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

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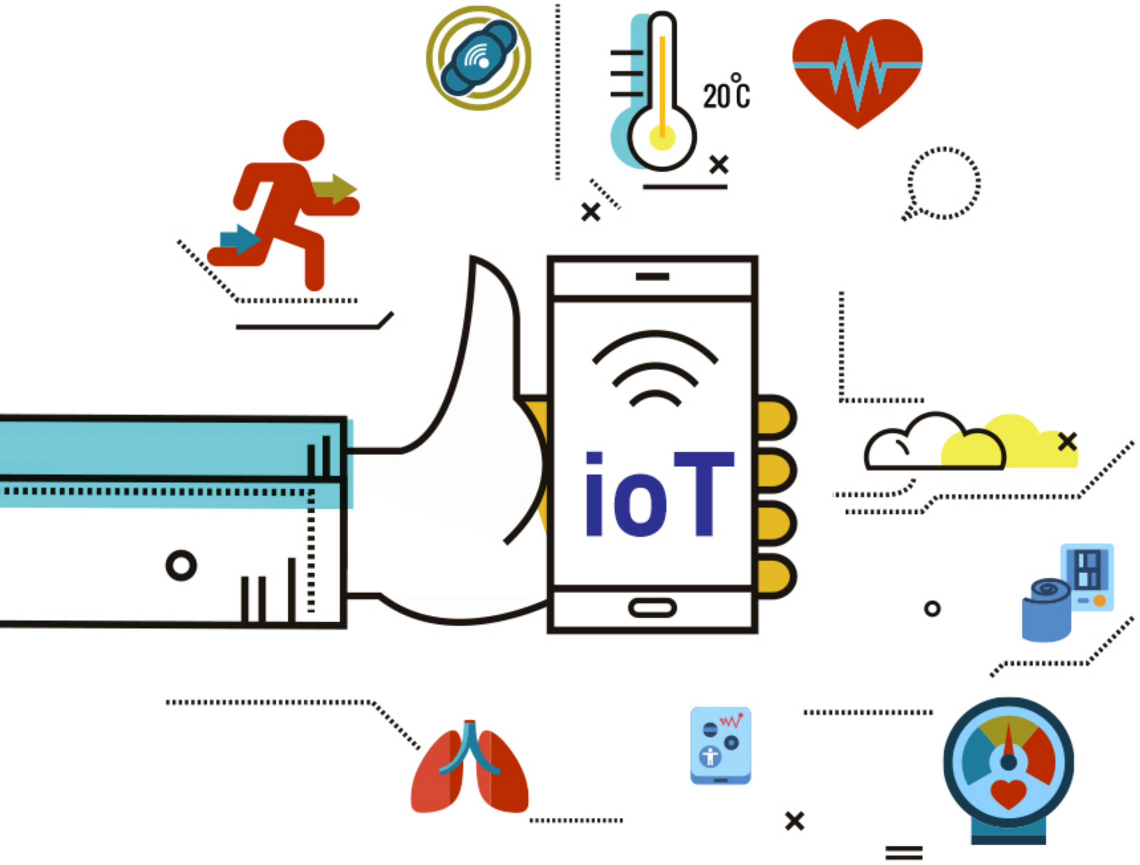
Università degli Studi del Molise

ASREM

HEALTHINF 2021

14TH INTERNATIONAL CONFERENCE ON HEALTH INFORMATICS



IoT for Healthcare

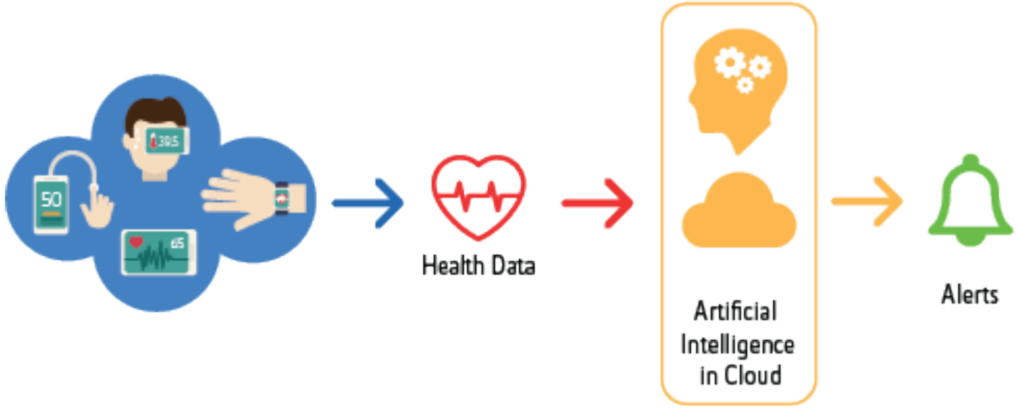
Internet of Medical Things

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 modelling(AR) is also applied to obtain the temporal structures of ECG waveforms. Then the support vector machine(SVM) with Gaussian kernel is used to classify different ECG heart rhythm. 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

The electrocardiogram (ECG) is routinely used in clinical practice, which describes the electrical activity of the heart. In physical checkups at hospitals, physicians record the ECG after the patient has exercised to check his/her cardiac condition. The Holter ECG device is used most frequently for recording the ECG. Physicians apply the device to a patient when they need to monitor his/her ECG to find the few abnormal cycles in the ECG throughout the day. Physicians then interpret the shapes of those waves and complexes. They calculate parameters to determine whether the ECG shows signs of cardiac disease or not. The parameters are the height and the interval of each wave, such as RR interval, PP interval, QT interval, and ST segment. Recognition of the fiducial points and calculations of the parameters is a tedious routine for the physician. Therefore, there is an urgent need for an automatic ECG recognition system to reduce the burden of interpreting the ECG.

