A machine learning approach for detecting ventricular fibrillation during out-of-hospital cardiac arrest

Erik Alonso [a], Elisabete Aramendi [a], Unai Irusta [a], Mohamud Daya [b]

[a] University of the Basque Country (UPV/EHU), Spain [b] Oregon Health & Science University (OHSU), USA

INTRODUCTION

Survival from out-of-hospital cardiac arrest (OHCA) relies heavily on early identification and defibrillation of ventricular fibrillation (VF) by an automated external defibrillator (AED).

The aim of this study was to develop and test an automated method based on a novel machine learning technique to detect VF using OHCA episodes.

MATERIALS

Data collection

Data from 169 OHCA patients treated by Tualatin Valley Fire & Rescue (Tigard, OR, USA) using the Philips HeartStart MRx monitor/defibrillator.

The dataset of the study contained 596 10-s ECG segments, 144 shockable and 452 non-shockable, annotated by consensus by a pool of four emergency medicine doctors.

- **Shockable:** VF and ventricular tachycardia.
- **Non-shockable:** organized rhythms (ORs).

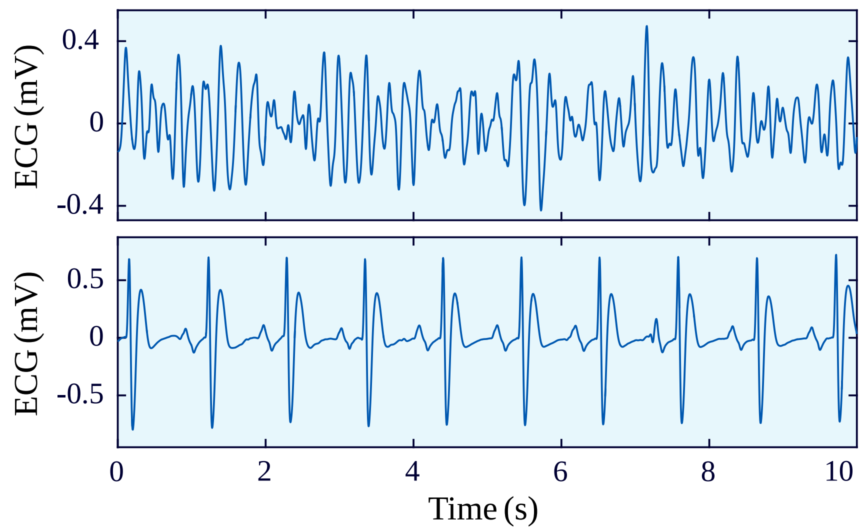

Figure 1. Examples of VF and OR rhythms of the dataset.

PREPROCESSING & FEATURE EXTRACTION

Preprocessing

The ECG segments were processed using the following procedure:

1. Mean subtraction.
2. High-pass filter (cutoff frequency of 1 Hz) to remove baseline drift.
3. Low-pass Butterworth filter (cutoff frequency 30 Hz) to eliminate high frequency noise

Feature extraction

From the processed ECG, a total of seven well-known shock/no-shock decision features were computed:

- **TCI**
  Thakor et al. IEEE Trans Biomed Eng 1990;37(9):837?843.
- **bCP, bWT, bW**
  Irusta et al. Resuscitation 2012;83(9):1090?1097.
- **x1, x2**
  Ayala et al. Biomed Res Int 2014;2014:ID=872470.
- **SampEn**
  Lake et al. Am J Physiol-Reg I 2002;283:R789?R797.

ARCHITECTURE OF THE MODEL

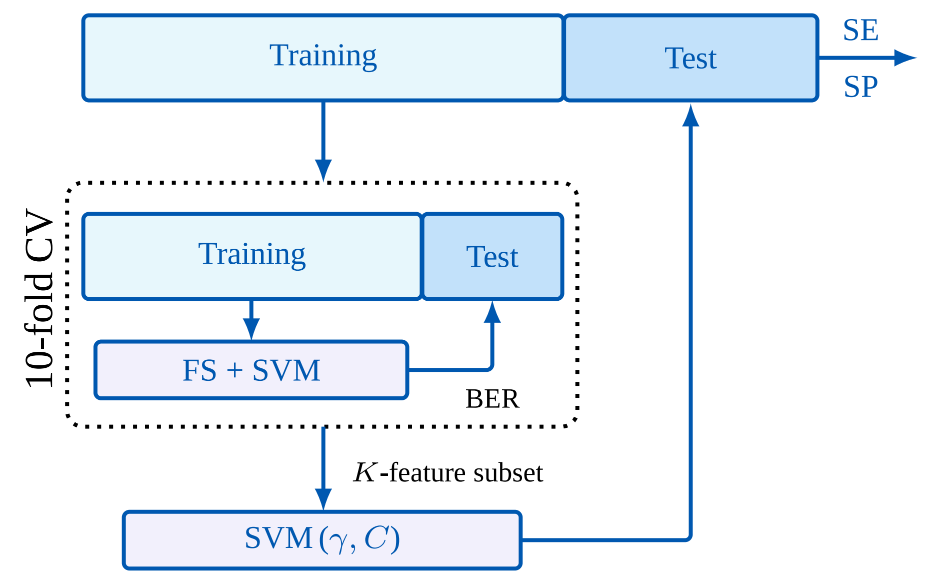

Figure 2. Overview of the procedure to develop/test the VF detection algorithm.

- Quasi-stratified training (60%) and test (40%) sets.
- **Training**
  - Patient-wise 10-fold cross validation (CV) for feature selection (FS).
  - Using the best K-feature subset optimize SVM hyperparameters (γ, C).
- **Test**
  - To measure performance of the method in terms of sensitivity (SE) and specificity (SP).

Feature selection

- Forward greedy wrapping approach using patient-wise 10-fold CV in the training set.
- The best 5-feature subset was selected.
- The criterion for feature selection was balanced error rate ($\text{BER}=1-\frac{\text{SE}+\text{SP}}{2}$) minimization.

Optimization & Evaluation

- The best 5-feature subset was used to build the optimal SVM classifier.
- The optimization of the SVM implies tuning two parameters: γ and C, the width of the Gaussian Kernel and the flexibility of the decision boundary, respectively.
- Optimal γ and C that minimized the BER were selected doing a 40x40 grid search in the ranges $10^{-2} < \gamma < 10^{0.1}$ and $10^{-1} < C < 10$ in the training set.
- The performance of the classifier was measured in terms of SE and SP using the test set.
- The whole training/test procedure was repeated 500 times to estimate the distributions of the performance metrics.

RESULTS & CONCLUSIONS

- The method showed a mean (standard deviation) SE and SP of 96.5% (2.5) and 97.0% (1.4), respectively.
- Minimum performance requirements of the American Heart Association (SE⩾90% and SP⩾95%) were met.
- The method required in average 279 (36) ms to make a shock/no-shock decision.

Feature	L	Feature	L
bCP	500	SampEn	348
bWT	500	bW	175
TCI	444	x1	158
x2	375		

Table 1. Number of times (L) each feature was selected in the 500 random repetitions.

An automated method based on a SVM accurately detects VF during OHCA. Its low computational cost makes it suitable for implementation into current defibrillators.

ERC 2018, 20-22 September 2018, Bologna (Italy).