ECG Arrhythmia Classification Using Non-Linear Features and Convolutional Neural Networks

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Abstract

Heart arrhythmia classification algorithms are an important tool for continuous monitoring of patients at risk. By analyzing 12 ECG-lead signals, these algorithms can help us to diagnose different cardiac diseases.

Thus, our team, CardioLux proposes a novel approach to denoise ECG signals and classify the nine cardiac arrhythmias using Convolutional Neural Networks (CNN) trained with more than 6700 ECG recordings as defined in the Physionet Challenge 2020.

First, a noise removal process is initially applied with Savitzky-Golay smoothing filters. Secondly, we extracted 300 features, clustered in time, frequency, and time-frequency groups, including linear and non-linear characteristics. Thirdly, 27 features were carefully selected to train our model using our feature-selection procedure. Finally, we implemented CNN to reduce noise-aware signals and bias during our training model.

The proposed methodology developed so far was tested with 10-fold cross-validation on the training set and yielded a challenge score of 0.22. Overall, the feature extraction and selection stage can help improve the performance of the heart arrhythmia training model by selecting the best characteristics. Our model keeps a high level of interpretability, demonstrating a high range of possibilities that can be configured using CNN.

1. Introduction

ECG is a standard non-invasive measurement that can reflect the physiology activities of the hearth [1]. Also, it is an indispensable tool for the diagnosis and prompt initiation of therapy in patients with heart diseases [2]. ECG data analysis can help to detect different arrhythmias. Heart arrhythmia classification algorithms are an essential tool for continuous monitoring and diagnosis of patients at risk to prevent future cardiac diseases. Therefore, early detection is necessary for its correct management.

These algorithms can help us to assess and diagnose cardiac diseases by analyzing 12 ECG-lead signals. Early detection is essential for correct management and treatment. Motion artifacts such as those of different intensity of movements can contaminate the signals, leading to a wrong diagnosis [3].

Thus, our team called CardioLux proposes a novel approach to denoise ECG signals and classify the nine cardiac arrhythmias defined in the Physionet Challenge 2020 [4]. First, a noise removal process was initially applied to the raw dataset using the Symlet wavelets family and Savitzky-Golay smoothing filters. Secondly, we extracted 300 features, clustered in time, frequency, and statistical measurement groups, including linear and non-linear characteristics, to obtain hidden information that models specific heart arrhythmia. Thirdly, 27 features were carefully selected to train our model using our feature-selection procedure. Finally, we implemented a Convolutional Neural Network (CNN). The dataset provided contained 6877 ECG recordings used for the creation of training models.

2. Methodology

The methodology proposed is shown in Figure 1. This methodology is composed of data pre-processing, filtering, features extraction and selection and training of neural network models to classify data into the nine categories defined.

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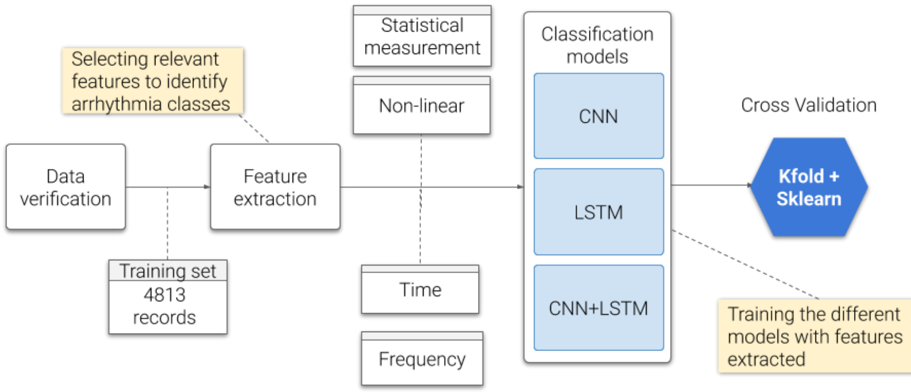

Figure 1. Model pipeline to classify 9 arrhythmia types on ECG signals.

2.1. Pre-processing

In this stage, the data is prepared before the feature extraction process. Firstly, data analysis was performed to verify the quantity and quality of the dataset. Fields such as "sex" were changed from characters to numbers, and the ones with missing values were filled using the mean value of the field. Secondly, a spectral analysis was performed using wavelet decomposition with Daubechies family wavelets and Symlet family wavelets, which determined that there was high and low-noise frequency on the bands: [5 - 60] hz, [75-90] hz, [160-170] hz frequencies of the signal.