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 get 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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Zhao et al. (2005)

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

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Zhao et al. (2005)

ARPN Journal of Engineering and Applied Sciences

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DETECTION OF SMALL VARIATIONS OF ECG FEATURES USING WAVELET

A. K. M. Fazlul Haque[1], Md. Hanif Ali[1], M. Adnan Kiber[2] and Md. Tanvir Hasan[3]

Haque et al. (2009)

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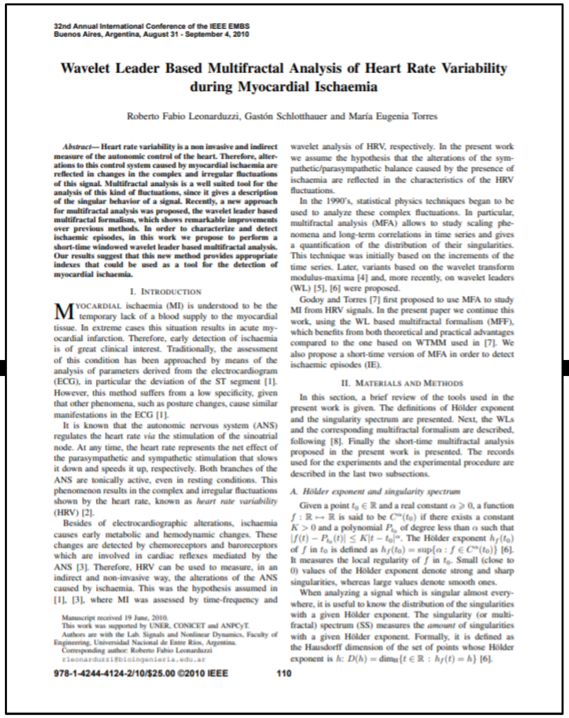

32nd Annual International Conference of the IEEE EMBS
Buenos Aires, Argentina, August 31 - September 4, 2010

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

Roberto Fabio Leonarduzzi, Gastón Schlotthauer and María Eugenia Torres

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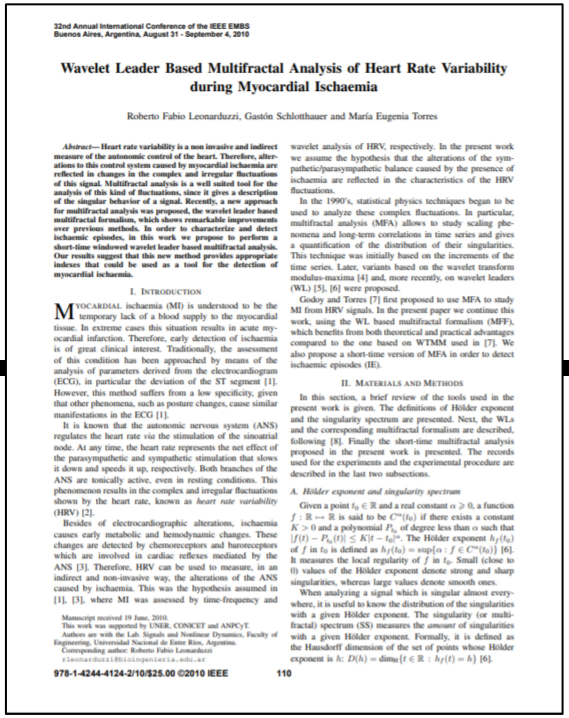

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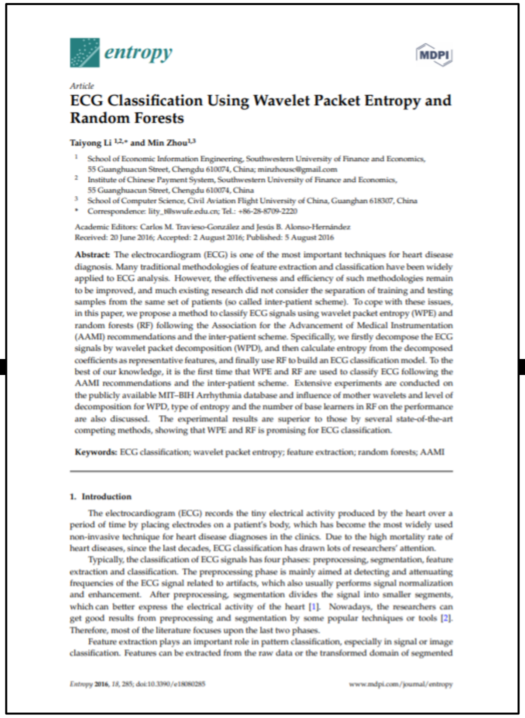


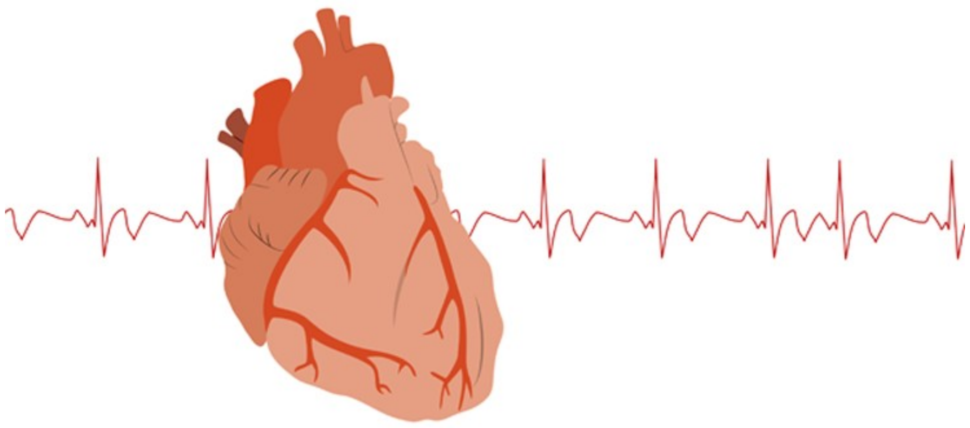
ECG Classification Using Wavelet Packet Entropy and Random Forests

Taiyong Li and Min Zhou

Li et al. (2016)

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

Nov**E**l **AP**proach for the aut**O**matic rea**L**-time beat-to-beat detect**I**on of arrhythmia condition**s** **(NEAPOLIS)**

