

Automatic Real-time Beat-to-beat Detection of Arrhythmia Conditions

Giovanni Rosa, Gennaro Laudato, Angela Rita Colavita, Simone Scalabrino, and Rocco Oliveto

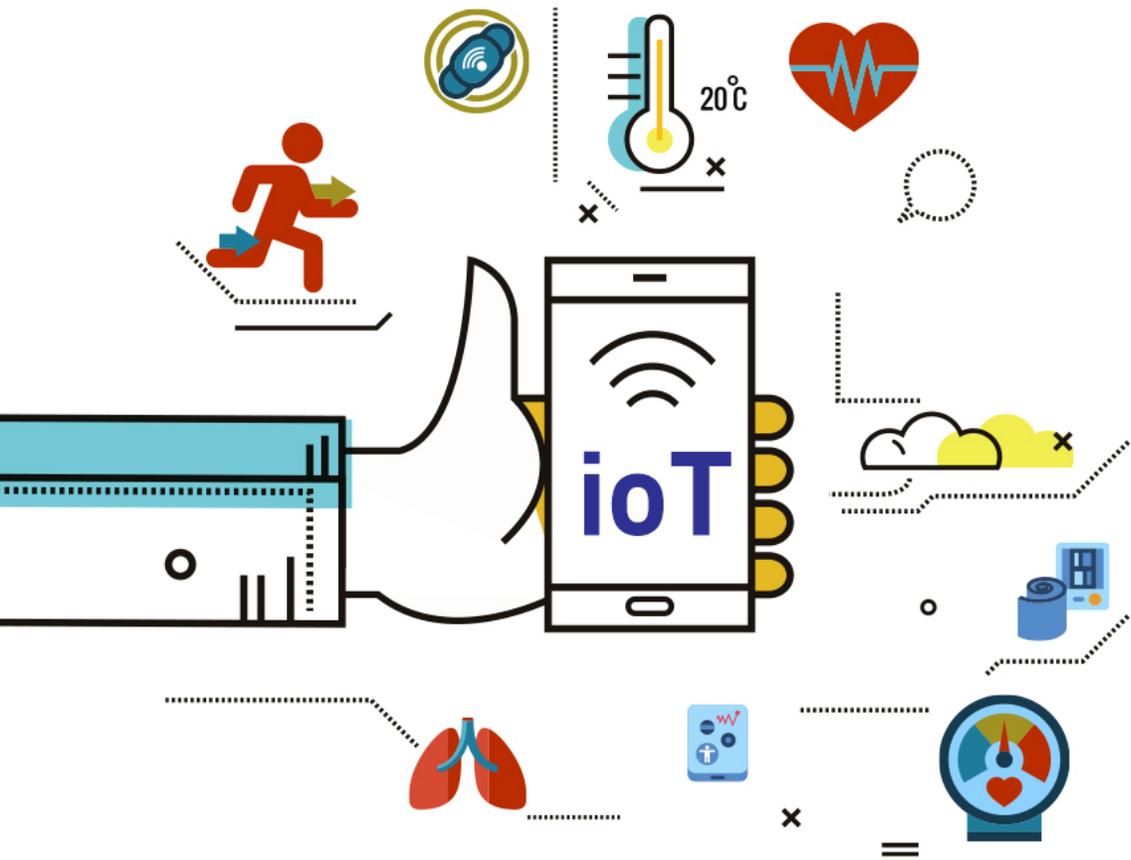


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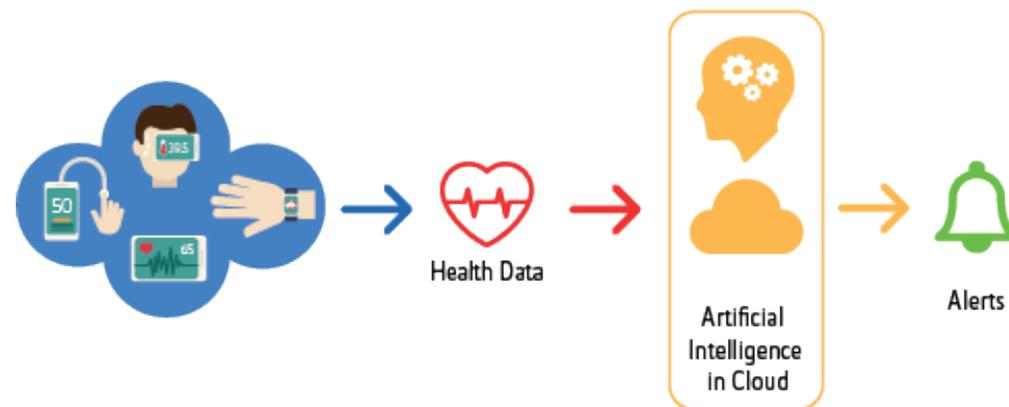


Preventive care

Long-term care and
chronic diseases

Internet of Medical Things

AI and Smart Wearables
for
early anomaly detection



Internet of Medical Things

Preventive medical support
thanks to
early notified anomalies



ECG Feature Extraction and Classification Using Wavelet Transform and Support Vector Machines

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Abstract—This paper presents a new approach to the feature extraction for reliable heart rhythm recognition. This system of classification is comprised of three components including data preprocessing, feature extraction and classification of ECG signals. Two different feature extraction methods are applied together to obtain the feature vector of ECG data. The wavelet transform is used to extract the coefficients of the transform as the features of each ECG segment. Simultaneously, autoregressive modeling(AR) is also applied to obtain the temporal structures of ECG waveforms. Then the support vector machines(SVM) with Gaussian kernel is used to classify different ECG heart rhythms. Computer simulations are provided to verify the performance of the proposed method. From computer simulations, the overall accuracy of classification for recognition of 6 heart rhythm types reaches 99.68%.

I. INTRODUCTION

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Various studies have been done for classification of various cardiac arrhythmias [1][2][3][4]. In this paper, we propose the combination of wavelet transform and AR model as the feature extraction method, then use the SVM to classify the ECG heartbeat. The proposed approach is validated in the MIT-BIH Arrhythmia Database[5] and got high accuracy of classification.

II. ECG DATA AND PREPROCESS

All ECG data were obtained from MIT-BIH arrhythmia database that contains records of many patients with heart troubles or abnormalities. The frequency of the ECG data was 360HZ. Each record has its respective annotation file that indicate the class of the heartbeat. A single channel ECG is collected and used to algorithm evaluation. Since there are few categories of abnormal QRS complexes in one record, we select different abnormal QRS complexes from several records. Six types of QRS complexes appeared frequently in the database. Therefore, we mainly deal with six types heartbeats which include normal beat(NORMAL), left bundle branch block beat(LBBB), right bundle branch block beat(RBBB), paced beat(PACE), premature ventricular contraction(PVC) and atrial premature contraction(APC).

In the data preprocessing process, continuous ECG signals must be separated into many segments which contain one heartbeat. The extracted data of ECG complexes is centered around R peak. Considered that some PVC duration is great and sometimes R peak detection may be not the center of the complex, we have selected segment of 250ms before the fiducial point and 400ms after that with the R peak point is the 90th point. The R peak is detected using the Pan and Tompkins algorithm[6]. Thus, each segment must contain one ECG heartbeat. Fig.1 shows typical waveforms of six types of ECG segments.

III. FEATURE EXTRACTION

The recognition of heart rhythms requires generation of the feature vector which represents the original ECG segment. A good recognition system should depend on the features representing the ECG signals in such a way, that the differences among the ECG waveforms are suppressed for the waveforms of the same type but are emphasized for the waveforms of belonging to different types of heartbeats. We perform the recognition process of heart rhythms on the single heartbeat of the ECG, proposing the description or representation by wavelet transform and AR model.

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DETECTION OF SMALL VARIATIONS OF ECG FEATURES USING WAVELET

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Recently wavelets have been used in a large number of biomedical applications. The wavelet packet method is a generalization of wavelet decomposition that offers a rich range of possibilities for signal analysis. The multi-resolution framework makes wavelets into a very powerful tool for feature extraction [6]. There are some works on precise detection of ECG using FFT and wavelet [7-15]. Karel *et al.* proposed the performance criteria to measure the quality of a wavelet, based on the principle of maximization of variance [7]. Mahmoodbadi *et al.* developed and evaluated an electrocardiogram (ECG) feature extraction system based on the multi-resolution wavelet transform [8]. David *et al.* presented a method to reduce the baseline wandering of an electrocardiogram signal [9]. Shantha *et al.* discussed the design of good wavelet for cardiac signal from the perspective of

orthogonal filter banks [12]. Nikolaev and Goltchev proposed a two-stage algorithm for electrocardiographic (EGG) signal denoising with Wiener filtering in the translation-invariant wavelet domain [13]. Most of the works focused on the large size abnormalities with respect to extreme noisy channel using conventional FFT and wavelet method. Most of the clinically useful information in the ECG is found in the intervals and amplitudes defined by its features (characteristic wave peaks, frequency components, and time duration). In this paper, FFT and wavelet methods are developed for the extraction of small variations of the ECG signal. Wavelet method of signal processing is found to be superior to the conventional FFT method in finding the small abnormalities in ECG signals.

2. MATERIALS AND METHODS

ECG signals both standard and noise corrupted have been generated using Matlab. These signals are analyzed by the wavelet method (Matlab wavelet Tool). Continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ

$$C(\text{scale position}) = \int f(t) \psi(\text{scale position} - t) dt$$

The results of the CWT are many wavelet coefficients C , which are a function of scale and position. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal.

For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. To gain a better appreciation of this process, it is performed a one-stage discrete wavelet transform of a signal. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree.

