Temporal Convolutional Networks for Automatic Features Extraction from ECG

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Introduction

Machine learning algorithms use heuristic and hand-crafted features as predictors. This might be a disadvantage since there is the possibility not to find the most appropriate and meaningful features to carry out an accurate prediction.

Aim

To build a Temporal Convolutional Network (TCN) to automatically extract features and carry out ECG classification.

Data

A total of 6667 adult individuals were included from the Danish population study Inter99 ([1]). 51% of the population was female and the average age was 43.3 with a standard deviation of 8.0.

10-second resting ECG was obtained from which individual. *Median* ECG was derived averaging the 10 seconds ECG. The measurements on the ECGs were obtained with the 12 SL algorithm by GE Healthcare.

Temporal Convolutional Networks

In this study, we only used lead V_5. The raw ECG is fed into the network as the only input. Features, automatically learnt from the ECG, are sequentially extracted by mean of convolutions. The terminal part of the networks consists of a fully connected (FC) layer, where the features are used to classify the ECG.

Two thirds of the dataset were used as training set, the remaining third was used to validate the model.

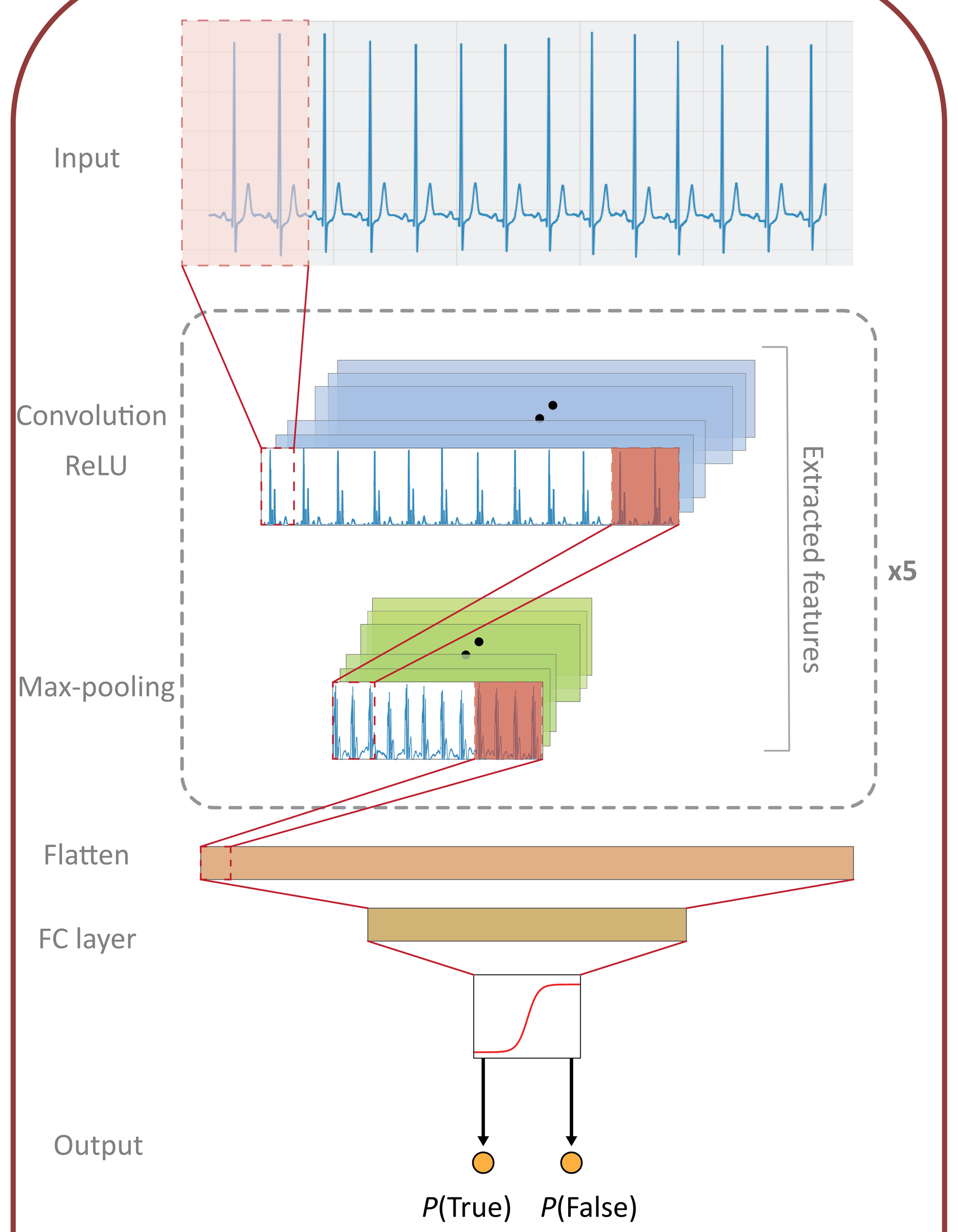
Both accuracy and balanced accuracy are used as metrics. Balanced accuracy is defined as the average of True Positive and True Negative rates:

$$\text{Balanced accuracy} = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right)$$

Class weights is used to balance the error function and the accuracy. Each class is weighted according to the occurrence of that class.