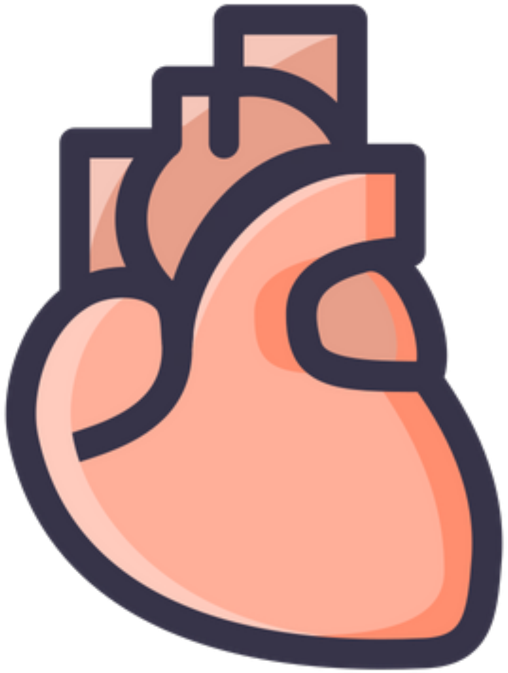


Arrythmia conditions

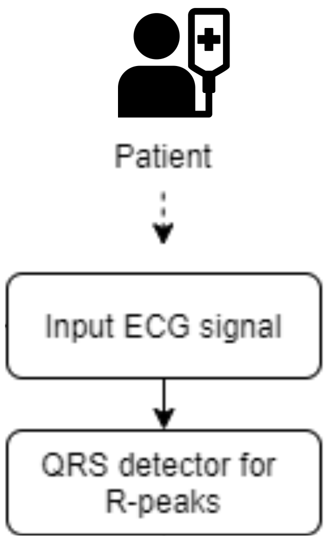
Left and **R**ight **B**undle **B**ranch **B**lock **(LBBB** and **RBBB)**

Premature **V**entricular **C**ontraction **(PVC)**

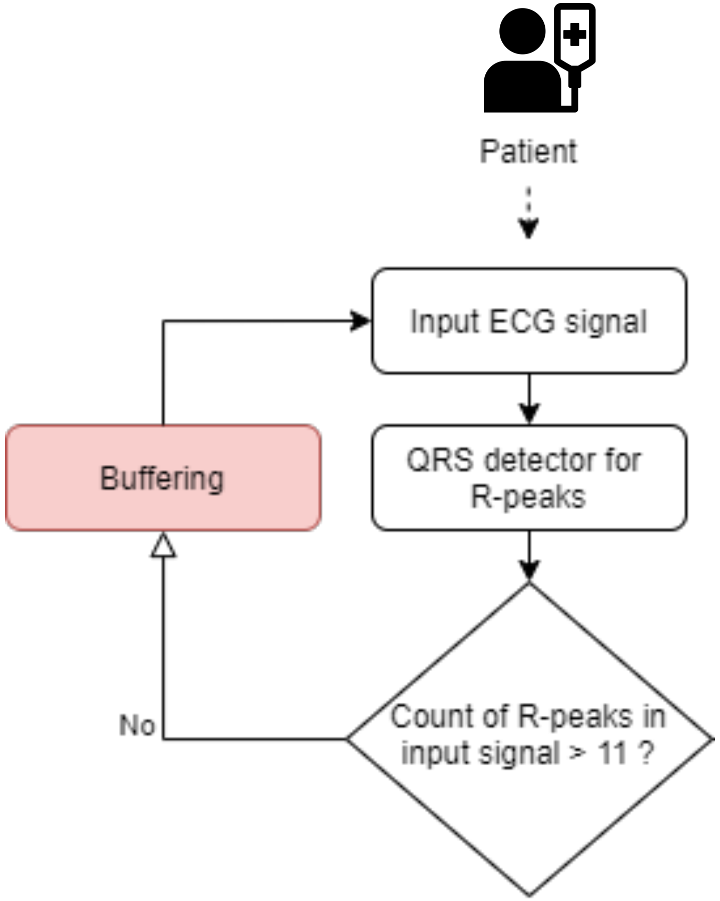
Atrial **P**remature **B**eats **(APB)**



