Overcoming data scarcity in life-threatening arrhythmia detection: A deep learning framework for life-saving interventions

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SUPPLEMENTARY MATERIAL

1 Datasets

1.1 *Pre-training (PT)* dataset

Dataset building

Four datasets from the PhysioNet Computing in Cardiology Challenge 2021 [1–3] have been exploited to build the *PT* dataset: *Ningbo Database* [3, 4], *Chapman-Shaoxing Database* [3, 5], *PTB-XL Database* [3, 6, 7] and *The Georgia 12-lead ECG Challenge Database* [3]. All of them contain 12-lead ECG recordings, sampled at a frequency of 500 Hz. *Ningbo Database* contains 34'905 recordings, *Chapman-Shaoxing Database* 10'646 recordings, *Georgia Database* 10'344 recordings, and *PTB-XL* Database 21'837 recordings from 18885 subjects. All these datasets contain 10-second ECG signals, except for *Georgia Database* whose instances last 5 (less than 2%) or 10 seconds. Each ECG is provided with a set of labels describing cardiac diagnosis, morphology and/or rhythm. These are assigned to the whole recording period and encoded through the SNOMED-CT standard.

From these four datasets, we included the recordings containing at least one rhythm label in the *PT* dataset and extracted only lead II. As regards *Georgia Database*, we excluded the ECGs lasting 5 seconds. Afterward, ECG recordings associated with noise label or underrepresented labels (around 3% of the remaining recordings) have been removed. A total of 72850 ECG signals from 70138 subjects associated with 14 different combinations of rhythm labels make up the final dataset. The labels distribution can be found in table 3. It can be noticed that LTAs (e.g. ventricular tachycardia, ventricular fibrillation) are not present in *PT* recordings.

Pre-processing and splitting

All the ECG signals have been resampled at 200 Hz. Each 10s recording has been truncated to obtain a sequence made by 7 256-sample segments (about 8.96s), to ensure compatibility with the architecture used during the pre-training phase. From the set of labels associated with each recording, we selected only the rhythm labels, resulting in one or more rhythms assigned to each sequence. The signals have been filtered with a Butterworth 4th order filter with cutoff frequencies of 0.5 and 40 Hz.

The sequences in *PT* dataset have been split on a subject basis and by exploiting a multi-label stratified strategy. 20% of the dataset has been kept unused for the test. The remaining 80% has been split into 80% for training and 20% for validation. Then, the data were standardized based on the mean and standard deviation computed on the training set.

1.2 *Fine-tuning LTA (FT-LTA)* dataset

Dataset building

For the LTA detection downstream task, three publicly available and widely used datasets have been exploited: *MIT-BIH arrhythmia database (MITDB)* [3, 8], *MIT-BIH malignant ventricular ectopy database (VFDB)* [3, 9] and *Creighton University*

ventricular tachyarrhythmia database (CUDB) [3, 10]. *MITDB* contains 48 30-minute ECG recordings, sampled at 360 Hz, from 47 subjects studied by the Beth Israel Hospital Arrhythmia Laboratory between 1975 and 1979. *VFDB* contains 22 30-minute ECG recordings, sampled at 250 Hz, of subjects who experienced episodes of sustained ventricular tachycardia, ventricular flutter, and ventricular fibrillation. *CUDB* contains 35 8.5-minute single-lead ECG recordings, sampled at 250 Hz, of subjects who experienced episodes of ventricular fibrillation. For all three datasets, rhythm annotations were provided, with the time reference of each rhythm change. For MITDB also beat labels were available.
To build the *FT-LTA* dataset we extracted lead II and selected the labels describing cardiac rhythm changes. The *FT-LTA* dataset includes a total number of 104 ECG recordings from subjects who have experienced LTAs. Table **??** reports the label distribution in each subset of the *FT-LTA* dataset.

