Arrhythmia Classification from ECG signal with Ensembling CNNs

Tetyana Yezerska

yezerska@ucu.edu.ua

Abstract

The task of arrhythmia classification from the ECG signal is widely researched. The main obstacle to this problem is highly imbalanced classes. In this research, I propose to use two steps pipeline Ensembling CNNs to deal with the imbalance problem. The first step is 1D CNN for binary classification of normal and abnormal beats. Next, abnormal beats are passed to 1D CNN that classifies beat into four categories. I achieve 93% accuracy.

Introduction

The ECG signal is a one-dimensional array-like representation of the electrical activity of the heart over a period of time. One cardiac cycle of the ECG signal consists of the P wave QRS complex and T waves. Any deviation from the norm of the QRS complex may be a sign of heart disease. Accurate detection and analysis of ECG artifacts allow detecting arrhythmias and other heart diseases. In the United States and Europe, the lifetime risk for developing arrhythmia has been estimated to be approximately 25%. For the healthcare system, it is crucial to analyze ECG (simplest test), and with automatic analysis, hospitals can save valuable doctor time spent on primary tasks.

Methodology

Data

In the research, MIT-BIH Arrhythmia Database is used. The dataset includes 48 half-hour excerpts of two-channel ambulatory ECG recordings obtained from 47 subjects with rhythm and beat annotation available. We classify beats and use only one channel of the signal. There are 19 beat annotations that by AAMI recommendation are mapped into 5 superclasses. The data is highly imbalanced: Normal 82%, Superventicular ectopic beat 2.7%, Ventricular ectopic beat 6.6%, Fusion 0.7%, and Unknown beat 7.4%. Publishers of the dataset propose the patients (not samples) train/test split of 50/50% .

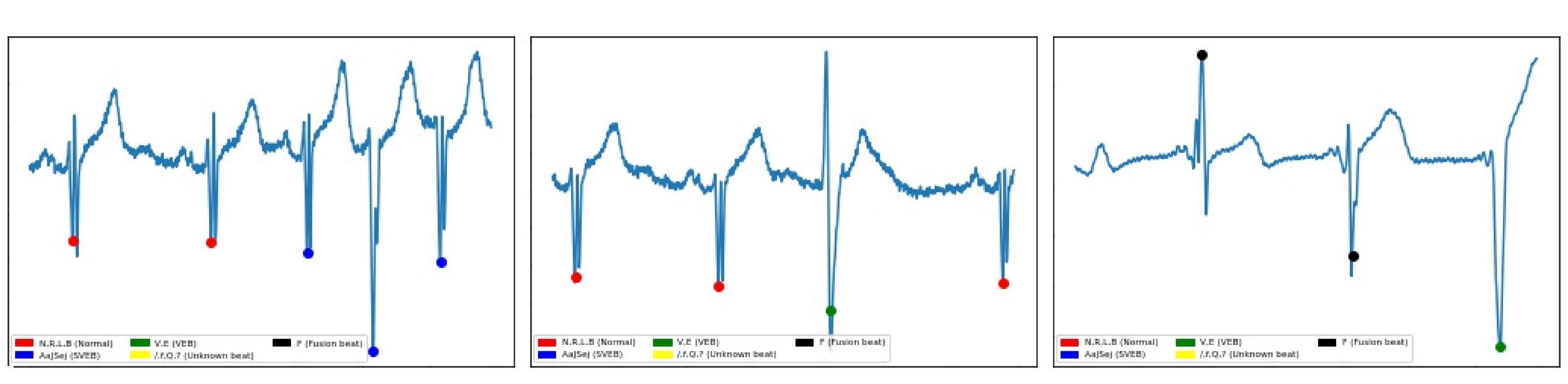

Figure 1: Examples of a) Superventicular ectopic beat; b)Ventricular ectopic beat; c) Fusion beat. *red marks represent normal beat.

Pipeline Preprocessing

Preprocessing consists of 3 steps: R peaks detection, segmentation, and denoising of the signal. R peaks should be detected to further segment signal to have samples of equal length as the Neural Network input. There are numerous algorithms for R peaks detection with have accuracy up to 100%, so I chose the Pan–Tompkins algorithm. Having the R peaks positions, the window of size 280 is used to segment the signals into samples of QRS complex of length 280. Given that the normal size of one heart cycle of 0.8 seconds, and with 360 sampling frequency, the window size of 280 is used. The last step is denoising with Wavelet transform to get a more smooth signal.