It should be highlighted that the wavelet analysis also involved a thresholding method, which helped us determine the high and low-frequency components of the noise in the frequency domain, showing that the ECG signal concentrates its information widely on the 1-10 Hz frequency band. However, we could even consider that the real concentration of the information is between 1-4 Hz (a very narrow band). This could be a problem, since the information signal is being overlapped with the noise frequency component inside this interval, making difficult the noise extraction. The main consequence over the signal of these so mentioned artefacts is the baseline drift, introduced principally because of the friction of the electrodes with the skin, the movement created by the patient normal activities and environmental variables, such as the temperature, which might change the normal electrical activity of the electrode's materials. The movement of the extremities causes this low-frequency noise. Another effect of these artefacts is the high-frequency noise, that can be witnessed as very slight and frequent peaks, sometimes imperceptible, which follow the curve of the signal.

2.2. Filtering

This stage was focused on finding the best denoiser to obtain better results over accuracy in the detection of 9 specific arrhythmias. Firstly, wavelets functions were used for denoising the signal, filtering out high frequency components of noise. On the best results, there is a coincidence over the wavelet decomposition method with Mallat's algorithm, using Symlet family in the majority of the cases. In two cases were obtained the best results using Daubechies family wavelets, which showed good overall results in the studies. However, linear filters yielded a better response, therefore, we decided to take this approach for denoising our signal more accurately.

The Savitzky-Golay smoothing filter is a type of digital filtering technique based on convolution, a process that fits successive segments of adjacent data with an adjustable degree polynomial regression, using the linear least squares criteria for fitting points [5].

The main advantage of this kind of filter is the preservation of the main characteristics of the original distribution of the signal, such as local maxima and minima. For this reason, and in our case, it can accurately reduce the level of noise without biasing the morphology of the ECG signal. It also discriminates high-frequency noise since it keeps low-frequency features such as baseline drift, but removes some others like high-frequency peaks, smoothing the signal. Thus, in order to reduce the baseline drift noise, which enables us to focus on the analysis of the fluctuations in the data about the trend, we created a detrend method for its exclusion, since it's a type of noise that could bias the backpropagation process during the model training: This method finds the trend of the original signal, using the number of desired breakpoints over the length of , making a similar process as method A. Then it links them using linear functions and returns a signal containing an estimate of the baseline drift over the entire length of the signal.

2.3. Feature Extraction

The result of this process found 300 features that were categorized into the following:

- Time features. Included the QRS intervals, RR intervals, energy, self-correlation, and centroid.

- Statistical measurements. Kurtosis and skewness were used to represent the variations to the normal distribution of the signals. Other measures were standard deviation, mean, median, and variance.
- Frequency features. Included the Power Spectral Density (PSD) and the spectral centroid. PSD describes the variation of power into different frequencies. If $X(f)$ is Fourier Transform of $x(t)$ signal, then [6]:

$$S_{xx}(f) = \mathcal{F}\{R_{xx}(\tau)\} \quad (1)$$

  Where R_{xx} is autocorrelation function of *x(t)*.

  The spectral centroid [7] provides the gravity center for the spectrum by considering the spectrum as a probability distribution. The spectral centroid is:

$$Ce = \frac{\sum f_k s_k}{\sum s_k} \quad (2)$$

  Where f_k is the frequency in k and s_k is the spectral value in k.
- Non-linear features, such as Shannon entropy and Spectral Entropy (SE) are considered. Firstly, the Shannon entropy is based on the information theory and used to evaluate the distribution complexity of heartbeat signal samples [8]. While, and Spectral Entropy is a generalization of information entropy and has been proposed to measure the distribution of frequencies [9]. If $x(i)$ is a signal and $X(m)$ is the Fourier Transform of $x(i)$, the probability distribution is:

$$P(m) = \frac{S(m)}{\sum_i S(i)} \quad (3)$$

  Where $S(m) = |X(f)|^2$ is the PSD.
  The SE $\boldsymbol{H}$ follow as [10]:

$$H = -\sum_{m=1}^{N} P(m) \log_2 P(m) \quad (4)$$

  SE is used in [11] as a measure of disorder applied to the power spectrum of periods of time series for detecting Atrial Fibrillation, were used in the most studies analyzed due these provide a better sensibility and accuracy in the result.

