3-D ECG images with Deep Learning Approach for Identification of Cardiac Abnormalities from a Variable Number of Leads

Giovanni Bortolan

[1] Institute of Neuroscience IN-CNR, Padova, Italy

Abstract

The objective of this study is to explore new imaging techniques with the use of Deep Learning method for the identification of cardiac abnormalities present in ECG recordings with 2, 3,4, 6 and 12-lead in the framework of the PhysioNet Challenge 2021. The training set is a public database of 88253 twelve-lead ECG recordings lasting from 6 seconds to 60 seconds. Each ECG recording has one or more diagnostic labels. The six-lead, four-lead, three-lead, and two-lead are reduced-lead version of the original twelve-lead data. The Deep Learning method considers images that are built from raw ECG signals. This technique considers innovative 3D images of the entire ECG signal, observing the regional constraints of the leads, obtaining time-spatial images, where the x-axis is the temporal evolution of ECG signal, the y axis is the spatial location of the leads, and the z axis (color) the amplitude.

These images are used for training Convolutional Neural Networks with GoogleNet for ECG diagnostic classification. Official result of the classification accuracy of the ECGs Test set of our team named 'Gio_new_img' produced a challenge validation score of 0.446, 0.454, 0.440, 0.447 and 0.457 for 12, 6, 4 , 3 and 2 lead. obtaining a full test score of 0.xxx, placing us Nth out of NN in the official ranking.

1. Introduction

After a long series of interesting annual Challenges, the PhysioNet/CINC Challenge 2020 and Challenge 2021 [1-3] provide the opportunity to address the complexity of ECG classification from different point of view and the effect of the analysis of different number of leads.

The main objective of this study is to test the deep learning approach for the automatic classification of ECG signals from a variable number of leads with the participation to the PhysioNet Challenge 2021. Then, a technique based on direct learning from ECG raw data from a variable number of leads through the Deep Learning methods is explored.

2. Challenge database

The Challenge provided a dataset with annotated 88253 12-leads ECG recordings lasting from 6 to 60 seconds [2]. The initial 107 diagnoses were further reduced to the 30 diagnostic classes considered in the Physionet / Challenge scoring system (see [2] for a full list of the diagnoses and codes). They reduce to 26 considering 4 equivalent classes. The seven considered datasets for the learning phase consist of:

1. CPSC DB- 6,877 recordings
2. CPSC extra DB - 3,453 recordings
3. INCART DB - 74 recordings
4. PTB DB - 516 recordings
5. PTB-XL DB- 21,837 recordings
6. G12EC DB - 10,344 recordings
7. Chapman-Shaoxing – 45152 recordings

All ECG data are resampled at 500 Hz (if necessary) for compatibility purposes.

This large dataset is consisting for a total of 88253 ECG recordings and 129024 diagnostic instances.

A random selection of ECG records with at most N_max instances for all the 26 considered diagnostic classes were determined for a more equilibrated distribution of their consistency and for a more efficient learning phase,

Table 1. Distribution of the 129024 diagnostic instances (INST) present in the entire database, and weighted number of records (WNR) of the subset S51K.

Code	INST	WNR	Code	INST	WNR
01 AF	5255	3567	14 NSIVCB	1768	709
02 AFL	8374	3940	15 NSR	28971	8600
03 BBB	522	180	16 SVPB*	224	1778
04 Brady	295	259	17 PR	1481	944
05CLBBB*	213	741	18 PRWP	638	212
06 CRBBB*	1779	3015	19 VPB*	659	846
07 IAVB	13534	1900	20 QAb	2076	722
08 IRBBB	1857	815	21 RAD	1280	527
09 LAD	7631	2615	22 SA	3790	2291
10 LAnFB	2186	755	23 SB	18918	5778
11 LPR	392	130	24 STach	9657	4276
12 LQRSV	1599	964	25 TAB	11380	3724
13 LQT	1904	998	26 Tinv	3989	1515
			TOTAL	129024	51522

(* Equiv: CRBBB & RBBB, PAC & SVPB and PVC & VPB, CLBBB&LBBB)

obtaining the following subsets:
S51K: N_max=5000 produces 51152 ECG records
S37K: N_max=2500 produces 37. 484 ECG records
Table 1 reports the distribution of the 129024 diagnostic instances present in the entire database, and the weighted number of records (WNR) of the subset S51K, consisting of 51522 ECG records.

3. Method

The ECG recordings are filtered to eliminate the power-line interference, the drift of the zero-line and the electromyographic noise (EMG). 12-lead, 6-lead (I, II, III, aVR, aVL, aVF), 4-lead (I, II, III, V2), 3-lead (I, II, V2), and 2-lead (I,II) are considered. 6-lead and 2-lead are equivalent from the informative point of view, as similarly 4-lead and 3-lead. In fact, in both cases the first set is directly derived from the second set of leads. Nevertheless, we have considered the similar situations as distinct ones, in order to test the diagnostic power of the different sets.

3.1 3-D ECG Images

The Deep Learning method considers images that are built from raw ECG signals [4,5].