Zhao et al. (2005)

Haque et al. (2009)

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27

Wavelet Leader Based Multifractal Analysis of Heart Rate Variability during Myocardial Ischaemia

Roberto Fabio Leonarduzzi, Gastón Schlotthauer and María Eugenia Torres

Abstract—Heart rate variability is a non-invasive and indirect measure of the autonomic control of the heart. Therefore, alterations to this control system caused by myocardial ischemia are reflected in changes in the complex and irregular fluctuations of this signal. Multifractal analysis is a well suited tool for the analysis of this kind of fluctuations, since it gives a description of the singular behavior of a signal. Recently, a new approach for multifractal analysis was proposed, the wavelet leader based multifractal formation, which shows remarkable improvements over previous methods. In order to characterize and detect ischemic episodes, in this work we propose to perform a short-time windowed wavelet leader based multifractal analysis. Our results suggest that this new method provides appropriate indexes that could be used as a tool for the detection of myocardial ischemia.

I. INTRODUCTION

MYOCARDIAL ischemia (MI) is understood to be the temporary lack of a blood supply to the myocardial tissue. In extreme cases this situation results in acute myocardial infarction. Therefore, early detection of ischemia is of great clinical interest. Traditionally, the assessment of this condition has been approached by means of the analysis of parameters derived from the electrocardiogram (ECG), in particular the deviation of the ST segment [1]. However, this method suffers from a low specificity, given that other phenomena, such as posture changes, cause similar manifestations in the ECG [1].

It is known that the autonomic nervous system (ANS) regulates the heart rate via the stimulation of the sinoatrial node. At any time, the heart rate represents the net effect of the parasympathetic and sympathetic stimulation that slows it down and speeds it up, respectively. Both branches of the ANS are tonically active, even in resting conditions. This phenomenon results in the complex and irregular fluctuations shown by the heart rate, known as heart rate variability (HRV) [2]. Besides of electrocardiographic alterations, ischemia causes early metabolic and hemodynamic changes. These changes are detected by chemoreceptors and baroreceptors which are involved in cardiac reflexes mediated by the ANS [3]. Therefore, HRV can be used to measure, in an indirect and non-invasive way, the alterations of the ANS caused by ischemia. This was the hypothesis assumed in [1], [3], where MI was assessed by time-frequency and

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wavelet analysis of HRV, respectively. In the present work we assume the hypothesis that the alterations of the sympathetic/parasympathetic balance caused by the presence of ischemia are reflected in the characteristics of the HRV fluctuations.

In the 1990's, statistical physics techniques began to be used to analyze these complex fluctuations. In particular, multifractal analysis (MFA) allows to study scaling phenomena and long-term correlations in time series and gives a quantification of the distribution of their singularities. This technique was initially based on the increments of the time series. Later, variants based on the wavelet transform modulus-maxima [4] and, more recently, on wavelet leaders (WL) [5], [6] were proposed.

Gosky and Torres [7] first proposed to use MFA to study MI from HRV signals. In the present paper we continue this work, using the WL based multifractal formation (MFF), which benefits from both theoretical and practical advantages compared to the one based on WTMM used in [7]. We also propose a short-time version of MFA in order to detect ischemic episodes (IE).

II. MATERIALS AND METHODS

In this section, a brief review of the tools used in the present work is given. The definitions of Hölder exponent and the singularity spectrum are presented. Next, the WLs and the corresponding multifractal formation are described, following [8]. Finally the short-time multifractal analysis proposed in the present work is presented. The records used for the experiments and the experimental procedure are described in the last two subsections.

A. Hölder exponent and singularity spectrum

Given a point $t_0 \in \mathbb{R}$ and a real constant $\alpha \geq 0$, a function $f: \mathbb{R} \rightarrow \mathbb{R}$ is said to be $C^\alpha(t_0)$ if there exists a constant $K > 0$ and a polynomial P_α of degree less than α such that $|f(t) - P_\alpha(t)| \leq K|t - t_0|^\alpha$. The Hölder exponent $h_f(t_0)$ of f in t_0 is defined as $h_f(t_0) = \sup\{\alpha : f \in C^\alpha(t_0)\}$ [6]. It measures the local regularity of f in t_0 . Small (close to 0) values of the Hölder exponent denote strong and sharp singularities, whereas large values denote smooth ones.

When analyzing a signal which is singular almost everywhere, it is useful to know the distribution of the singularities with a given Hölder exponent. The singularity (or multifractal) spectrum (SS) measures the amount of singularities with a given Hölder exponent. Formally, it is defined as the Hausdorff dimension of the set of points whose Hölder exponent is h : $D(h) = \dim_H\{t \in \mathbb{R} : h_f(t) = h\}$ [6].

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Wavelet Based Multifractal Analysis of Heart Rate Variability during Myocardial Ischaemia

Roberto Fabio Leonarduzzi, Gastón Schlotthauer and María Eugenia Torres

Abstract—Heart rate variability is a non-invasive and indirect measure of the autonomic control of the heart. Therefore, alterations to this control system caused by myocardial ischemia are reflected in changes in the complex and irregular fluctuations of this signal. Multifractal analysis is a well suited tool for the analysis of this kind of fluctuations, since it gives a description of the singular behavior of a signal. Recently, a new approach for multifractal analysis was proposed, the wavelet leader based multifractal formalism, which shows remarkable improvement over previous methods. In order to characterize and detect ischemic episodes, in this work we propose to perform a short-time windowed wavelet leader based multifractal analysis. Our results suggest that this new method provides appropriate indexes that could be used as a tool for the detection of myocardial ischemia.

I. INTRODUCTION

MYOCARDIAL ischemia (MI) is understood to be the temporary lack of a blood supply to the myocardial tissue. In extreme cases this situation results in acute myocardial infarction. Therefore, early detection of ischemia is of great clinical interest. Traditionally, the assessment of this condition has been approached by means of the analysis of parameters derived from the electrocardiogram (ECG), in particular the deviation of the ST segment [1]. However, this method suffers from a low specificity, given that other phenomena, such as posture changes, cause similar manifestations in the ECG [1].

It is known that the autonomic nervous system (ANS) regulates the heart rate via the stimulation of the sinoatrial node. At any time, the heart rate represents the net effect of the parasympathetic and sympathetic stimulation that slows it down and speeds it up, respectively. Both branches of the ANS are tonically active, even in resting conditions. This phenomenon results in the complex and irregular fluctuations shown by the heart rate, known as heart rate variability (HRV) [2].

Besides of electrocardiographic alterations, ischemia causes early metabolic and hemodynamic changes. These changes are detected by chemoreceptors and baroreceptors which are involved in cardiac reflexes mediated by the ANS [3]. Therefore, HRV can be used to measure, in an indirect and non-invasive way, the alterations of the ANS caused by ischemia. This was the hypothesis assumed in [1], [3], where MI was assessed by time-frequency and

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wavelet analysis of HRV, respectively. In the present work we assume the hypothesis that the alterations of the sympathetic/parasympathetic balance caused by the presence of ischemia are reflected in the characteristics of the HRV fluctuations.

In the 1990's, statistical physics techniques began to be used to analyze these complex fluctuations. In particular, multifractal analysis (MFA) allows to study scaling phenomena and long-term correlations in time series and gives a quantification of the distribution of their singularities. This technique was initially based on the increments of the time series. Later, variants based on the wavelet transform modulus-maxima [4] and, more recently, on wavelet leaders (WL) [5], [6] were proposed.

Gosky and Torres [7] first proposed to use MFA to study MI from HRV signals. In the present paper we continue this work, using the WL based multifractal formalism (MFF), which benefits from both theoretical and practical advantages compared to the one based on WTMM used in [7]. We also propose a short-time version of MFA in order to detect ischemic episodes (IE).

II. MATERIALS AND METHODS

In this section, a brief review of the tools used in the present work is given. The definitions of Hölder exponent and the singularity spectrum are presented. Next, the WLs and the corresponding multifractal formalism are described, following [8]. Finally the short-time multifractal analysis proposed in the present work is presented. The records used for the experiments and the experimental procedure are described in the last two subsections.

A. Hölder exponent and singularity spectrum

Given a point $t_0 \in \mathbb{R}$ and a real constant $\alpha > 0$, a function $f: \mathbb{R} \rightarrow \mathbb{R}$ is said to be $C^\alpha(t_0)$ if there exists a constant $K > 0$ and a polynomial P_α of degree less than α such that $\|f(t) - P_\alpha(t)\| \leq K|t - t_0|^\alpha$. The Hölder exponent $h_f(t_0)$ of f in t_0 is defined as $h_f(t_0) = \sup\{\alpha : f \in C^\alpha(t_0)\}$ [6]. It measures the local regularity of f in t_0 . Small (close to 0) values of the Hölder exponent denote strong and sharp singularities, whereas large values denote smooth ones.

When analyzing a signal which is singular almost everywhere, it is useful to know the distribution of the singularities with a given Hölder exponent. Formally, it is defined as the Hausdorff dimension of the set of points whose Hölder exponent is h : $D(h) = \dim_H \{t \in \mathbb{R} : h_f(t) = h\}$ [6].



