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Deep Learning for ECG Classification

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Abstract. The importance of ECG classification is very high now due to many current medical applications where this problem can be stated. Currently, there are many machine learning (ML) solutions which can be used for analyzing and classifying ECG data. However, the main disadvantages of these ML results is use of heuristic hand-crafted or engineered features with shallow feature learning architectures. The problem relies in the possibility not to find most appropriate features which will give high classification accuracy in this ECG problem. One of the proposing solution is to use deep learning architectures where first layers of convolutional neurons behave as feature extractors and in the end some fully-connected (FCN) layers are used for making final decision about ECG classes. In this work the deep learning architecture with 1D convolutional layers and FCN layers for ECG classification is presented and some classification results are showed.

1. Introduction

Most part of heart problems, like Myocardial Infarction, AV Block, Ventricular Tachycardia and Atrial Fibrillation etc. can all be diagnosed from ECG signals with an estimated hundreds of millions ECGs recorded annually [1, 2]. We investigate the task of arrhythmia detection from a single short ECG lead. This is known to be a challenging task for computers but can usually be determined by an expert from a single, well-placed lead.

The importance of ECG classification is very high now due to many current medical applications where this problem can be stated. Currently, there are many machine learning (ML) solutions which can be used for analyzing and classifying ECG data. However, the main disadvantages of these ML results are use of heuristic hand-crafted or engineered features with shallow feature learning architectures. The problem relies in the possibility not to find most appropriate features which will give high classification accuracy in this ECG problem. One of the proposing solution is to use deep learning (DL) architectures where first layers of convolutional neurons behave as feature extractors and in the end some fully-connected (FCN) layers are used for making final decision about ECG classes. In this work the deep learning architecture with 1D convolutional layers and FCN layers for ECG classification is presented and some classification results are showed.

2. Current results in ECG Classification

As stated before, ECG classification problem is very important and had a strong attention from not only medical community but also community of computer scientists especially from AI field [1, 2]. The latest results were obtained from Andrew Ng's scientific group (Pranav Rajpurkar, Awni Y. Hannun, Masoumeh Haghpanahi, Codie Bourn), where they used 34-layer convolutional neural network and exceed the average cardiologist performance in both recall and precision [2].

One of the crucial property of the latter work was use of a dataset with more than 500 times the number of unique patients than other well-known corpora. Other works present two-class ECG classification algorithms with simple neural network architecture (ischemic heart disease or normal sinus rhythm), which works well but in case of low amount of data and special problem statement [3–5]. Unfortunately, mostly researchers don't have a possibility to use such kind of dataset due to many reasons. Obvious solution for this is to use of data augmentation technics, which are well fitted to time series classification problems [6–9]. Further, we will describe the available medical data and propose the classification algorithm.

3. Problem statement and data

This current ECG classification task can be described as task to decide to which class patient's ECG can be assigned. The number of classes are four: normal sinus rhythm, arrhythmic, other kind of rhythm, very noisy [10]. The given data is non-balanced, most part of belongs to normal sinus rhythm (60% of data). The Figure 1 presents the brief summary of the available data.

There were used different operations for creating balanced dataset like multiplication of existing ECG for some class by means of shifting time values. In addition there was a try to create some unified length of ECG by means of duplication time-series values.

Type	# recording	Time length (s)				
		Mean	SD	Max	Median	Min
Normal	5154	31.9	10.0	61.0	30	9.0
AF	771	31.6	12.5	60	30	10.0
Other rhythm	2557	34.1	11.8	60.9	30	9.1
Noisy	46	27.1	9.0	60	30	10.2
Total	**8528**	**32.5**	**10.9**	**61.0**	**30**	**9.0**

Figure 1. The Data Summary

It is crucial to look into ECG data which can be obtained from patients and decide what kind of preprocessing and machine learning algorithm we have to use. Firstly, most ECG data is time series data with duration about 30 or 60 s with sampling time about 0.003 s. There are many machine learning algorithms with some appropriate choice of features which deal with time series data. But as it stated in introduction the work presents use of feature extractors – convolutional neural networks (CNN) in special case (Figure 2). This feature extraction should free the developers from use of expert knowledge and hand-crafted features. It is not remove expert knowledge at all from development process but decrease the time to show the first prototype of ECG classification algorithm.