[1] Jørgensen T, Borch-Johnsen K, Thomsen TF, Ibsen H, Glümer C, Pisinger C. A randomized non-pharmacological intervention study for prevention of ischaemic heart disease: baseline results Inter99 (1). European Journal of Cardiovascular Prevention & Rehabilitation. 2003 Oct;10(5):377-86.

The network



N. filters = [16,64]

Filter size = [7,22]

Dilation rate = [1,7]

Optimizer = Adam (learning rate = 0.005)

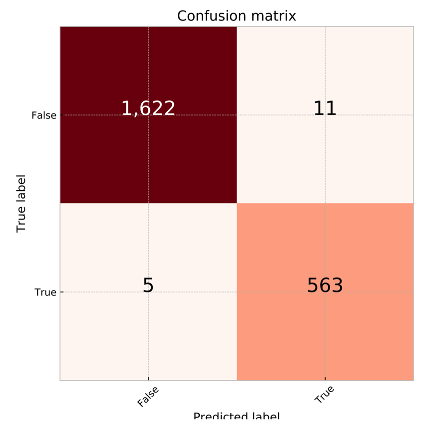
Loss function = Binary Cross-Entropy

Conclusions

Automated extracted features can be used as predictors to correctly classify ECGs.

Results

Sinus Bradycardia

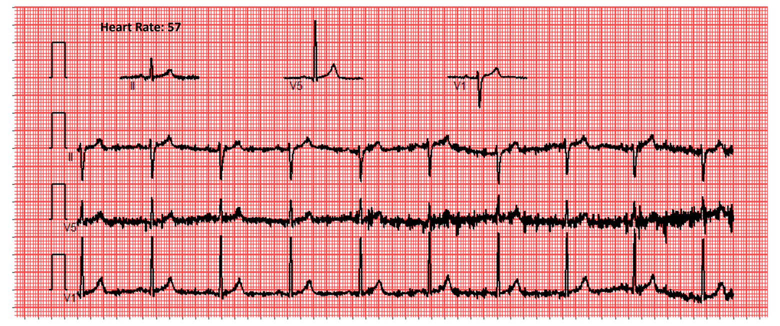


Balanced Accuracy = 99.2%

False Negative HR = [59, 59, 57, 49, 40]

False Positive HR = [62, 60, 60, 59, 59, 59, 59, 59, 57, 48, 42]

In the False Positive set, some ECGs are Sinus Bradycardia Negative because HR>60, others are negative because there is no sinus rhythm even if HR<60.



12SL algorithm: Sinus Bradycardia NEGATIVE

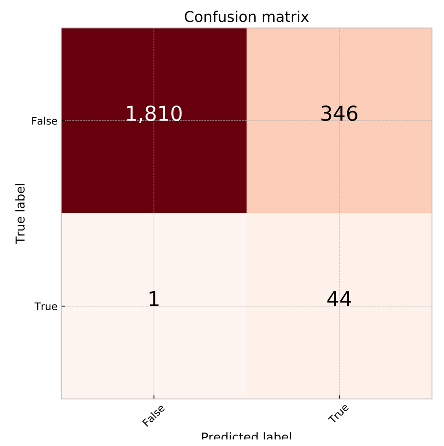
TCN algorithm: Sinus Bradycardia POSITIVE

The ground truth is wrong because, according to 12SL, this is Junctional bradycardia.

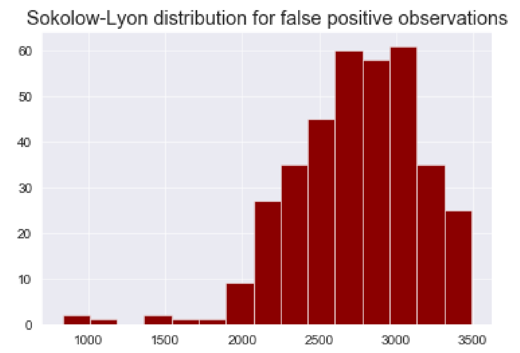
Left Ventricular Hypertrophy

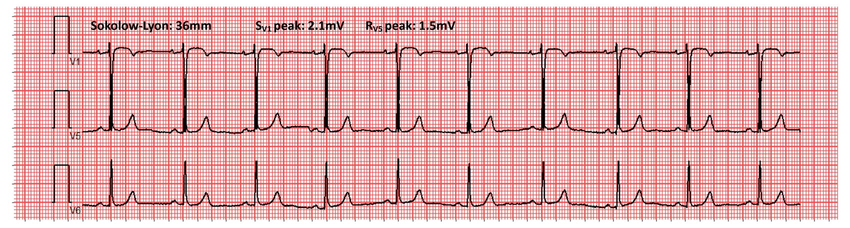
The network was trained with the median ECG.