Article

ECG Classification Using Wavelet Packet Entropy and Random Forests

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Abstract: The electrocardiogram (ECG) is one of the most important techniques for heart disease diagnosis. Many traditional methodologies of feature extraction and classification have been widely applied to ECG analysis. However, the effectiveness and efficiency of such methodologies remain to be improved, and much existing research did not consider the separation of training and testing samples from the same set of patients (so called inter-patient scheme). To cope with these issues, in this paper, we propose a method to classify ECG signals using wavelet packet entropy (WPE) and random forests (RF) following the Association for the Advancement of Medical Instrumentation (AAMI) recommendations and the inter-patient scheme. Specifically, we firstly decompose the ECG signals by wavelet packet decomposition (WPD), and then calculate entropy from the decomposed coefficients as representative features, and finally use RF to build an ECG classification model. To the best of our knowledge, it is the first time that WPE and RF are used to classify ECG following the AAMI recommendations and the inter-patient scheme. Extensive experiments are conducted on the publicly available MIT-BIH Arrhythmia database and influence of mother wavelets and level of decomposition for WPD, type of entropy and the number of base learners in RF on the performance are also discussed. The experimental results are superior to those by several state-of-the-art competing methods, showing that WPE and RF is promising for ECG classification.

Keywords: ECG classification; wavelet packet entropy; feature extraction; random forests; AAMI

1. Introduction

The electrocardiogram (ECG) records the tiny electrical activity produced by the heart over a period of time by placing electrodes on a patient's body, which has become the most widely used non-invasive technique for heart disease diagnosis in the clinics. Due to the high mortality rate of heart diseases, since the last decades, ECG classification has drawn lots of researchers' attention.

Typically, the classification of ECG signals has four phases: preprocessing, segmentation, feature extraction and classification. The preprocessing phase is mainly aimed at detecting and attenuating frequencies of the ECG signal related to artifacts, which also usually performs signal normalization and enhancement. After preprocessing, segmentation divides the signal into smaller segments, which can better express the electrical activity of the heart [1]. Nowadays, the researchers can get good results from preprocessing and segmentation by some popular techniques or tools [2]. Therefore, most of the literature focuses upon the last two phases.

Feature extraction plays an important role in pattern classification, especially in signal or image classification. Features can be extracted from the raw data or the transformed domain of segmented

Entropy 2016, 18, 265; doi:10.3390/entropy1808265

www.mdpi.com/journal/entropy

Zhao et al. (2005)

Haque et al. (2009)

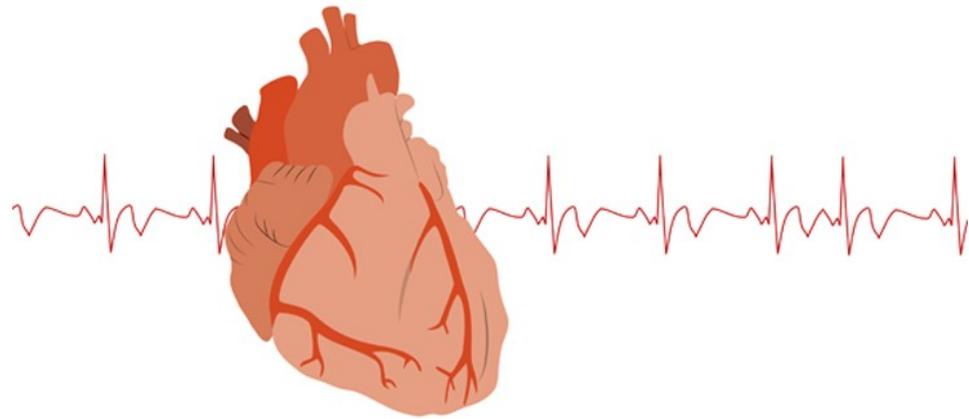
Leonarduzzi et al. (2010)

Li et al. (2016)

A need for automatic systems having **real-time** anomaly detection with **high accuracy**



NovE **AP**proach for the aut**O**matic
rea**L**-time beat-to-beat detect**I**on
of arrhythmia condition**S**
(NEAPOLIS)

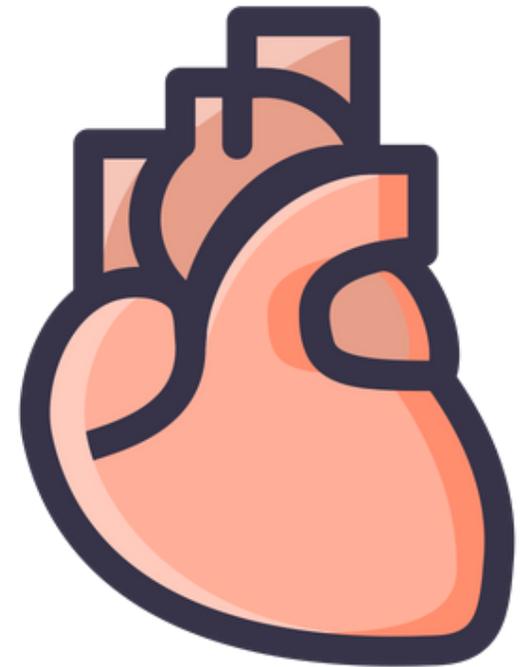


Arrhythmia conditions

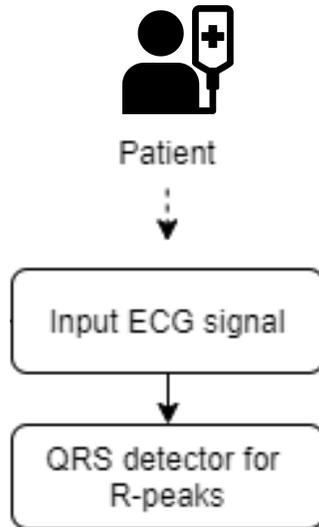
Left and **R**ight **B**undle **B**ranch
Block (**LBBB** and **RBBB**)

Premature **V**entricular
Contraction (**PVC**)

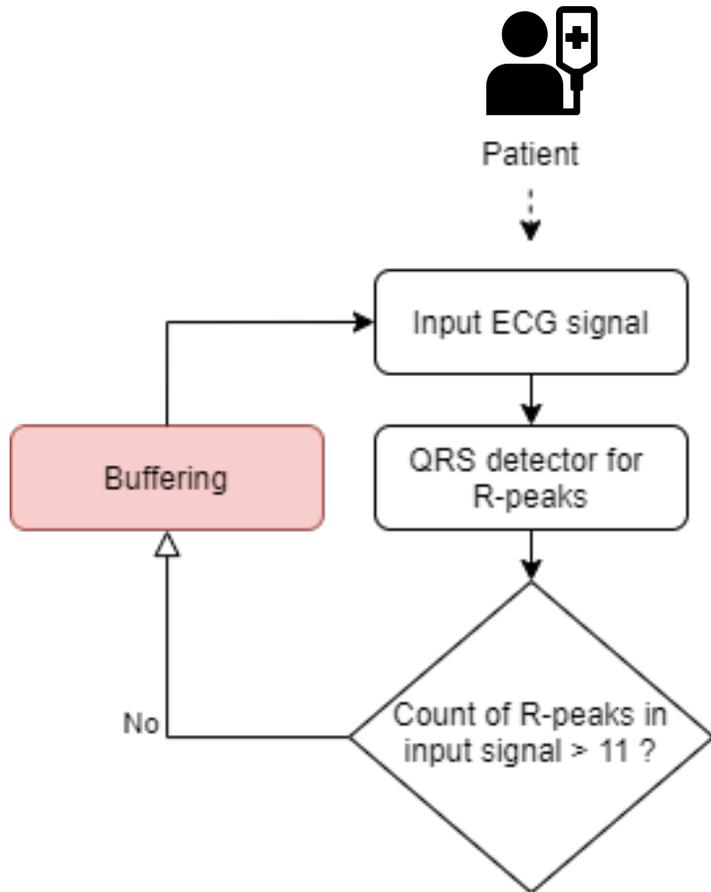
Atrial **P**remature **B**eats (**APB**)