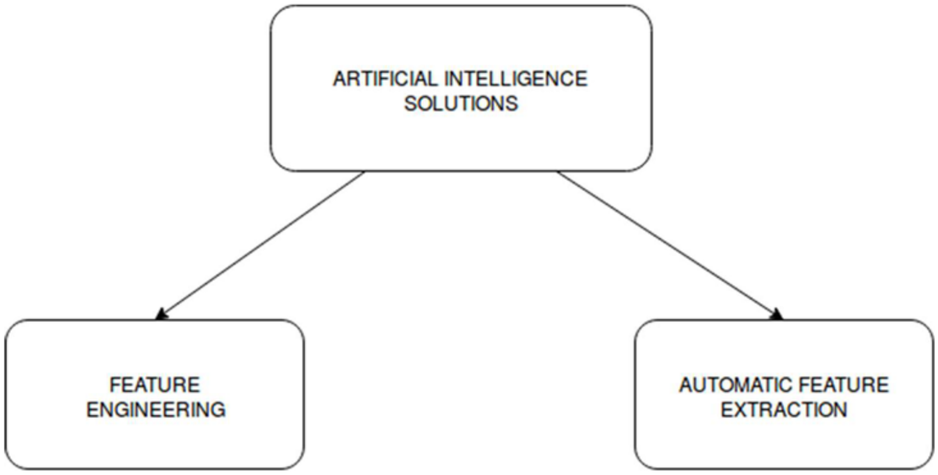

Figure 2. The simplified structure of AI solutions

This special case of ECG differs from usual one where CNN is used – image recognition task. In the latter case, data is always presented as 2D data with some color channels in contrary to time series where usually 1D data is used (Figure 3).

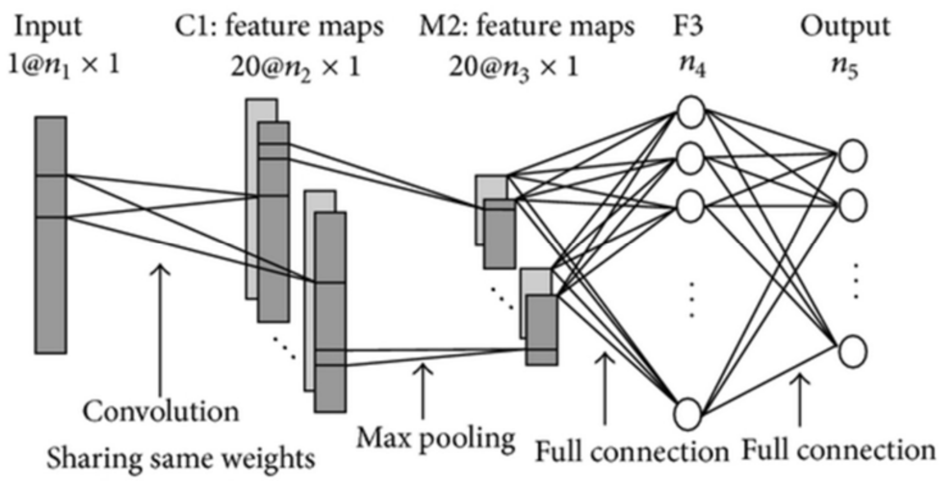

Figure 3. The example of CNN for Time series

In any case, CNN with appropriate architecture, which depends on data dimensionality and its structure, can give high accuracy in classification task. In current case, we use CNN 1D with the following architecture: 7 convolutional layers with filter width 5 and 128 neurons + max-pooling and dropout after every layer + GlovalAveragePooling + 3 FCN layers with (256/128/64) neurons + dropout after every layer + softmax layer with 4 outputs.

Also, there was used some standard preprocessing procedure like subtraction the mean from time-series values and division by standard deviation value, the batch size was equal to 256. All parts of this algorithm was implemented by means of Keras framework [11].