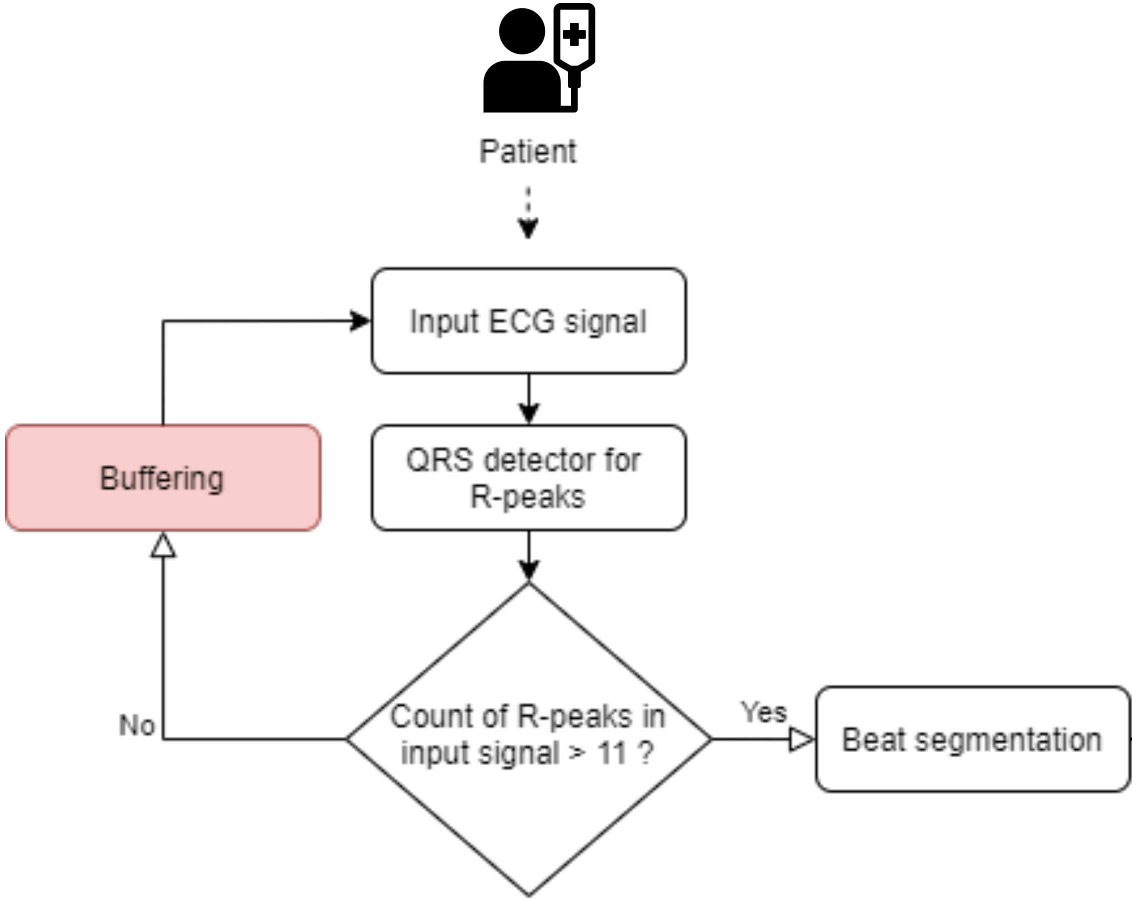
NEAPOLIS in a nutshell



NEAPOLIS in a nutshell



NEAPOLIS in a nutshell



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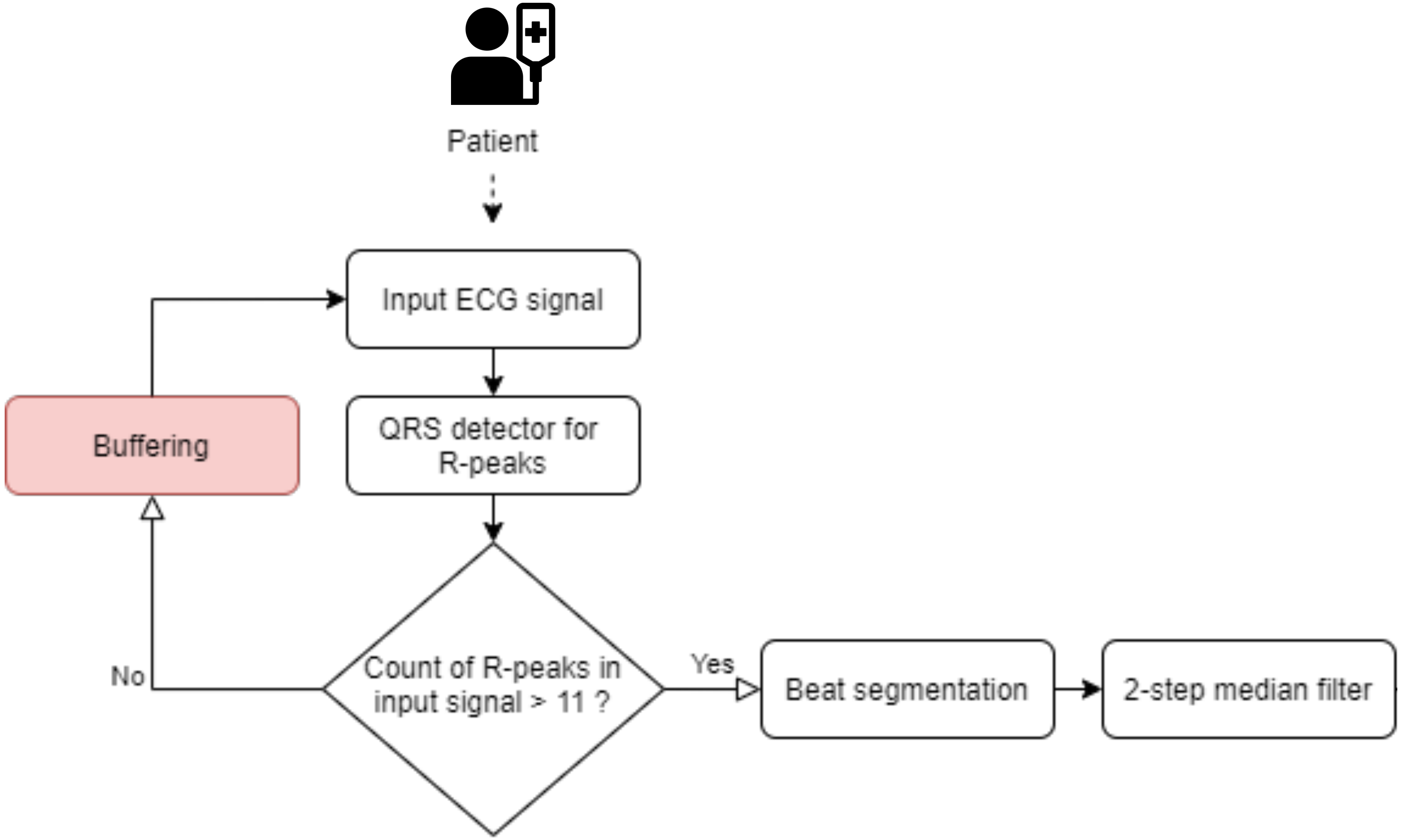
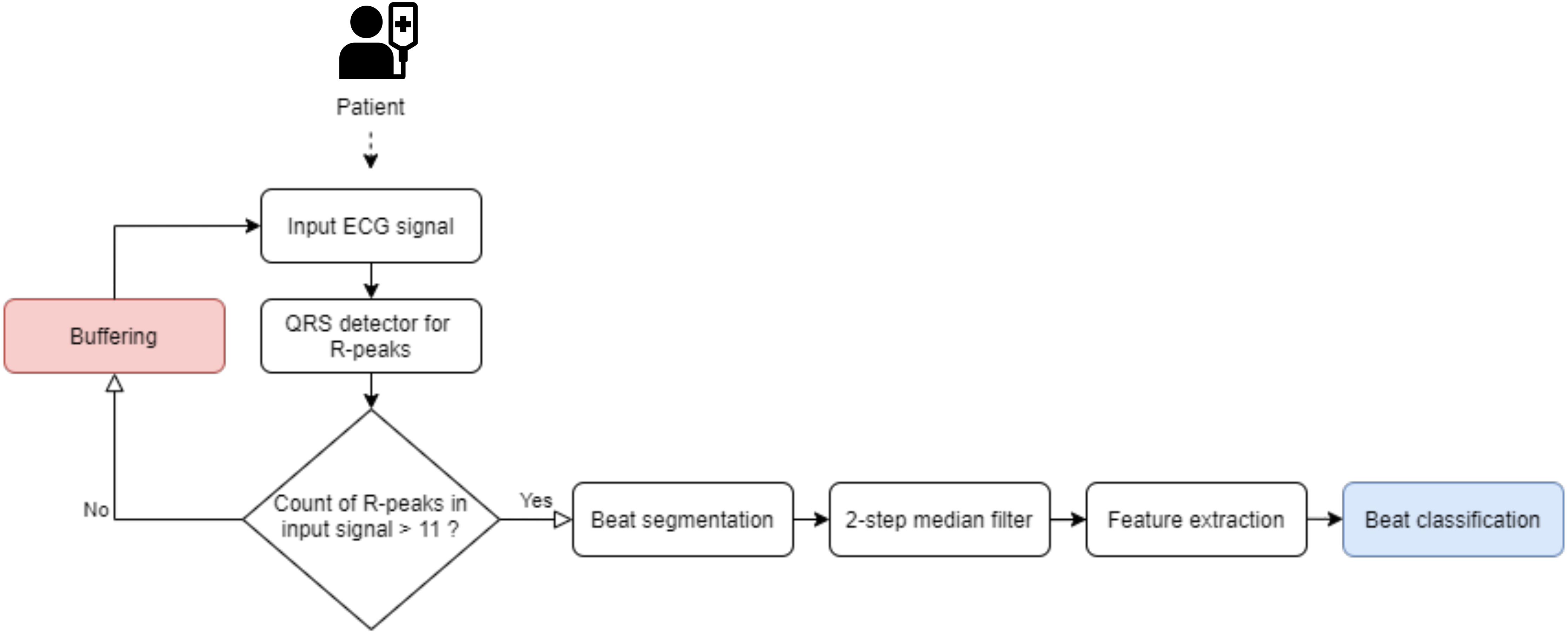
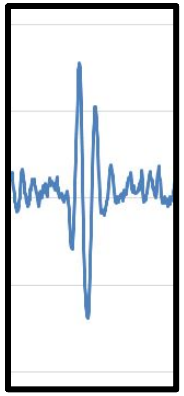