This technique considers innovative 3D images of the entire ECG signal, observing the regional constraints of the leads, obtaining time-spatial images. Three-dimensional display format of the 6 peripheral leads or the 6 limb leads are described in the literature [6-7]. For example Chang et al. [6] proposed the reverse Cabrera sequence (III, aVF, II, -aVR, I, aVL) and the orderly sequence of (V1, V12, V3, V4, V5, V6) which represents the projection of the cardiac signal from the right to left side of the body. In this paper we define a unique 3-D view of the 12 leads, considering the regional constraints reported in Table 2, in order to have a unique 3-D top-view display, with a proper sequence. In particular, regional and anatomical positions placing aVR as –aVr between I and II, and the Cabrera system are posed in its orderly display.
Consequently, a two-fold image is produced, because the regions are not strictly in the same plane (the precordial leads in an horizontal plane and the limb leads in a frontal plane), but it reflect a regional contiguity. Two examples of this 3-D display are reported in Fig. 1 and Fig. 2, where the x axis represents the temporal evolution of the ECG signal, the y axis represents the spatial location of the leads and the color (z axis) represents the voltage of the ECG signal. This three-dimensional display of the 12 leads is a temporal-space ECG representation.

In particular, ten additional samples between two contiguous leads with cubic, spline or linear interpolation method were added and the 'nearest' extrapolation method was considered.

Table 2. Regional limits of the 12 leads and the considered leads in 12, 6, 4, 3 and 2-lead systems.

		12	6	4	3	2
V1	Septal	X				
V2		X		X	X	
V3	Anterior	X				
V4		X				
V5	Antero-Lateral	X				
V6		X				
aVL	Lateral	X	X			
I		X	X	X	X	X
-aVR		X	X			
II	Inferior	X	X	X	X	X
aVF		X	X			
III		X	X	X		

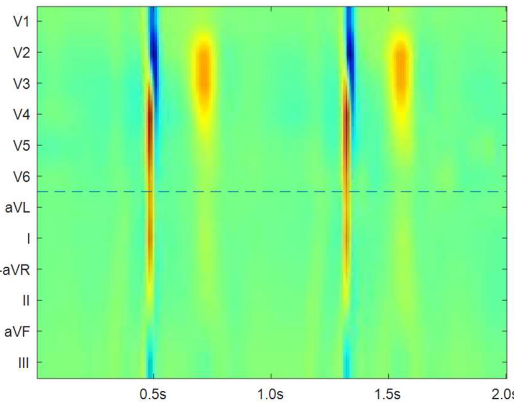

Fig. 1. Example of two ECG beats from A00038 (NSR)

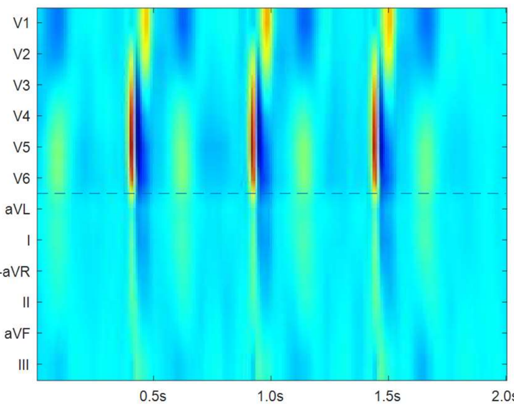

Fig. 2. Example of three ECG beats from A01027 (RBBB & AF)

3.2 Deep Learning Networks

The two kinds of images described previously and obtained considering only raw ECG signals (CWT and 3-D), are then used for training Convolutional Neural Networks for ECG diagnostic classification. Pretrained image CNN classification network that has already learned to extract powerful and informative features from natural images has been used as a starting point to learn a new classification task [4-5].

One pre-trained CNN for image classification have been used: GoogleNet. This is a model pretrained on a subset of the ImageNet database, which is used in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [5, 9 - 10].

GoogleNet is a convolutional neural network characterized by 22 layers, and it is pretrained to classify images into 1000 object categories Each layer can be considered as a filter, consequently the first ones characterize more common features while the deeper ones characterize more specific features in order to differentiate the considered diagnostic classes [4].

Two examples of 3D- ECG view are reported in Fig. 3 (A008874 – NSR) and in Fig. 4 (J00289 - AF), where x axis is time, the y-axis is lead position , and z axis (color) is the magnitude.

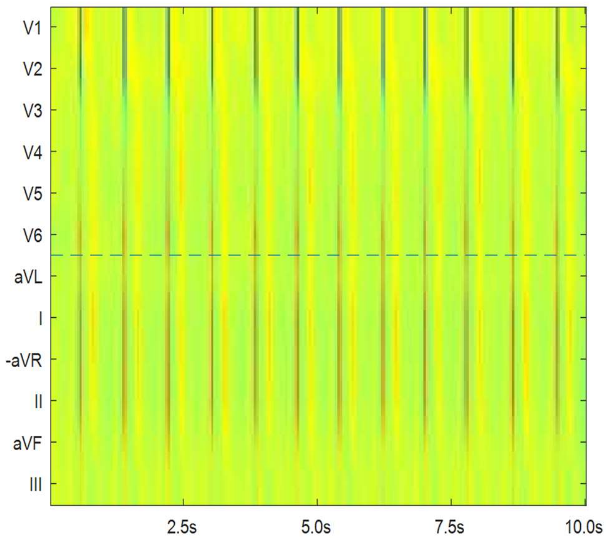

Fig 3. Example of 3-D ECG view (A008874 - NSR)