To improve the algorithm's efficiency, the PCA selection performs a dimensionality reduction by choosing enough eigenvectors to account for some variance in the original feature data. The process Principal Component Analysis (PCA) was used to extract the features used in the classification. From the 300 features, 27 were useful for the classification algorithm.

Features selected were normalized for fitting the model using the Keras normalization module.

3. Neural Networks

Initially, the combination between a Recurrent Neural Networks and Long Short-Term Memory Recurrent Neural Networks was proposed to classify the different arrhythmias classes. However, in light of the results obtained, the use of convolutional neural networks (CNN) was prioritized because they showed better performance.

Our CNN is composed of a one-dimensional convolutional neural network (1D-CNN), which uses four output filters, a kernel size of four for the convolutional window, one size-stride for the window shifting, input shape determined by the 27-sequence data and a ReLU activation function is adopted for the activation.

The use of various denoising techniques was executed over different neural network architectures, where the focus falls in tachycardias and bradycardias. For example, we consider using Daubechies family with thresholding method which in our case removes the high-frequency noise components by thresholding only the wavelet coefficient of the detail sub-bands, however, this approach is taken as future work to investigate in detail its possible results after applying our classification method. The new research path could be, either by using more levels of decomposition, or by also discriminating between the approximation levels, or by using wavelet packages instead of the decomposition that is done only towards the approximation component.

4. Evaluation

We performed K-fold cross-validation with K=10 in the training data to obtain the challenge score. For this process, we devised the following process.

The challenge provides all the patient data in separate files. One file contains all 12-lead ECG records per patient. Also, driver, training, and scoring functions are defined to provide a single challenge score. The driver function has input and output folders with M files; and the scoring function takes the M outputs and calculates accuracy, precision, F-measure and the Challenge Score.

Our algorithm creates K-folders with an equal number of files from the patients data, distributed randomly. Each i fold from the K folders is chosen as a test subset and the remaining K-1 folders as training subsets. Output predictions are saved per i fold, and therefore used into the scoring function to calculate the challenge score. K scores are obtained. Finally, the average challenge score is obtained from the K-fold scores.

5. Discussions and conclusions

In this paper, we proposed a methodology that allows identifying the nine arrhythmia classes from 12-lead ECG signals. The filtering process encompasses a wide variety of denoising techniques with different families of wavelets and smoothing filters. We aimed at performing a comparative analysis that would allow us to find a denoiser-classifier combination which produces satisfactory results and an improvement over accuracy in the detection of 9 specific arrhythmias. Results throw a coincidence over the Savitzky-Golay smoothing filter and a baseline detrended filter as the best method for cleaning the signal. Then, we focused on implementing a Convolutional Neural Network (CNN), in order to classify the nine arrhythmias, which was trained using more than 6800 ECG recordings, reaching a challenge score of 0.22 during the K-Fold cross-validation on the training data. Other neural networks were developed as well, including RNN, and LSTM and hybrid architectures that involved a mixture of both and with CNN.

Better denoising methods can be applied to highlight specific relevant sections over the ECG morphology, which could be helpful to zoom in certain arrhythmia features. In order to obtain better results, we also tested the moving average filter over the entire training set. However, since it is a regular low-pass filter due to its slow roll-off and poor stopband attenuation, we also implemented a Butterworth filter to suppress the high frequencies over the interval [160-170] HZ. Similarly, different denoising techniques with family wavelets with higher decomposition levels can be applied to obtain similar or better results, as obtained by Savitzky-Golay Smoothing filter.

Another esencial fact to consider is that the sole use of ECG signals can perform well into a classification problem, but the results are reinforced when other types of complementary signals such as additional signals are used, such as PPG or ABP.

Future work involves the enhancement of our CNN architecture by incorporating a windowing segmentation method with the Hanning window to perform the feature extraction process using R peaks from the signal. Using this approach might yield better for the classification of different types of arrhythmia. However, due to lack of computational resources and lack of time, these results could not be presented for the challenge testing score, but optimistic results could be expected since more feature-wise information could incrementally feed our model.

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