NEAPOLIS in a nutshell



Selected features



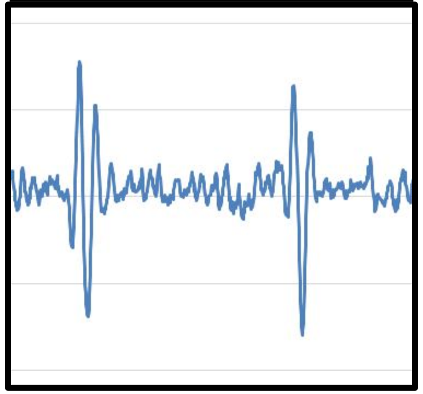
Single beat

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

Pandey and Janghel (2020)

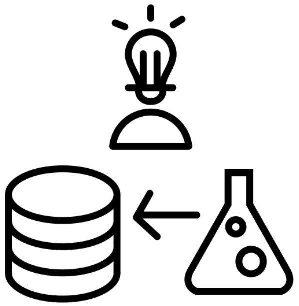
Selected features

ECG Signal



Extracted features

- **M**aximum **O**verlap **D**iscrete **W**avelet **T**ransform (MODWT)
- **A**utoregressive **M**odel (AR)
- Multifractal Wavelet Leader
- **F**ast **F**ourier **T**ransform (FFT)
- R-R interval descriptors



Experiment

MIT-BIH Database

48
ECG Recordings

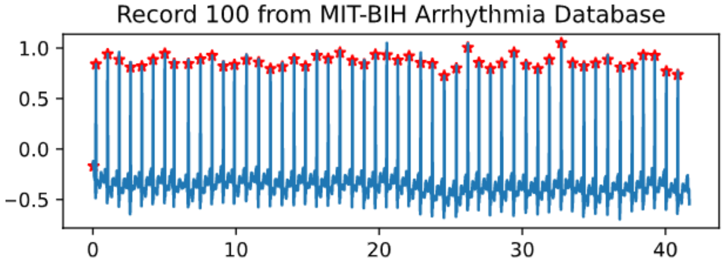
PhysioNet
The Research Resource for Complex Physiologic Signals

30
Minutes of recording

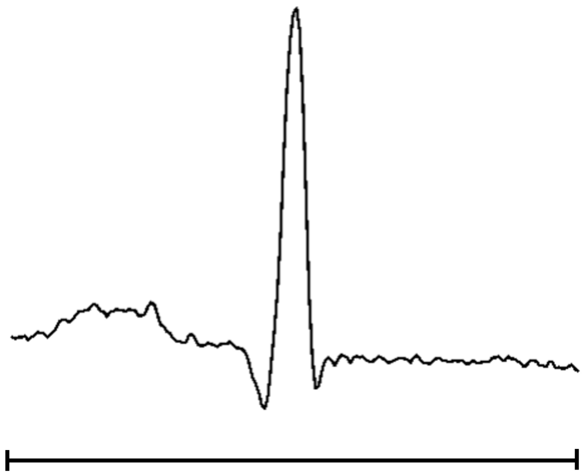
~110,000
Labelled heart beats

Goldberger et al. (2000); Moody and Mark (2001)

