0.8735**	0.7682	0.8489	0.8205
SVM	9	0.9023	0.8705	0.7619	0.8449	0.8262
SVM	21	0.9022	0.8712	0.7632	0.8455	**0.8278**

The best classification results are highlighted in bold in the table. Therefore, the random tree method (Random Forest), as in [6], gives a more accurate classification by individual classes, and the support vector method (SVM) gives the best general results of the final classifier, although with a small advantage.

In general, the accuracy is comparable to the best known models [3-5] and even prevails in individual classes.

Therefore, in general, the method can be adapted for integration with mobile cardiographs for further implementation and use in real-time ECG analysis scenarios.

7. Conclusions

In this work, a new method of electrocardiogram classification is proposed, which consists of the following stages:

1) data filtering (moving average and Butterworth filters),

2) localization of R peaks,

3) ECG "cutting" and resampling,

4) classification of “Noisy” - “NotNoisy”,

5) classification of “Normal”, “Atrial Fibrillation”, “Other” using an ensemble of classifiers from 1D CNN and the final ensemble classifier.

The proposed method has high accuracy indicators according to the F_1 metric and application efficiency (accuracy and speed).

Also, the authors proposed a new method of localization of R-peaks of QRS cycles of cardiograms, which proved to be effective in terms of accuracy.

The model proposed by the authors can be the basis for further research due to the new combination of the ensemble structure of the classification decision, as well as improvements and implementation through the integration into the "full cycle" analysis system using mobile ECG readers for the purpose of early detection of abnormalities in the cardiogram and rapid preliminary diagnosis.

Also, it worth to note, that the obtained results are not as high as expected, and in [13] one could find more precise approach and method in terms of F_1 measure score. But nevertheless this research presents a promising approach which could be extended to more qualitative outcomes in the future works.

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