The Figure 4 and Figure 5 present the loss and accuracy values for the training steps consequently, the same works for Figure 6 and Figure 7 which show results for validation step.

In all computational experiments we use GPU NVIDIA GeForce GTX 1080 and CPU i5 – 6600 3.3 GHz. The obtained results can be compared to existed ones which were gained in other previous works in terms of precision.

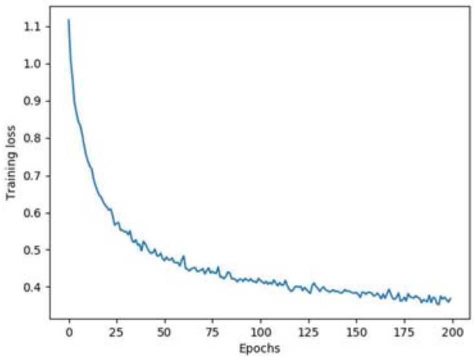

Figure 4. Plot of logarithmic loss for training step

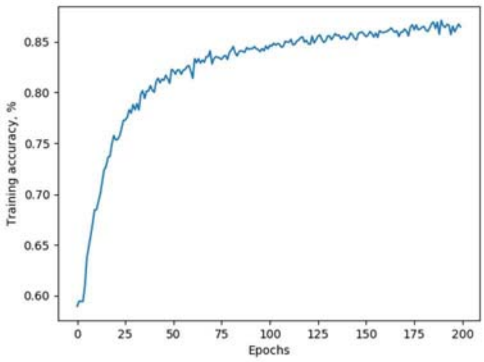

Figure 5. Plot of accuracy for training step

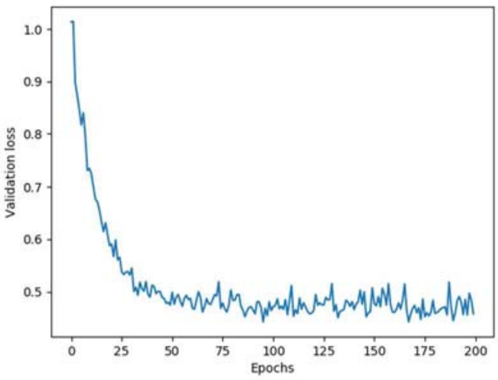

Figure 6. Plot of logarithmic loss for validation step

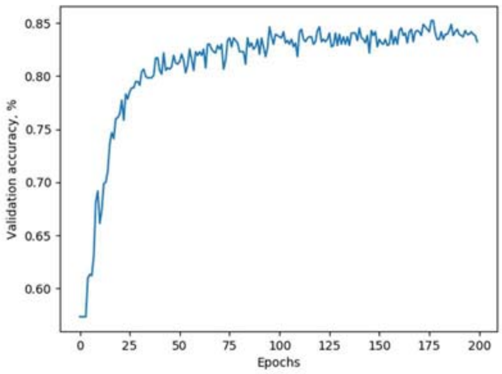

Figure 7. Plot of accuracy for validation step

4. Discussion

The obtained classification results show that the proposed DL solution can be used in task of ECG classification in the case when training data is unstructured, unbalanced and can be represented as 1D time series with standard time duration for portable single lead ECG devices. Also the algorithm's ability to extract features is very useful in the cases when there is no any medical or related subject specialists for feature engineering due to some reasons. Disadvantages of the work can be described as unsatisfied comparison to other DL solutions in terms of computational complexity, proposed architecture and optimization methods. Also, it is interesting to test a recurrent neural net (RNN, LSTM etc.) in ECG classification task because of its implicit ability to work with historical data like time series. In any case the main open problem is to decide exactly what kind of architecture should be used for given datasets – what number of neurons, layers and type of optimization method.

5. Conclusions

This work presented some ECG classification results about use of 1D convolutional neural networks with FCN layers on preprocessed time-series data. The best resulted accuracy on validation data is about 86%. In future there can be some upgrade in accuracy by means of some other preprocessing procedures and creating more balanced dataset by use of GAN networks. In any case, the main goal is to present and use some machine learning algorithm without any feature engineered procedure and competing classification accuracy in comparison to human results.

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