Data extraction



Extraction of R peaks annotations →

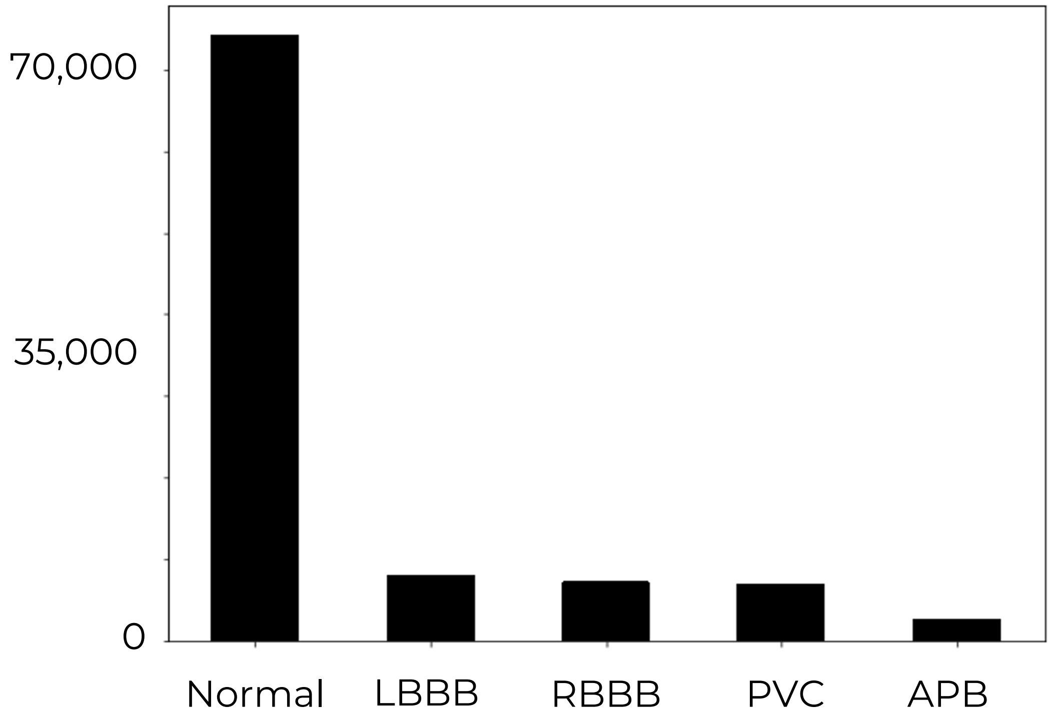


Beat segmentation →

2-step median filter
↓
200 ms
↓
600 ms
↓
Filtered ECG signal

Baseline removal

Data extraction



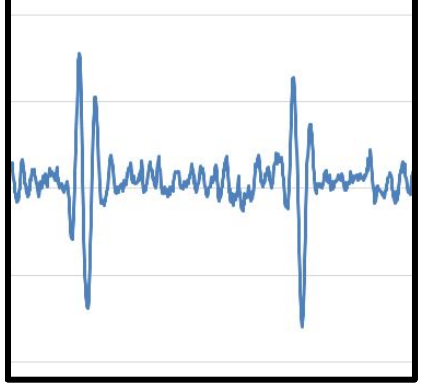
~99,000
heart beats

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

RQ1

Selected features

ECG Signal



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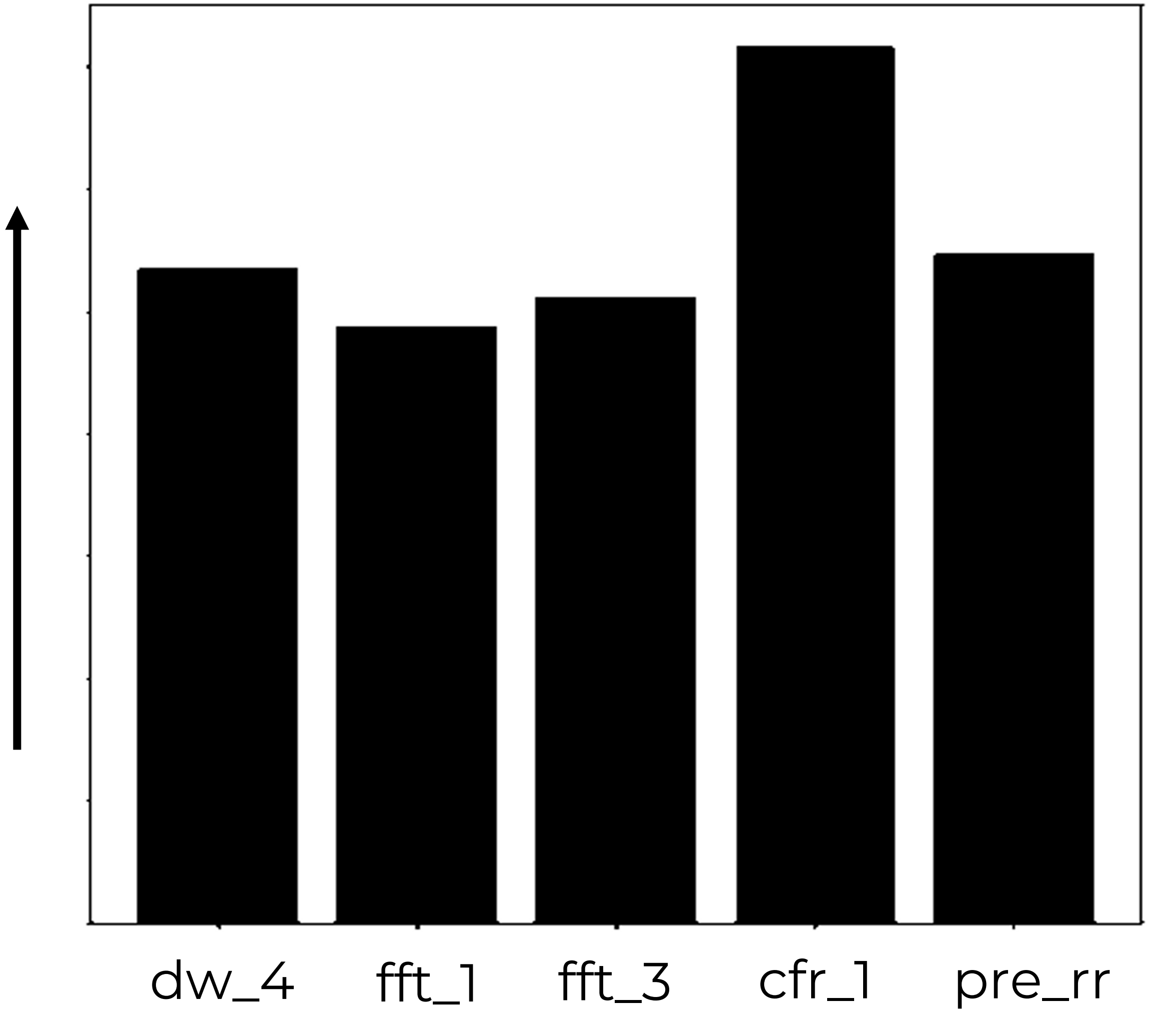
- **A**utoregressive **M**odel (AR)
- Multifractal Wavelet Leader
- **F**ast **F**ourier **T**ransform (FFT)
- R-R interval descriptors