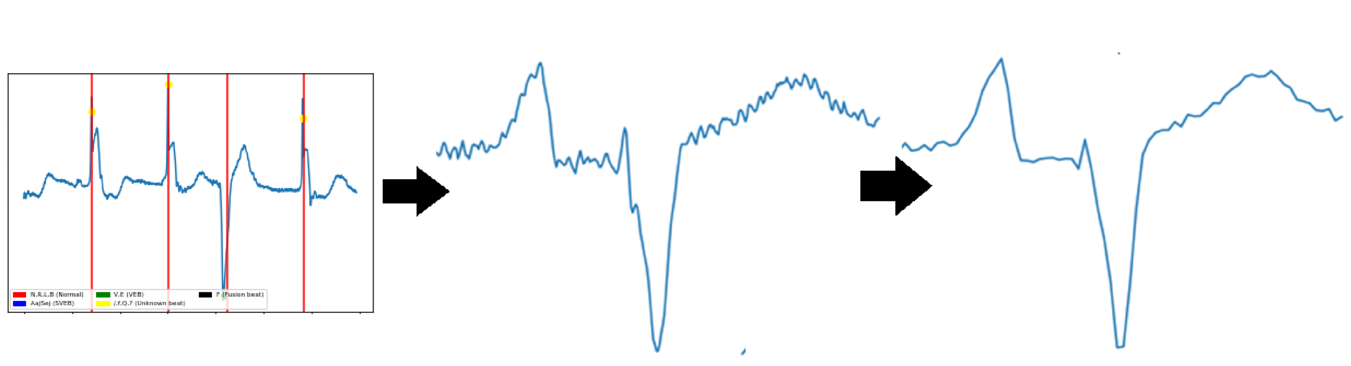

Figure 2: Preprocessing pipeline: signal, sample, denoised sample

Pipeline CNNs Architecture

Because of the high imbalance of classes, one model for classification of all classes, including the biggest normal class is hard to train. From experiments, the model learns the distribution of majority class very well but not minority classes. As a solution, I use two models of the same architecture. The first CNN classifies samples as Normal or Abnormal. The accuracy of classification is 95%. I use the Dropout technique to prevent any overfitting. The second model classifies only abnormal beats into four classes. The accuracy achieved by the multiclass CNN is 96%. See the confusion matrix below. Comparing to baseline SVM, the CNN network performs better due to the ability to learn more complicated functions.

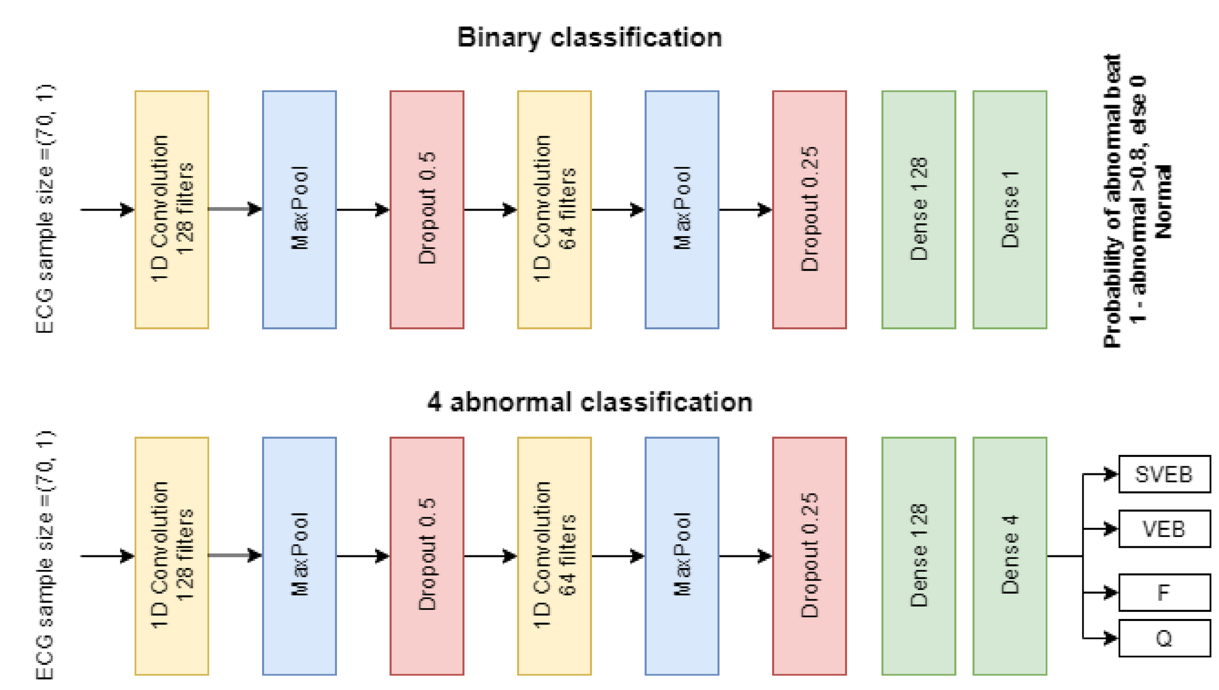

Figure 3: Ensembling CNNs architecture

Pipeline SVM baseline

As a baseline, the SVM classifier was implemented. The features were hand-generated and included denoised signal with a Wavelet transform level 2 (35 values), the entropy of the signal, the interval between given R peak and previous R peak, the interval between given R peak and next R peak, and the average interval between neighboring 10 R peaks. With parameters tunning and class weights added, the SVM classifier with a radial basis kernel achieved 88% accuracy on the test set.

Results

The dataset was split into train/validation/test sets 50% 25% 25% accordingly. Both networks were trained on train set, and hyperparameters were tunned on the validation set. Bellow, the confusion matrices based on the test set for both networks are displayed with corresponding classes. The binary classifier networks achieve average accuracy on the test set 92%, which has definitely to be improved. I also tried the SVM binary classifier, but its performance was 88%. I believe the networks overfit to the Normal class, so it is to be improved. The 4 class network learns distributions of abnormal classes well and performs at 96% accuracy on the test set.

	SVEB	VEB	Fusion	Unknown
SVEB	1876	13	15	0
VEB	18	695	9	0
Fusion	1	1	0	0
Unknown	0	2	0	0

a)

	0	1
0	22981	568
1	958	2077

b)

Figure 4: Confusion matrix for a) 4-class CNN; b) Binary CNN

Conclusion

In this research, I have proposed a full pipeline for ECG signal processing and abnormal beat classification. Two approaches were validated: Support Vector Machine and Deep CNNs. I managed to deal with the imbalanced class problem using two steps classification. As a result, neural networks for this task could be used, and they outperform classical ML approaches.