Sokolow-Lyon is used to assess LVH.



Balanced Accuracy = 90.9%

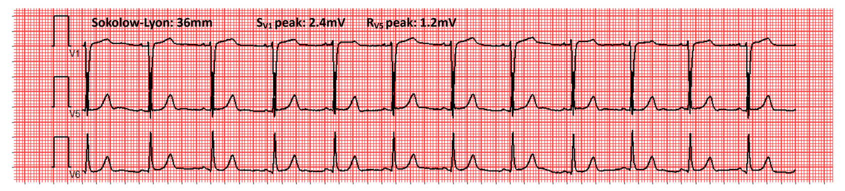




12SL LVH POSITIVE

TCN algorithm: LVH POSITIVE

Showing that the network is not only learning a threshold for R_{V5}



12SL LVH POSITIVE

TCN algorithm: LVH NEGATIVE

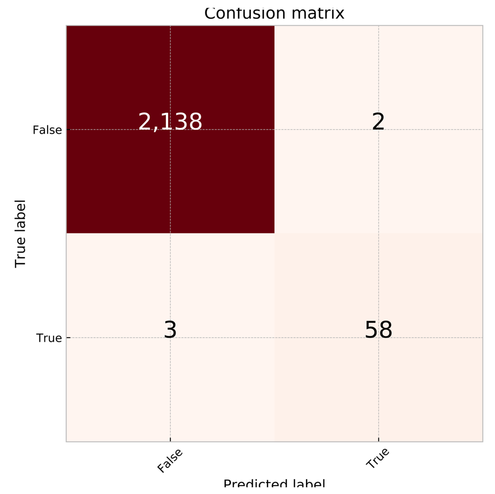
False Negative example of LVH.

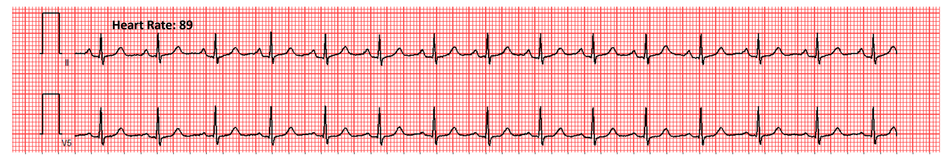
Fast Heart Rate (HR>90)

Balanced accuracy = 97.5%

False Positive HR: 89, 89

False Negative HR: 114, 104, 106

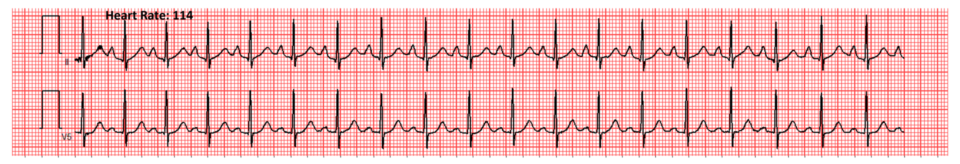




12SL Fast HR NEGATIVE

TCN algorithm: Fast HR POSITIVE

Borderline ECG, the HR is close to 90.



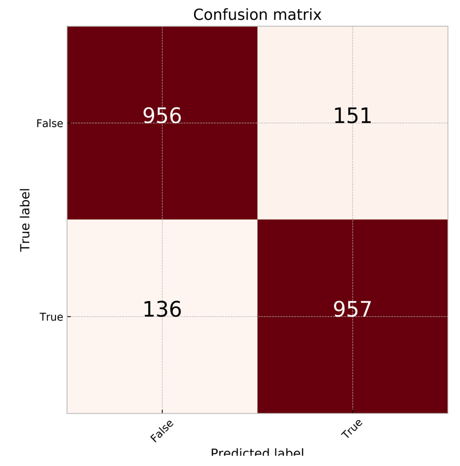
12SL Fast HR POSITIVE

TCN algorithm: Fast HR NEGATIVE

True mistake of the TCN algorithm.

Gender

The network was trained with the median ECG.



Accuracy = 86.9%

Benchmarked with a logistic models:

$Gender \sim QT + QRS + PR + RR$ Accuracy = 74.3%