Pre-processing and splitting
All the recordings have been down-sampled to 200 Hz and converted in uV for consistency with the pre-training data. Each recording has been split into non-overlapping sequences of 7 256-sample segments. The rhythm labels have been divided into two classes: *LTA*, including ventricular tachycardia (VT), ventricular fibrillation (VF), ventricular flutter (VFL) and polymorphic ventricular tachycardia (PVT), and *other*, including all the other rhythms. Then a unique class (*LTA* or *other*) was associated with each 256-sample segment, obtaining 7 labels per sequence. The most frequent class has been assigned in case of multiple rhythms. The segments labeled with "noise" have been removed since a clear rhythm could not be assigned. Each sequence has been pre-processed following the procedure proposed in [11] and exploited also in [12–14]. It consists of four steps: mean subtraction, five-order moving average filter, high-pass filter at 1Hz for drift suppression, and low-pass Butterworth filter at 30 Hz. The 1–30 Hz is a typical monitor bandwidth used in AEDs to distinguish shockable vs non-shockable rhythms.
Each of the three datasets has been split on a subject basis into train, validation, and test sets. 20% of the dataset has been kept unused for the test, while the remaining 80% has been split into 80% for training and 20% for validation. Finally, the whole dataset was standardized based on the mean and standard deviation calculated on the training set.