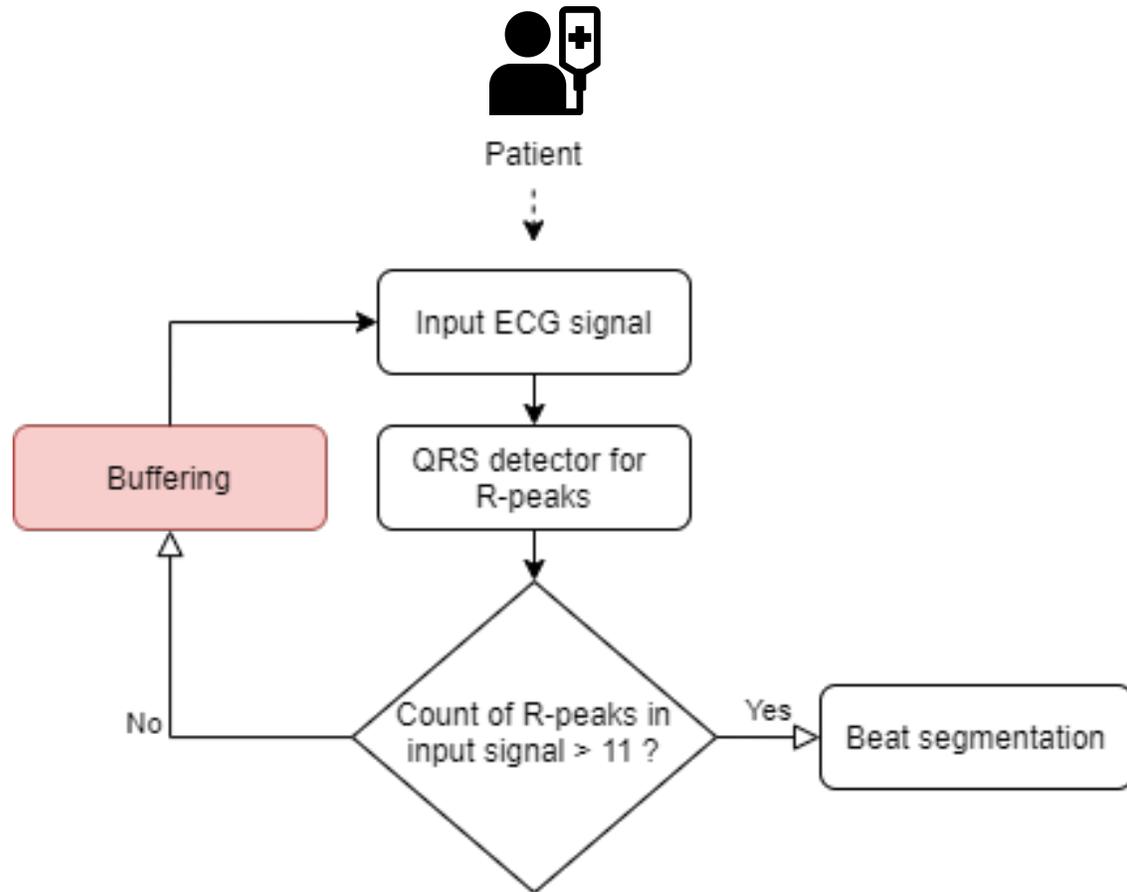
NEAPOLIS in a nutshell



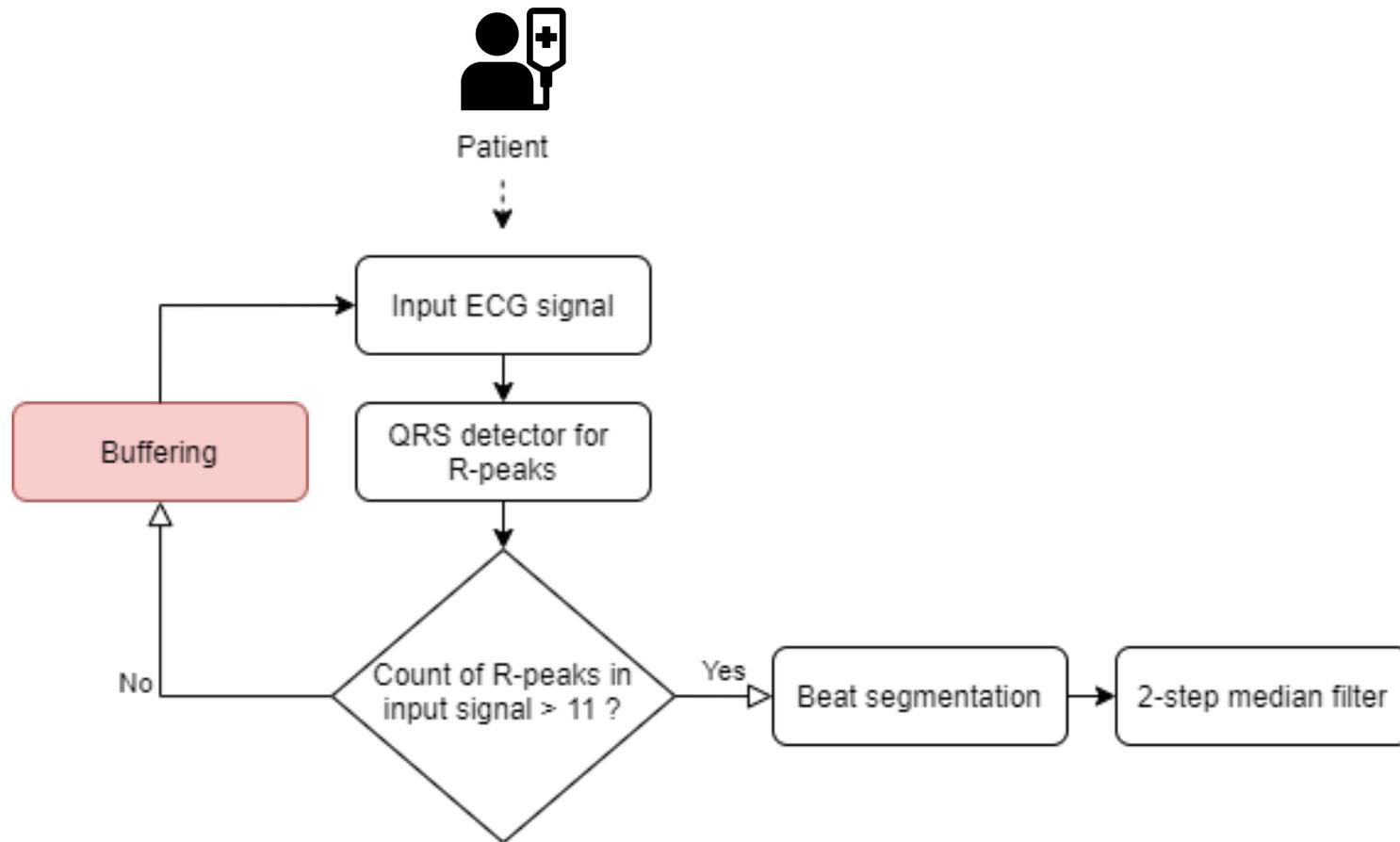
NEAPOLIS in a nutshell



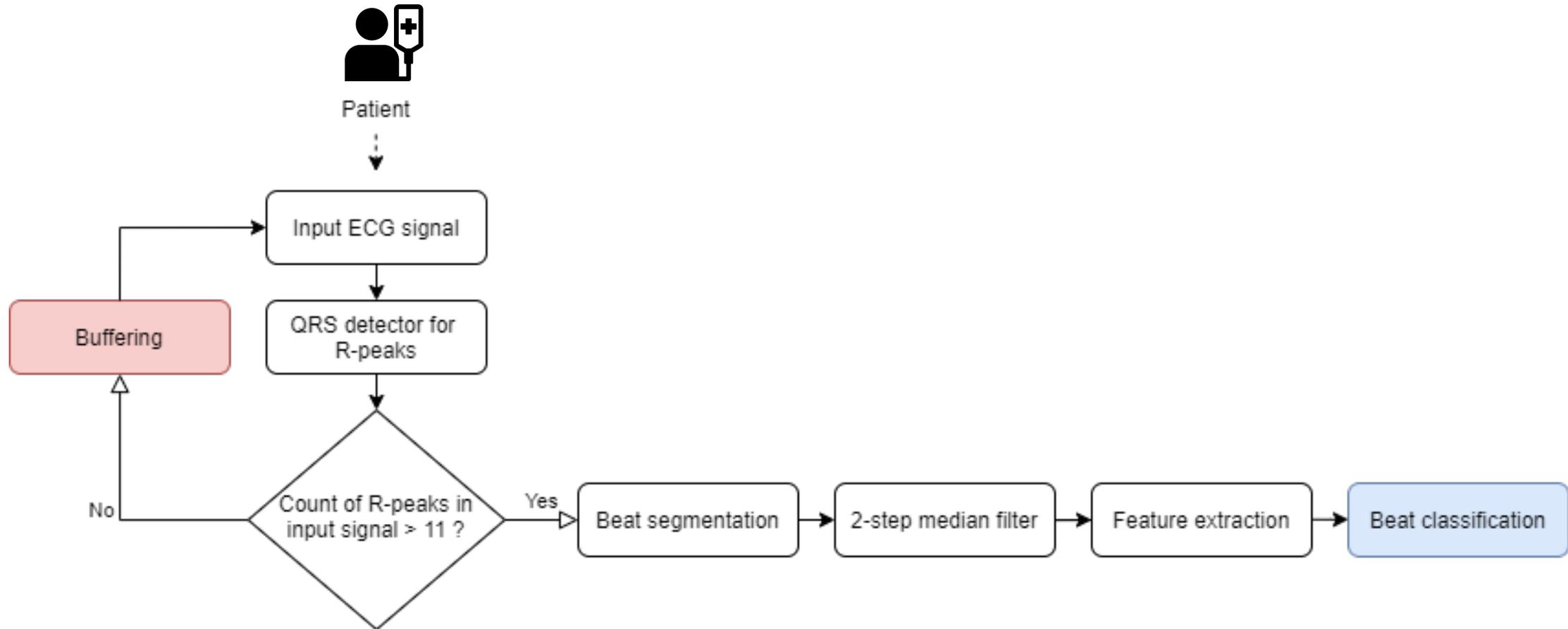
NEAPOLIS in a nutshell



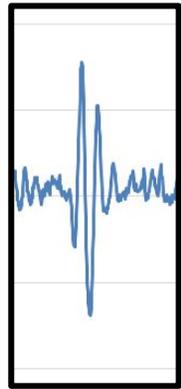
NEAPOLIS in a nutshell



NEAPOLIS in a nutshell



Selected features



Single beat



pre-RR interval



Previous and current heart beats

post-RR interval



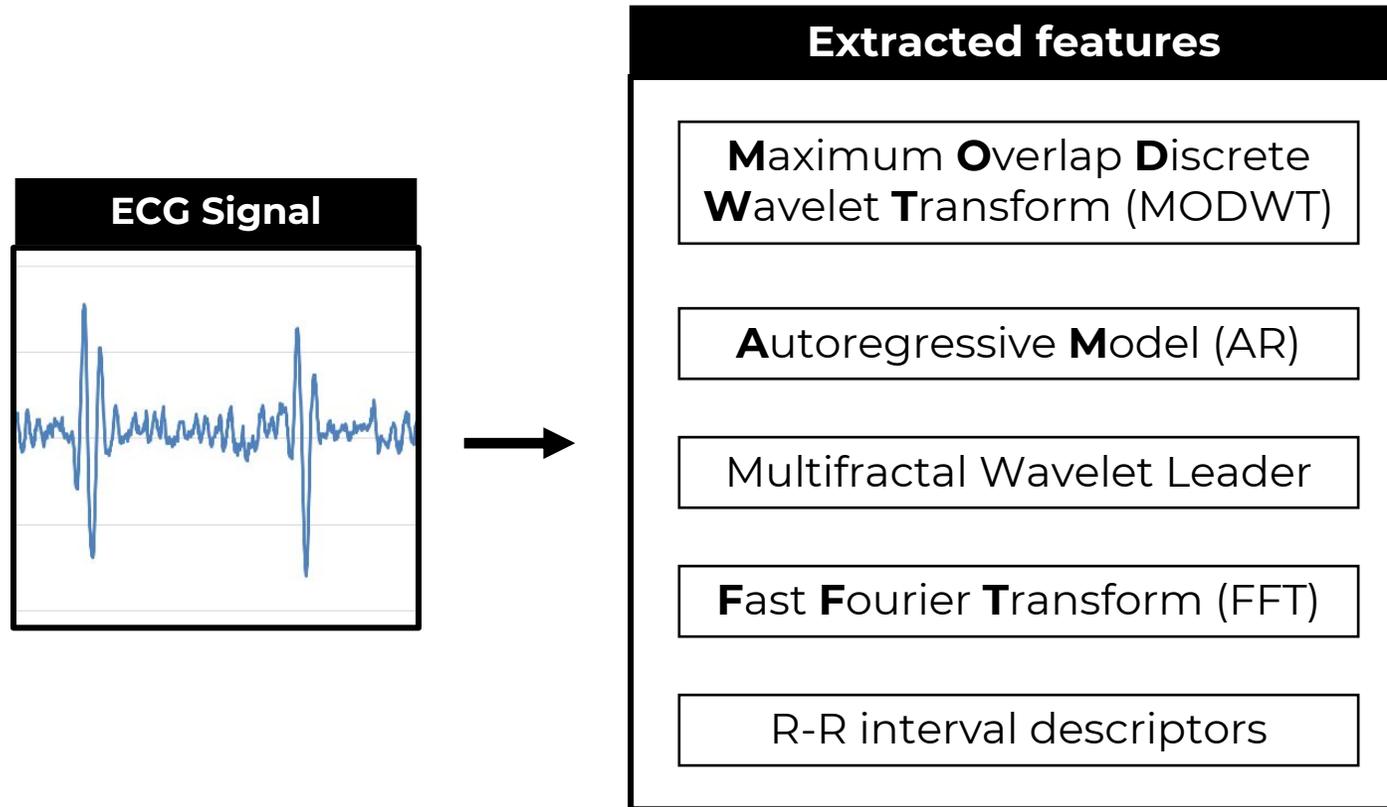
Current and post heart beats

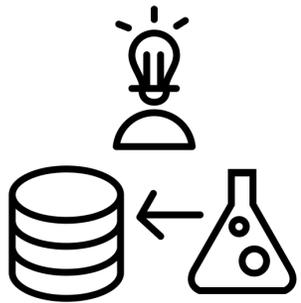
local-RR interval



Requires at least 10 heart beats

Selected features





Experiment

MIT-BIH Database

48

ECG Recordings

30

Minutes of recording

The PhysioNet logo is presented within a dark grey banner that features a faint grid pattern. The text 'PhysioNet' is written in a large, white, sans-serif font. Below the main title, the tagline 'The Research Resource for Complex Physiologic Signals' is written in a smaller, white, sans-serif font.