Feature selection

- Remove co-correlated features (**Pearson > 0.9**)
- Feature selection using **Random Forest**

Selected features - Top 5

Importance level



dw = Discrete Wavelet

fft = Fast Fourier Transform

cfr = AR model reflection coefficient

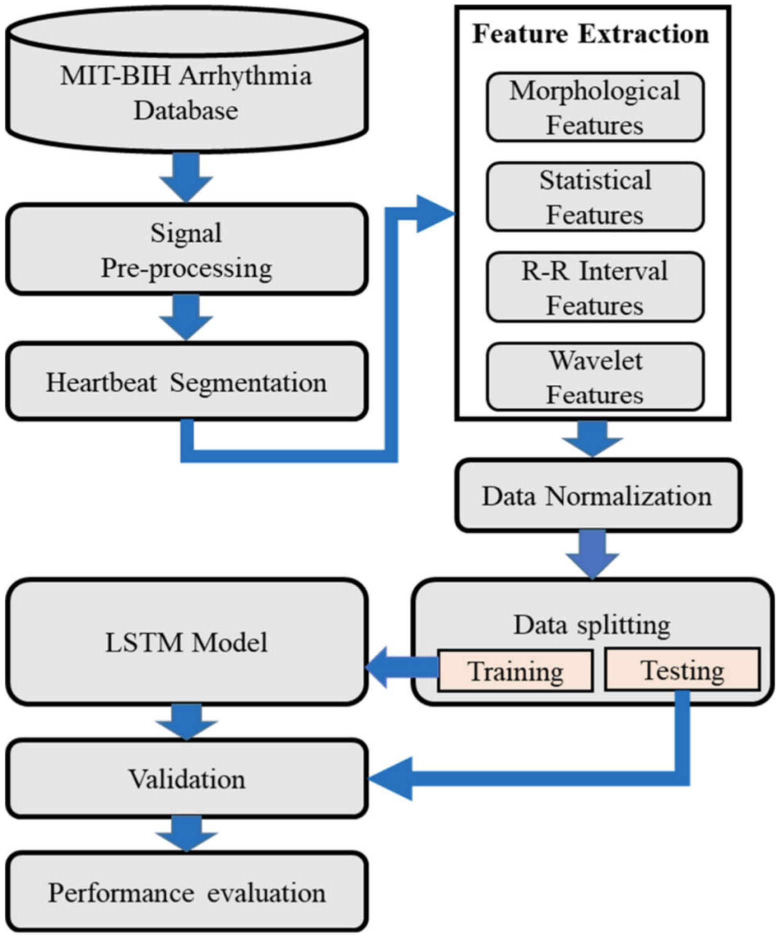
pre_rr = pre-RR interval

What is the accuracy of NEAPOLIS?

RQ2

Selected baseline

Heart Beats classification via LSTM Model



Pandey and Janghel (2020)

