Hybrid Arrhythmia Detection on Varying-Dimensional ECG

Combining Deep Neural Networks and Clinical Rules

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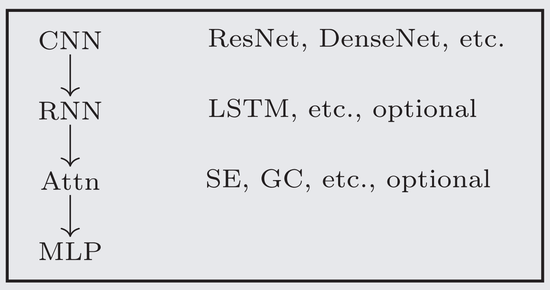
Introduction

- 26 ECG abnormalities (equivalent ones counted as 1) are split into 2 categories:
  - "Brady", "LAD", "RAD", "LQRSV", and "PR": clear and easy-to-describe **clinical diagnostic criteria**
  - the rest: subtle morphological and spectral changes, mainly dealt with **deep neural networks (DNNs)**
- We develop an ECG deep learning framework, in which classification is treated by convolutional (recurrent) neural networks (C(R)NNs). Considering that ECGs are varying-dimensional, we designed "lead-wise" CNNs via grouped convolutions and normalizations. This also makes it possible for parameters reuse, and general-purposed pretrained "backends" as in computer vision.
- We explicitly model ECG spectral characteristics via multi-branch CNNs with different dilations, so that each has different receptive fields.

Neural Network Architecture

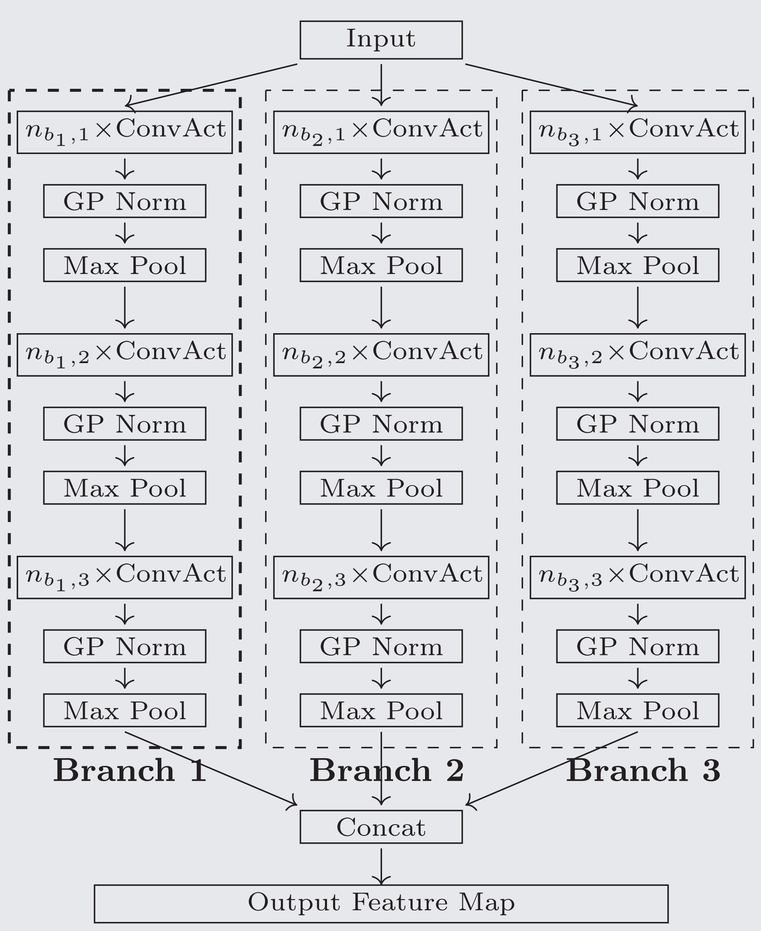
ECG deep learning framework at https://github.com/DeepPSP/torch_ecg
For classification, we use C(R)NN:



For our challenge entries,

- explicitly model spectral characteristics via multi-branch CNNs each with different **dilation** factor
- Attention module: SE (reduction=8)

Architecture of multi-branch CNNs:



- GP Norm: group (= #leads) norm
- ConvAct: group conv. + ReLU
- Branch 1 no dilation, Branch 2 mild dilations, Branch 3 very large dilations

Detectors via Clinical Rules

- "Brady": average heart rate $\leq$ 60 BPM or equivalently average RR-intervals $\geq$ 1s.
- "LAD" and "RAD": positivity checking of QRS complexes of leads I, aVF (the "2-lead" method); or of leads I, II, aVF (the "3-lead" method).
- "LQRSV": peak-to-peak amplitudes of more than 80% of the QRS complexes are $\leq$ 0.5 mV in the limb leads (I, II, III, aVR, aVL, aVF), or $\leq$ 1 mV in the precordial leads (V1-V6). If R peak detection fails, amplitude check will be done within sliding windows of length 0.12s.
- "PR": raw ECGs are high-pass filtered with cutoff frequency 47 Hz, and spike (peak) detection with prominence threshold of 0.3 follows.

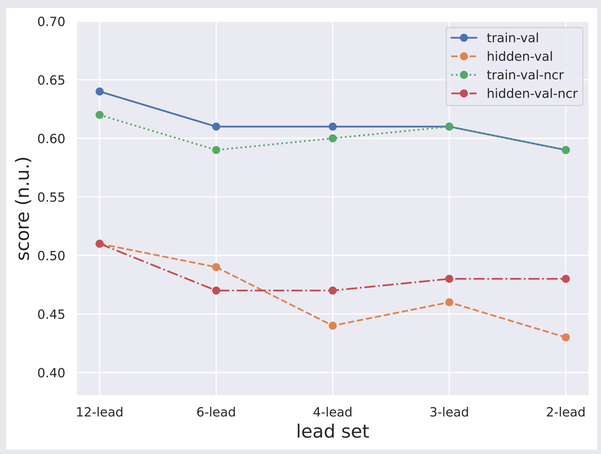
Preprocessing and Augmentations For Training DNNs

- ECGs resampled to 500Hz, bandpassed (0.5-60Hz), and cropped or zero-padded to 10s.
- if "LQRSV" is not to be predicted, ECGs are normalized, otherwise not.
- reduce overfit: random masking.
- reduce overconfidence: label smoothing.

Training Setups

- loss function: weighted binary cross entropy; class weights inverse proportional to # records
- optimizer: AMSGrad variant of **AdamW** with lr 0.001 (planed **OneCycleLR** scheduler)
- train-val split: 80% – 20%
- batch size 32 or 64; epoch number $\leq$ 30 with early stopping

Submission Results



2 configurations for challenge submissions:

- DNN (21-dim. out) + clinical-rule detector (5-dim. out) $\rightarrow$ 26-dim. out
- pure DNN (26-dim. out, with "-ncr" suffix)

Offline Train-Eval Results

2 typical experiments on standard 12-lead set under the 2 configurations resp.

Limitations and Discussions

- Reduced-lead ECGs, even 2-lead ECGs in the extreme case, provide sufficient information for making reliable auxiliary diagnoses.
- Multi-branch CNNs for feature extraction are far from optimal, whose structures and hyperparameters have to be optimized. Moreover, a thorough search for more effective architectures should be and is undertaken in our ECG deep learning framework.
- Hyperparameters of clinical rules based detectors are set empirically, which should be optimized via grid searches.
- Label heterogeneity (across datasets) and insufficiency (debate on labels) should also be noted.
- "Lead-wise" CNNs provides flexible light weight solutions to reduced-lead ECGs. Mechanism of parameters reuse is to be further established.

Acknowledgements

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Code, configs, etc. available at https://github.com/DeepPSP/cinc2021.