2 Methods

2.1 Architecture

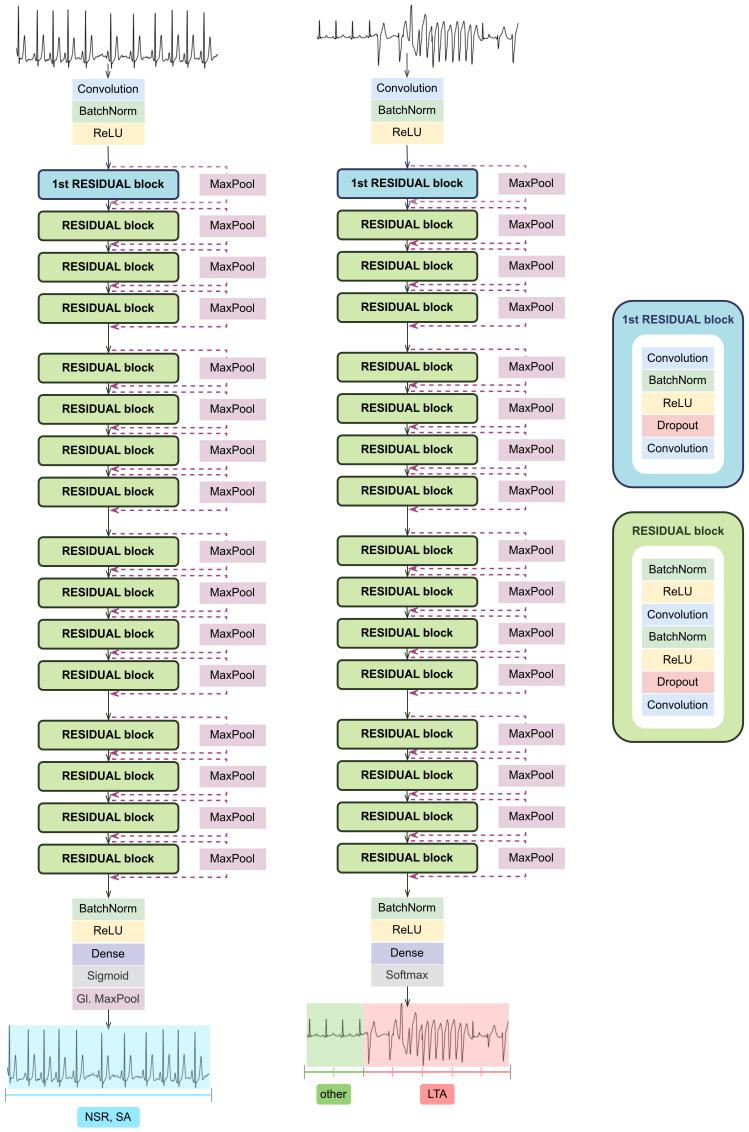

Fig. 1: Architecture of ECGnet-v0 and ECGnet-v1

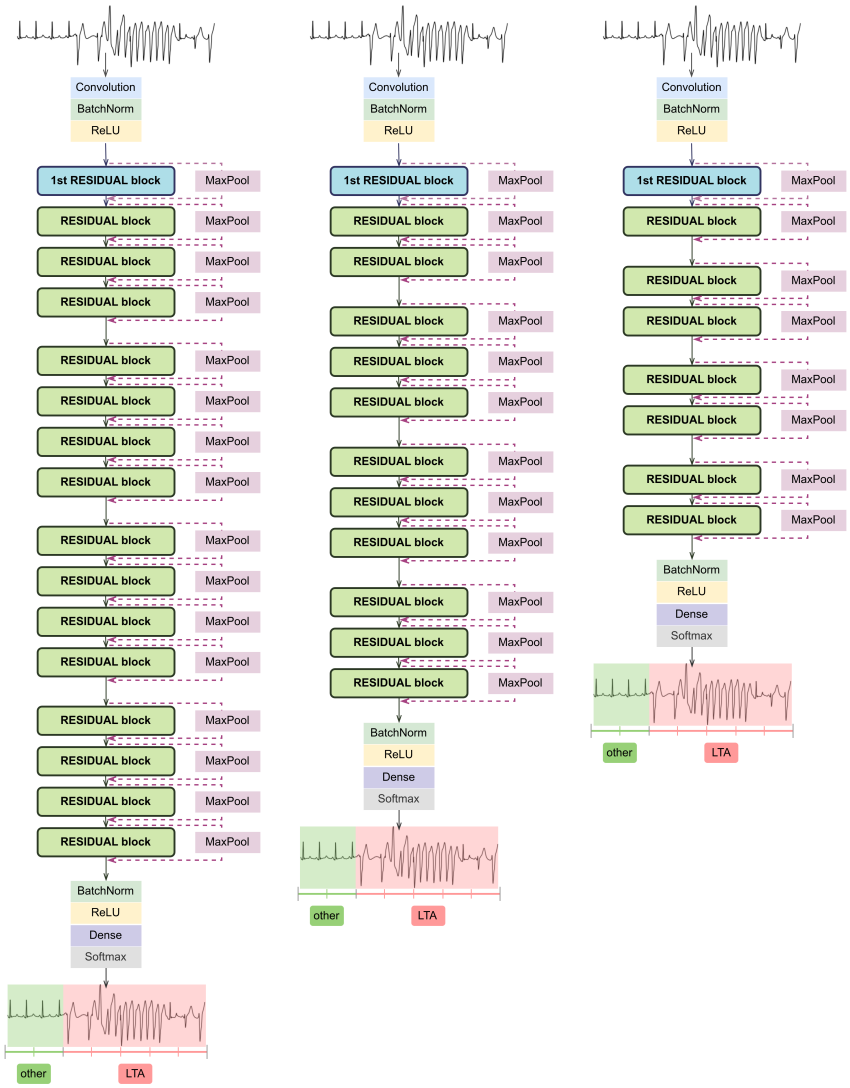

Fig. 2: Architecture of *ECGnet-v1-L*, *ECGnet-v1-M* and *ECGnet-v1-S*

3 Results

3.1 Optimization of the freezing configuration

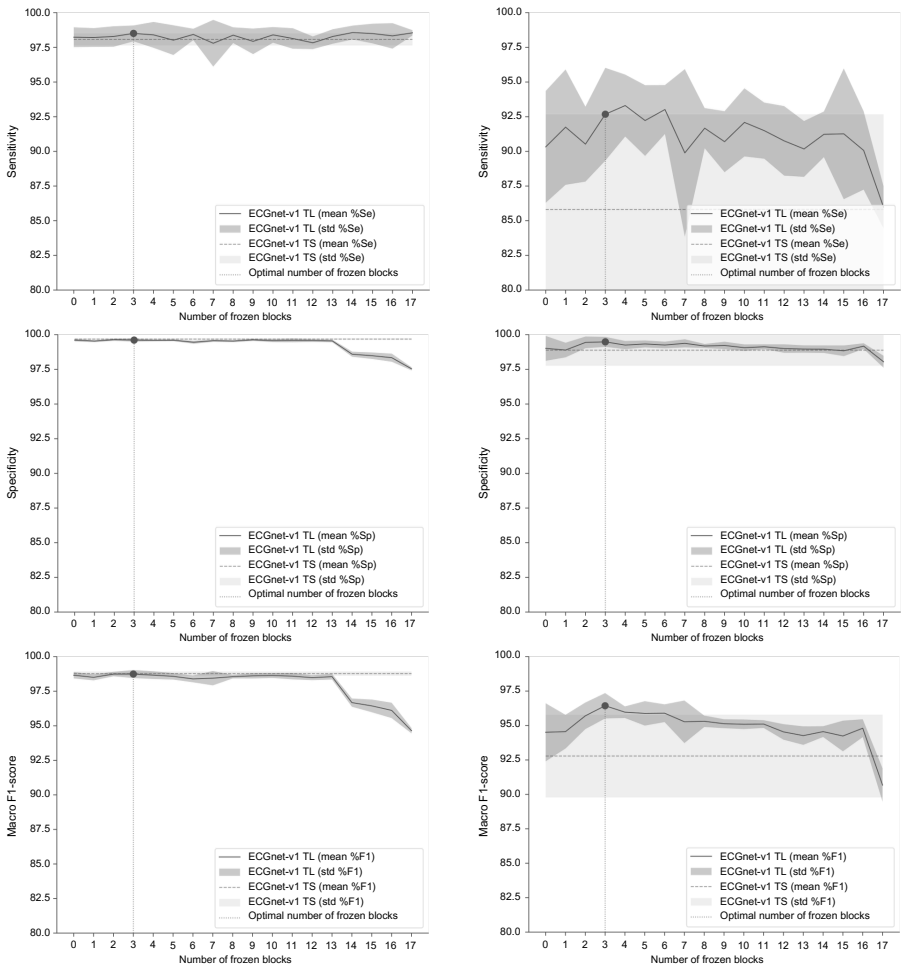

Fig. 3: Sensitivity, specificity and macro F1-score of *ECGnet-v1* TL on the *FT-LTA* validation set (first columns) and test set (second column) varying the freezing configuration. The x-axis reports the number of frozen blocks during the fine-tuning phase (from no frozen blocks to all but the last frozen block)

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Table 1: Number of subjects (N sub), recordings (N rec) and 7-segment sequences (N seq) in each source dataset for each subset (train, validation, and test) in PT dataset.

	Train			Validation			Test			Total		
	N sbj	N rec	N seq	N sbj	N rec	N seq	N sbj	N rec	N seq	N sbj	N rec	N seq
Chapman	2885	2885	2885	2598	2598	2598	4691	4691	4691	10174	10174	10174
Georgia	1813	1813	1813	1272	1272	1272	2544	2544	2544	5629	5629	5629
Ningbo	22072	22072	22072	5247	5247	5247	5995	5995	5995	33314	33314	33314
PTB-XL	16374	18727	18727	1665	1947	1947	240	288	288	18279	20962	20962
CPSC							2139	2139	2139	2139	2139	2139
CPSC-extra							536	536	536	536	536	536
INCART							9	9	9	9	9	9
PTB							58	87	87	58	87	87
Tot	43144	45497	45497	10782	11064	11064	16212	16289	16289	70138	72850	72850