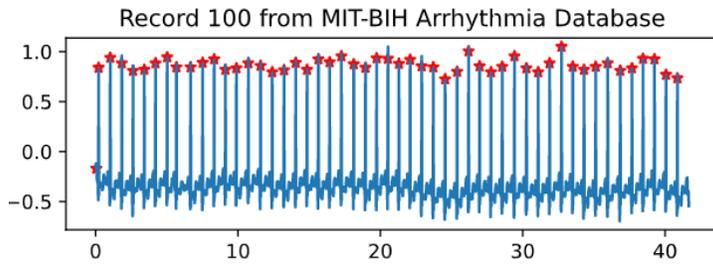
PhysioNet

The Research Resource for Complex Physiologic Signals

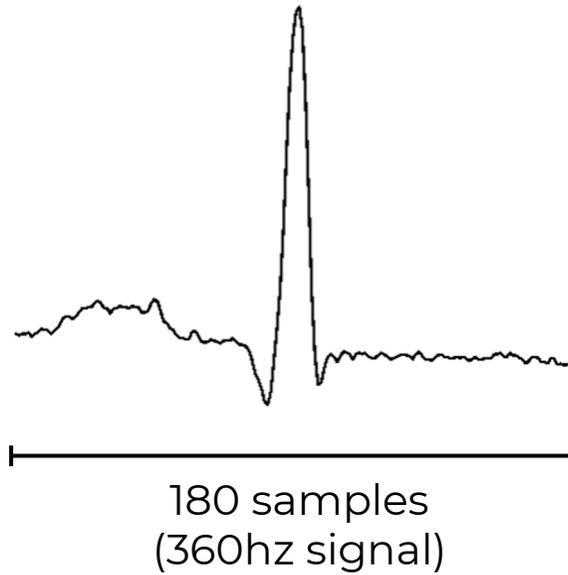
~110,000

Labelled heart beats

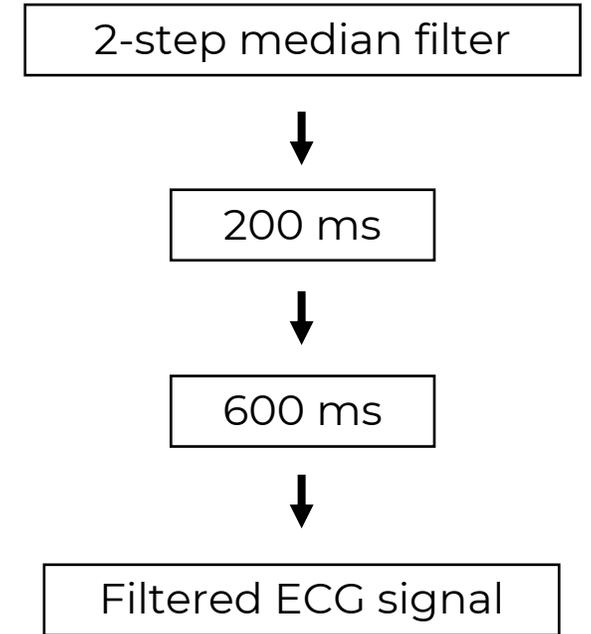
Data extraction



Extraction of R peaks annotations

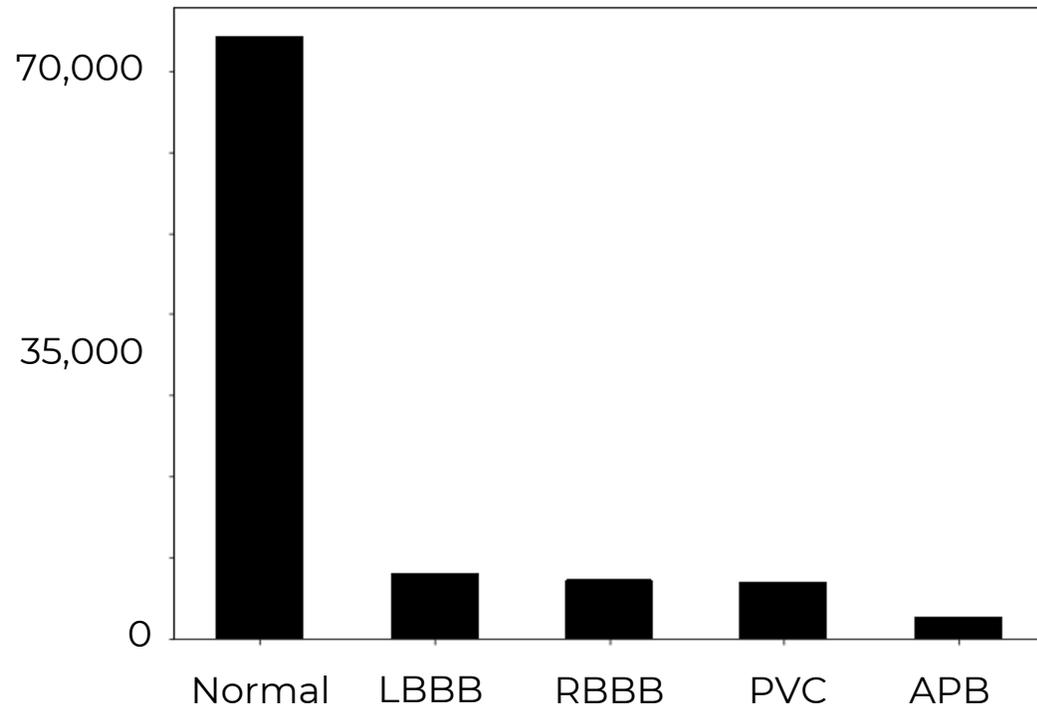


Beat segmentation



Baseline removal

Data extraction



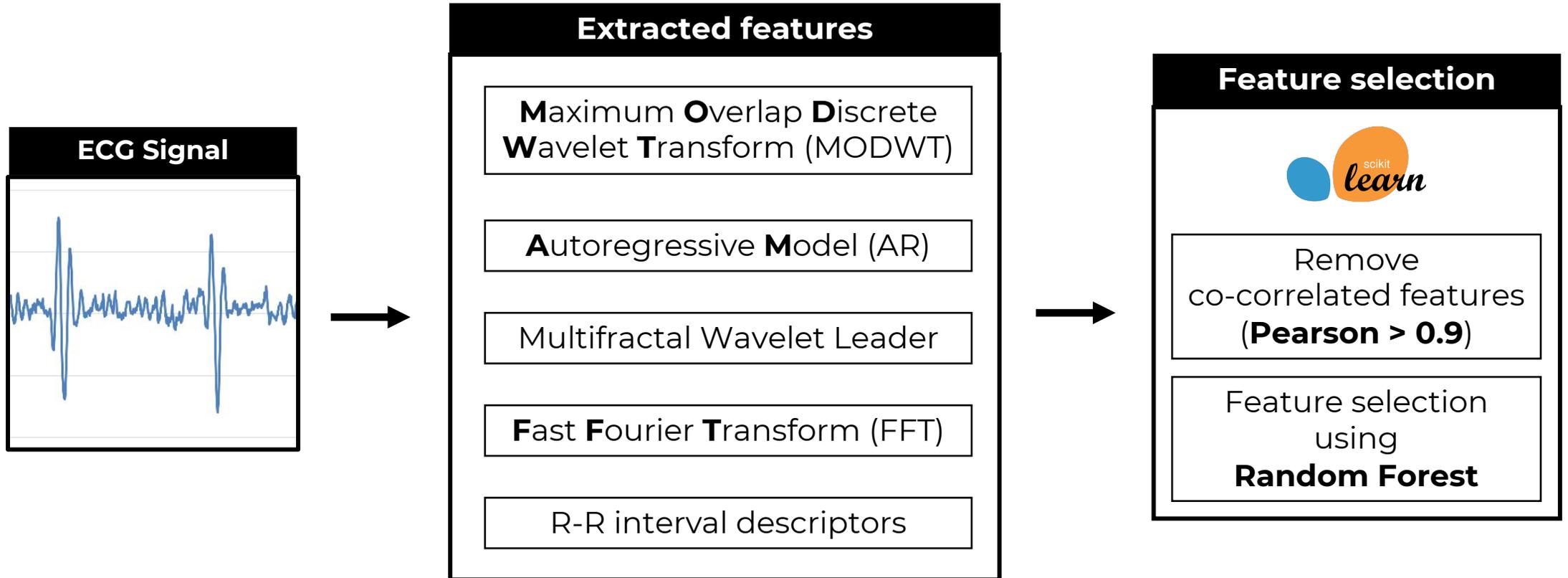