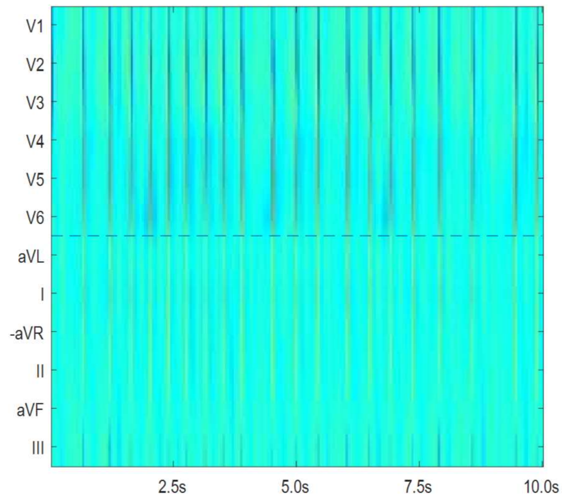

Fig. 4 Example of 3-D ECG view (J00289 - AF)

Particular techniques have been developed in order to adapt the general task to this particular problem:

- Class imbalance is addressed with random oversampling (ROS) algorithm, with a duplication of records in the learning set in order to have a more uniform and balanced distribution of the diagnostic classes
- the learning process of the Deep Learning method was adapted in order to cope with multiple diagnoses classification (comorbidity)
- ten seconds of ECG signal are considered for the analysis of 12-lead , 6-lead, 4-lead, 3-lead,or 2-lead.

4. Results and Discussion

The score indices of the first and second phase of the Challenge (validation scores) are defined and reported in [2,3]. Our team named 'Gio_new_img'participated successfully to the unofficial and official phases of the Challenge.

In the first phase the learning process considered 12-lead, 6-lead, 3-lead and 2-lead systems. In this phase the class imbalance technique with random over-sampling (ROS) algorithm was tested. Table 3 reports the challenge metric with and without ROS technique. It is clear that the ROS does not produce any significant improvement of the scores, and consequently in the second phase the ROS technique has been avoided. In the official Challenge phase, the Deep Learning process was performed and tested by cross-validation techniques.

Table 3. Results of the unofficial phase

	Challenge metric score			
	12	6	3	2
3D+ROS	0.391	0.388	0.386	0.378
3D	0.396	0.396	0.388	0.384

Table 4. Cross Validation results in the learning subsets S51K and S37K with the use of 3-D images

	score	AUROC	AUPRC	subset
12-lead 3-D	0.518	0.852	0.359	S51K
6-lead 3-D	0.521	0.847	0.360	S51K
4-lead 3-D	0.522	0.853	0.362	S51K
3-lead 3-D	0.512	0.850	0.359	S51K
2-lead 3-D	0.535	0.859	0.377	S51K

Table 5. Second Phase – Challenge Validation score considering 3-D images

	score	cpu time	#it	subset
12-lead	0.446		4(+10)	
6-lead	0.454		4(+12)	
4-lead	0.440	3166 min	4(+16)	S51K
3-lead	0.447		4(+18)	
2-lead	0.457		4(+20)	

Table 4 reports 3-fold cross validation indices tested in the database S51K considering 3-D ECG images for the various lead groups. In particular, the challenge scores with the 3-D images in the 5 lead groups were in the short interval [0.512 – 0.535].

Table 5 reports the results official Challenge Validation score for the 5 lead groups with the highest score obtained considering 3-D images. The submitted algorithms started the training phase from pre-trained networks like those reported in Table 4. For example, the deep learning process with 3-D ECG images of 12 leads resumed the training from a previously saved pre-trained network (3-fold cross-trained for 10 iterations) for an additional 4 iterations over the same learning subset, S51K, producing a score of 0.446. Similarly, the 3-D & 2-lead system, produced the highest score (0.457).

The results produced some interesting considerations. The scores reported in Table 5 were in the range [0.440 : 0.457], indicating that all these algorithms have a similar behaviour in the various lead groups. In particular the 2-lead scores are surprisingly similar compared to those obtained with 3, 4, 6, and 12 leads. The comparison between 2 and 12 leads is the most surprising point. This aspect is related to two possible explanations: the pattern recognition capacity of the DL approach is able to recognize and classify ECG signal both with 2 or 12 leads, and, on the other hand, the characteristics of the considered cardiac abnormalities are able to be extracted also from a limited number of leads.

The final official results of our team named 'Gio_new_img', achieved a challenge validation score of 0.000 and a full test score of 0.000 placing us Nth out of N in the official ranking.

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Address for correspondence.
Giovanni Bortolan
IN-CNR
Corso Stati Uniti 4, - 35129 – Padova, Italy
e-mail: giovanni.bortolan@cnr.it