Table 2: Number of subjects (N sub), recordings (N rec) and 7-segment sequences (N seq) in each source dataset for each subset (train, validation, and test) in *FT-LTA* dataset.

	Train			Validation			Test			Total	
	N sbj	N rec	N seq	N sbj	N rec	N seq	N sbj	N rec	N seq	N sbj	N rec	N seq
CUDB	23	23	915	5	5	145	7	7	324	35	35	1384
MITDB	29	29	3549	7	7	623	9	9	1279	45	45	5451
VFDB	15	15	2950	3	3	406	4	4	908	22	22	4264
Tot	67	67	7414	15	15	1174	20	20	2511	102	102	11099

Table 3: Number of 7-segment sequences (N seq) and 256-sample segments (N segm) in each rhythm class (or group of classes in case of multiple labels) for each subset (train, validation, and test) in PT dataset.

	Train		Validation		Test		Total	
	N seq	N segm	N seq	N segm	N seq	N segm	N seq	N segm
N	17441	122087	4176	29232	5951	41657	27568	192976
SB	11226	78582	2797	19579	3536	24752	17559	122913
ST	5696	39872	1417	9919	2057	14399	9170	64190
AFL	4754	33278	1186	8302	1527	10689	7467	52269
AF	2488	17416	552	3864	2036	14252	5076	35532
SA	1472	10304	356	2492	452	3164	2280	15960
SA, SB	510	3570	127	889	159	1113	796	5572
P	450	3150	102	714	123	861	675	4725
SVT	436	3052	108	756	140	980	684	4788
N, SA	410	2870	96	672	123	861	629	4403
N, SB	234	1638	55	385	65	455	354	2478
N, ST	156	1092	36	252	44	308	236	1652
ARH	129	903	32	224	40	280	201	1407
AT	95	665	24	168	36	252	155	1085
Tot	45497	318479	11064	77448	16289	114023	72850	509950

N: normal synus rhythm, SB: sinus bradycardia, ST: sinus tachycardia, AFL: atrial flutter, AF: atrial fibrillation, SA: sinus arrhythmia, P: paced rhythm, SVT: supraventricular tachycardia, ARH: atrial rhythm, AT: atrial tachycardia