~99,000
heart beats

What are the most important features for the beat-to-beat classification of arrhythmia conditions?

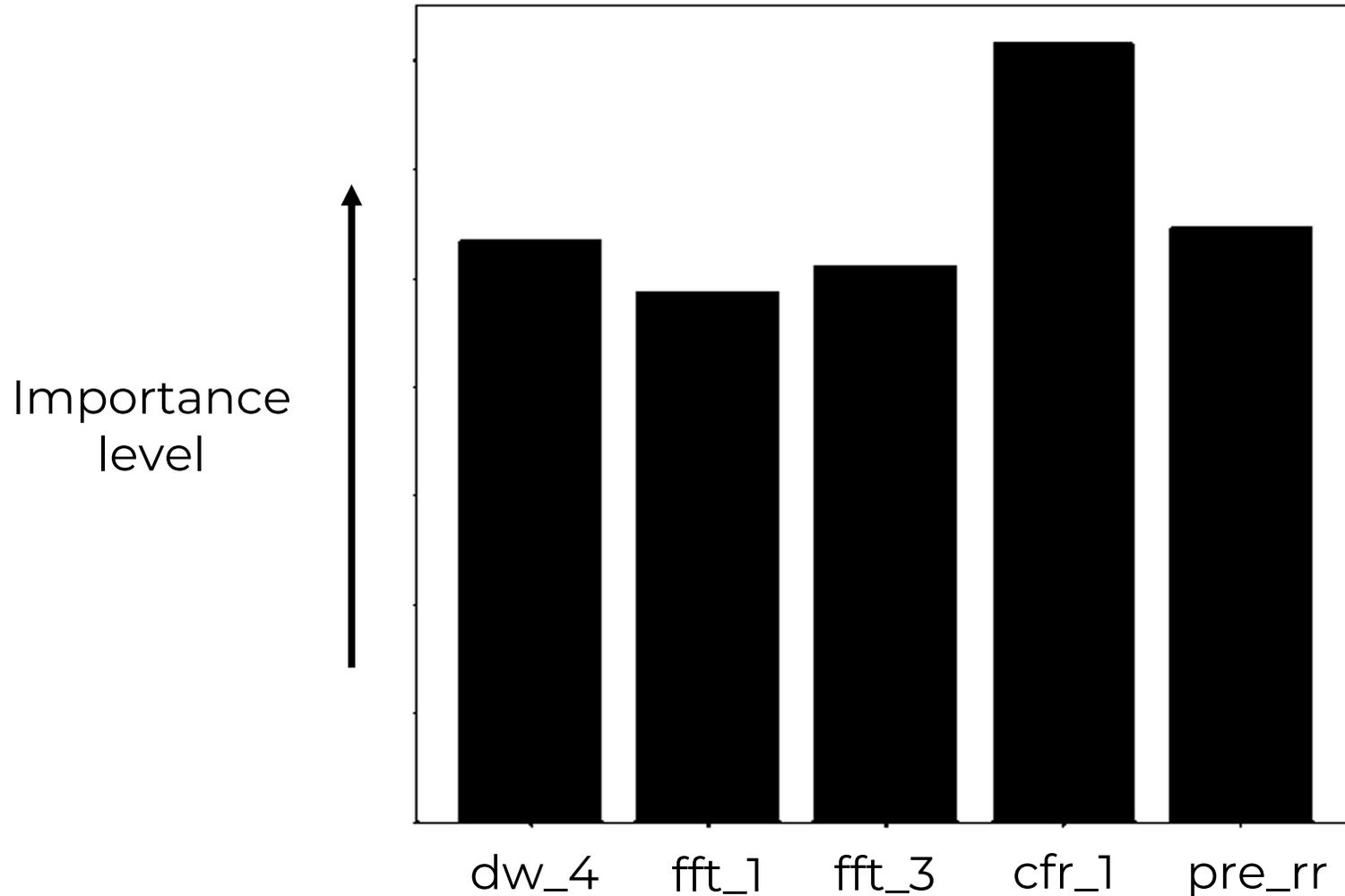
RQ1



Selected features



Selected features - Top 5



dw = Discrete Wavelet

fft = Fast Fourier Transform

cfr = AR model reflection coefficient

pre_rr = pre-RR interval

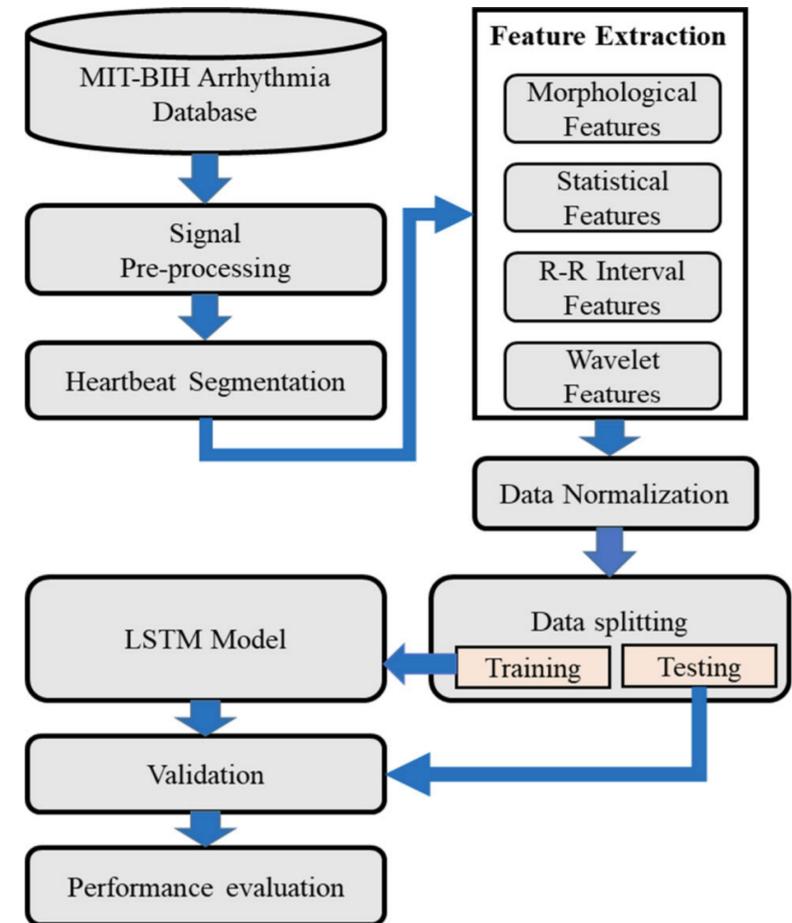
What is the accuracy of NEAPOLIS?

RQ2



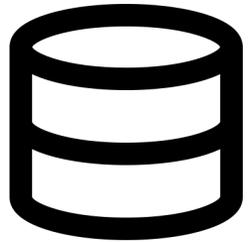
Selected baseline

Heart Beats classification
via LSTM Model

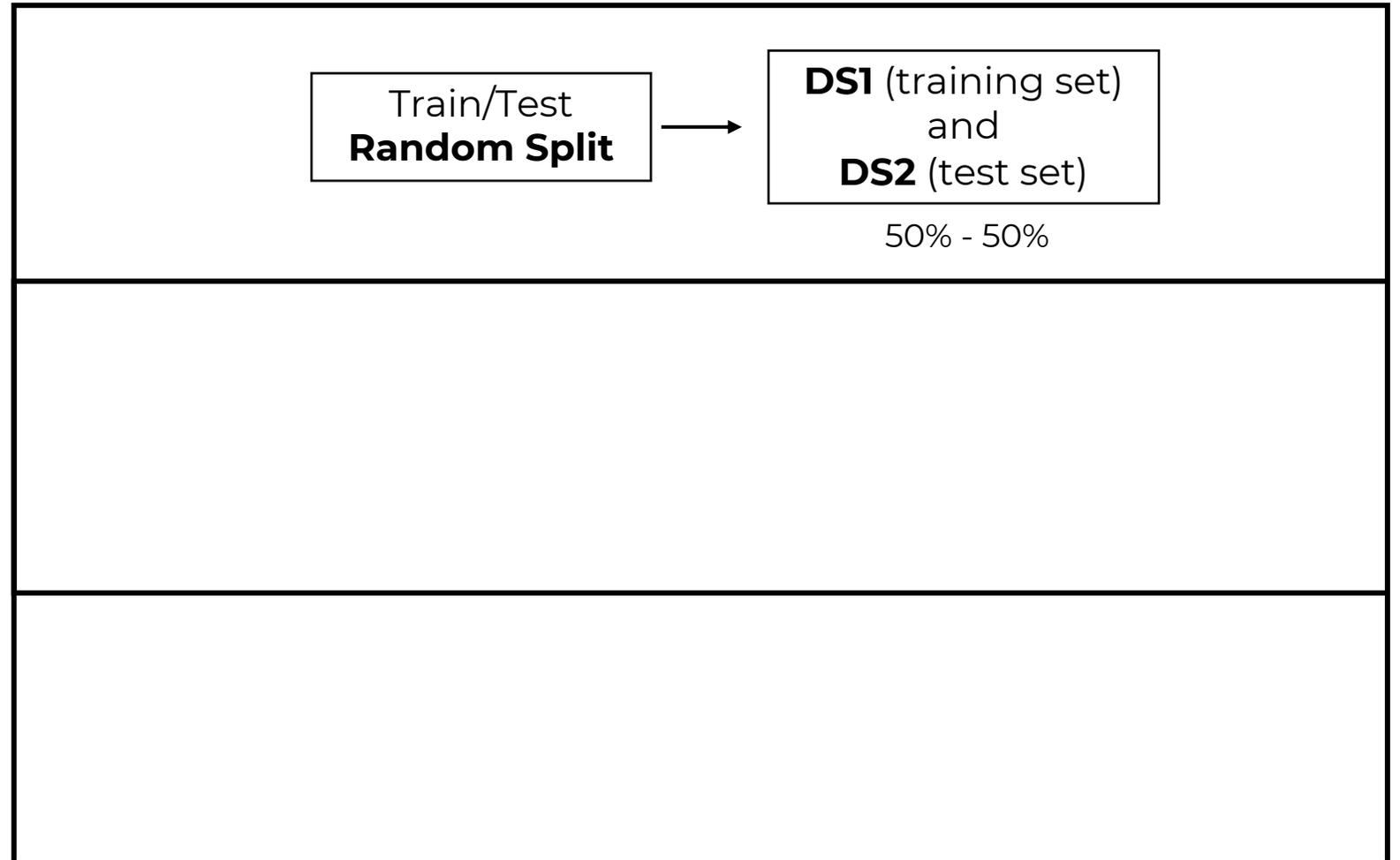


Pandey and Janghel (2020)

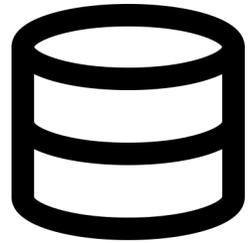
Classification



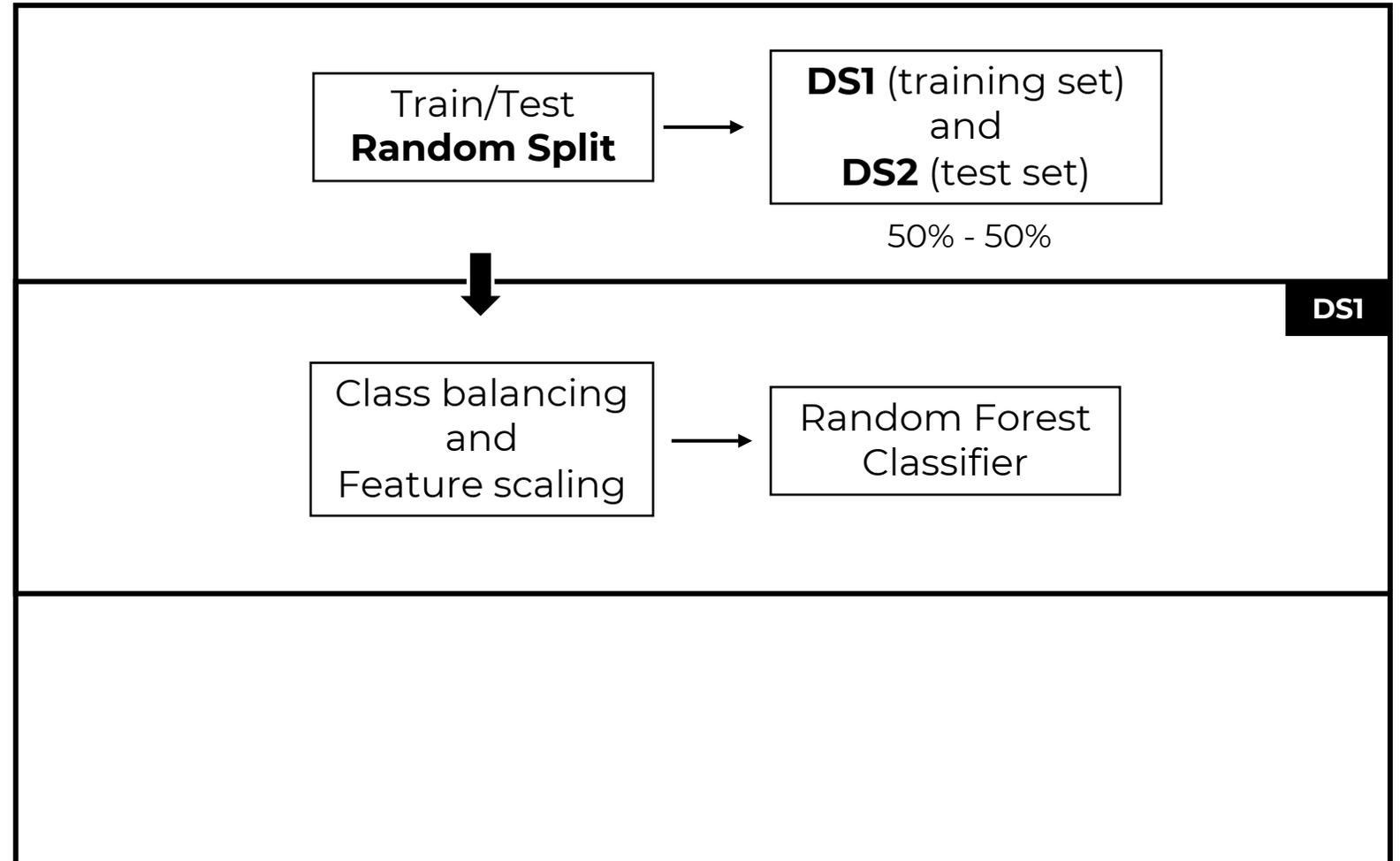
Repeated **1,000 times**, due to split randomness



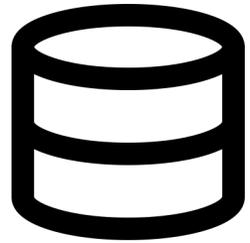
Classification



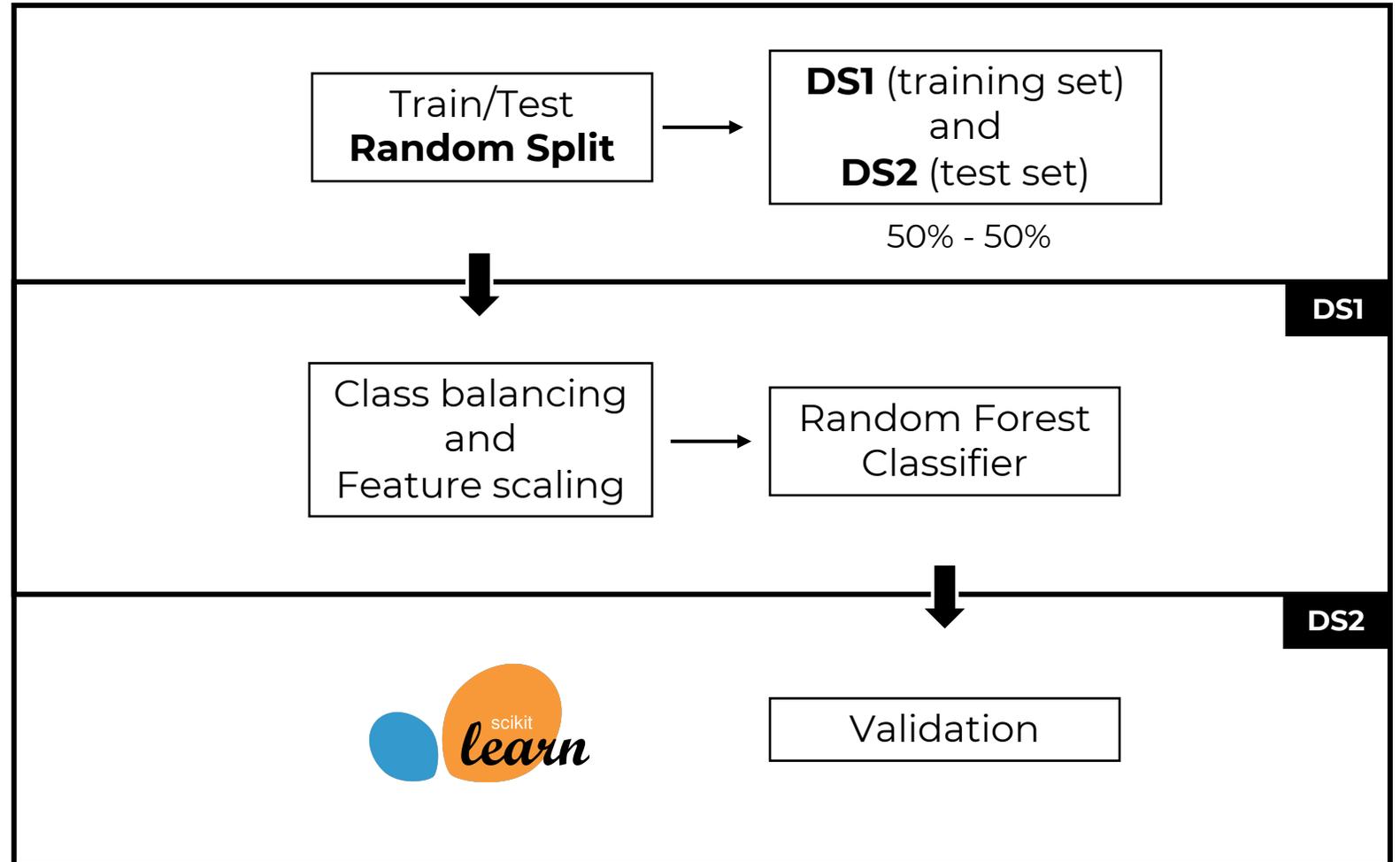
Repeated **1,000 times**, due to split randomness



Classification



Repeated **1,000 times**, due to split randomness



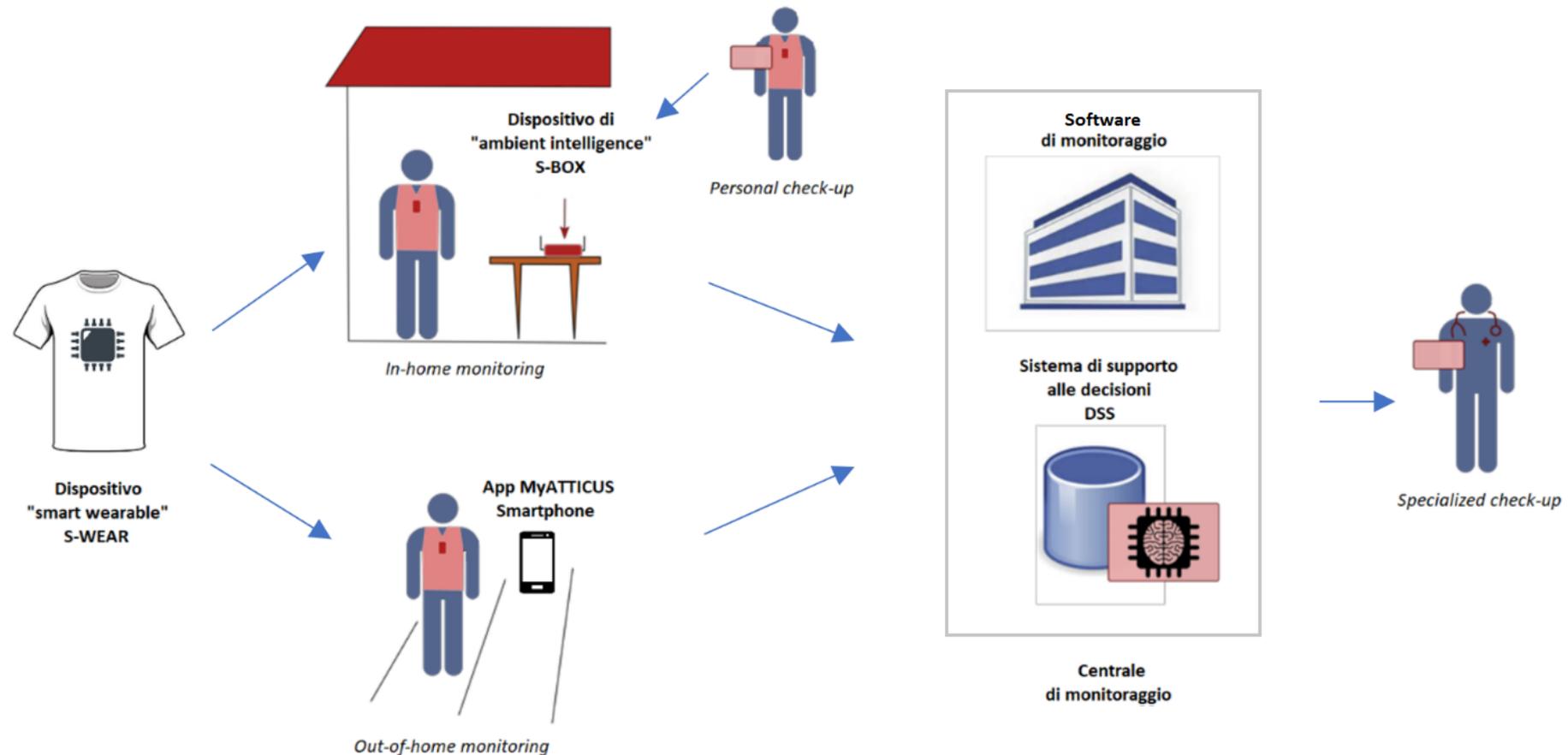
Overall Results

Average metrics	NEAPOLIS	(Pandey et al., 2020)
Sensitivity	97.16 (+ 2.27)	94.89
Specificity	99.53 (+ 0.39)	99.14
Precision	97.22 (+ 0.49)	96.73
F1 score	97.18 (+ 1.41)	95.77

Results (for each class)

Metric	Normal	LBBB	RBBB	PVC	APB
Sensitivity	99.34 (+ 0.03)	98.53 (+ 1.01)	99.18 (+ 0.21)	98.28 (+ 3.10)	90.48 (+ 7.00)
Specificity	98.29 (+ 1.84)	99.96 (+ 0.04)	99.97 (+ 0.04)	99.61 (- 0.02)	99.81 (+ 0.02)
Precision	99.43 (+ 0.59)	99.50 (+ 0.45)	99.68 (+ 0.63)	95.02 (- 0.05)	92.49 (+ 0.85)
F1 score	99.39 (+ 0.32)	99.01 (+ 0.73)	99.43 (+ 0.42)	96.62 (+ 1.49)	91.47 (+ 4.10)

NEAPOLIS is part of a real IoMT system



ATTICUS

Ambient-intelligent Tele-monitoring System



Summary

Internet of Medical Things

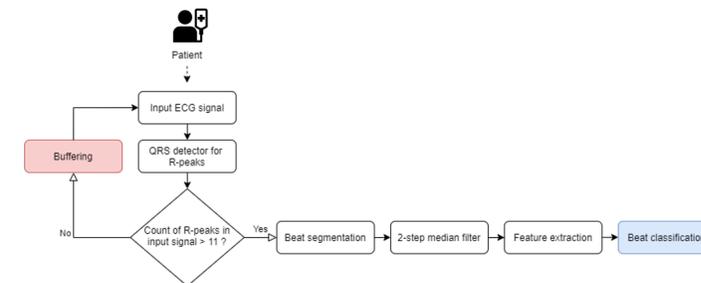


Preventive care

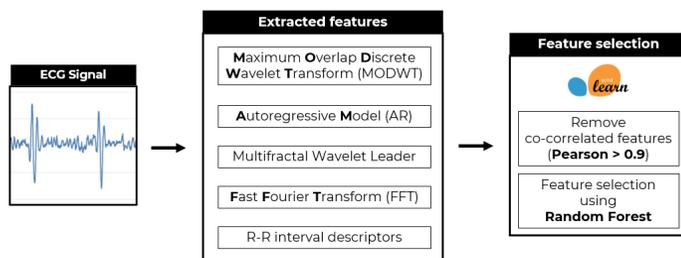
Long-term care and chronic diseases



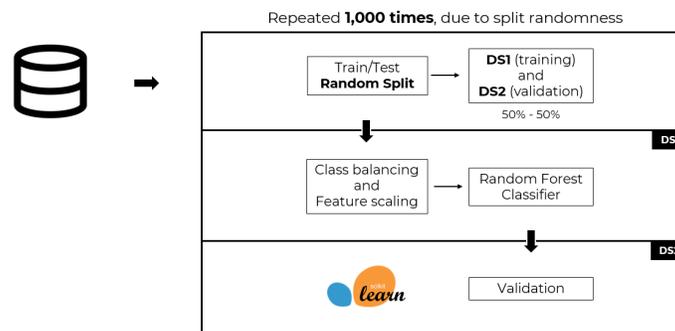
NEAPOLIS in a nutshell



Selected features



Classification



Results - for each class

Metric	Normal	LBBB	RBBB	PVC	APB
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