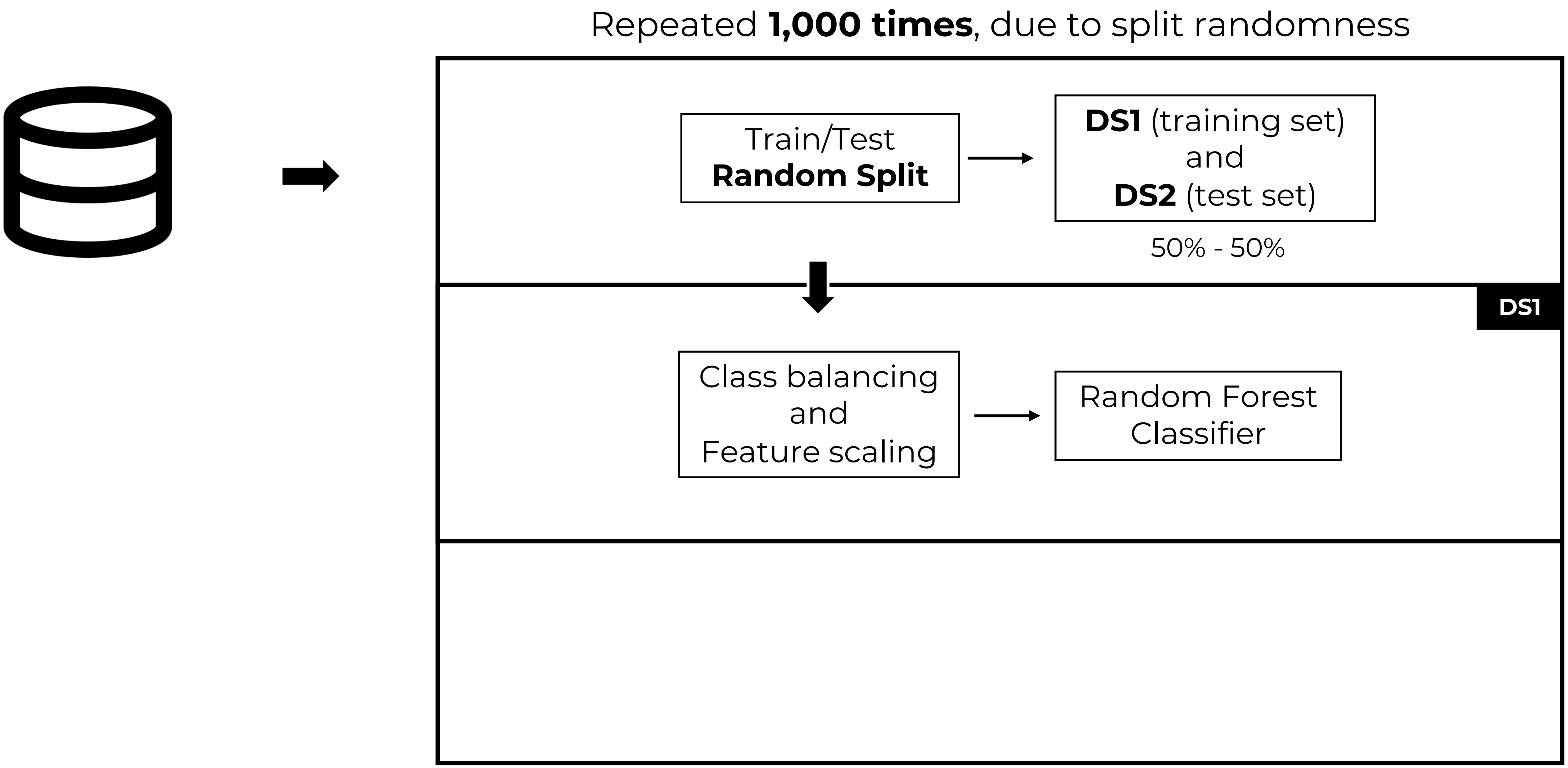
Classification

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

Train/Test **Random Split** → **DS1** (training set) and **DS2** (test set)

50% - 50%

Classification



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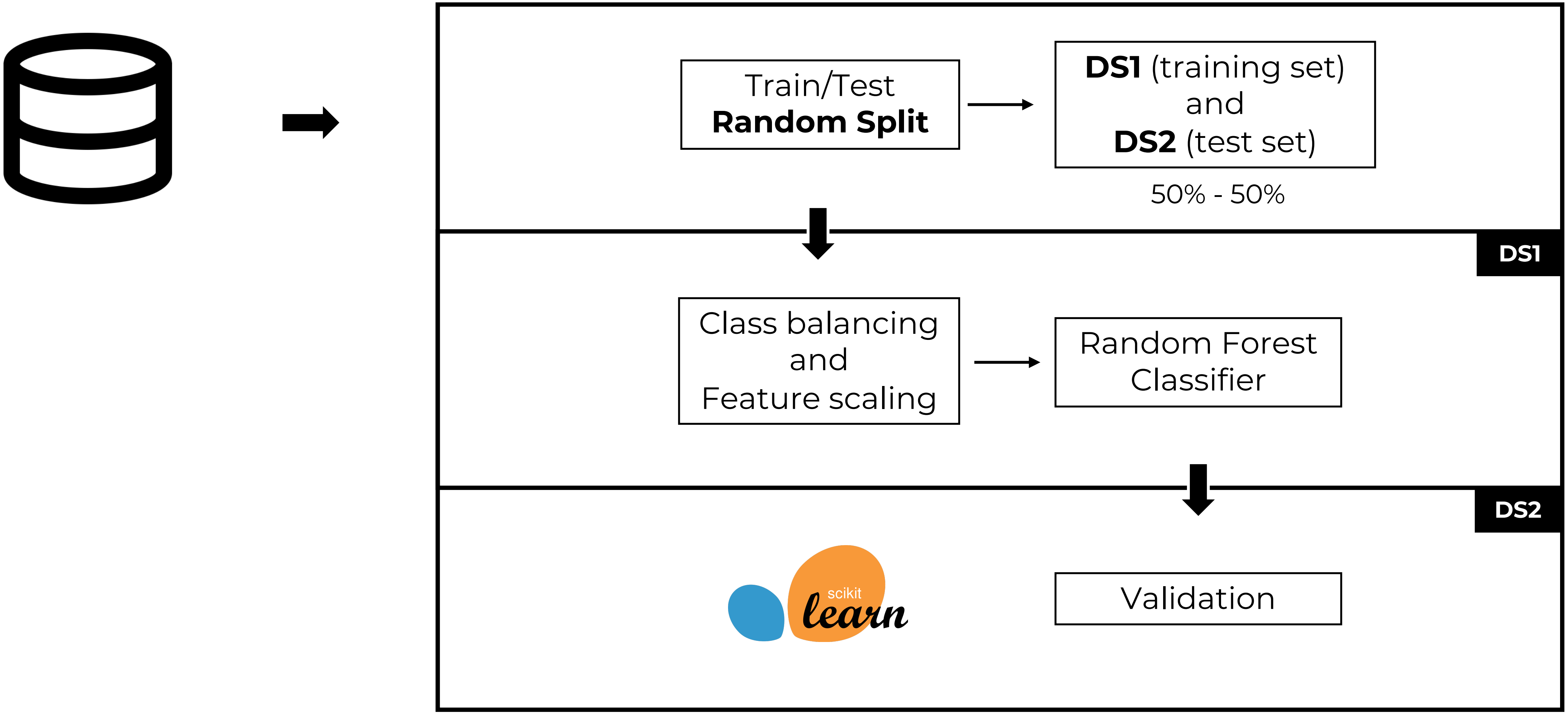


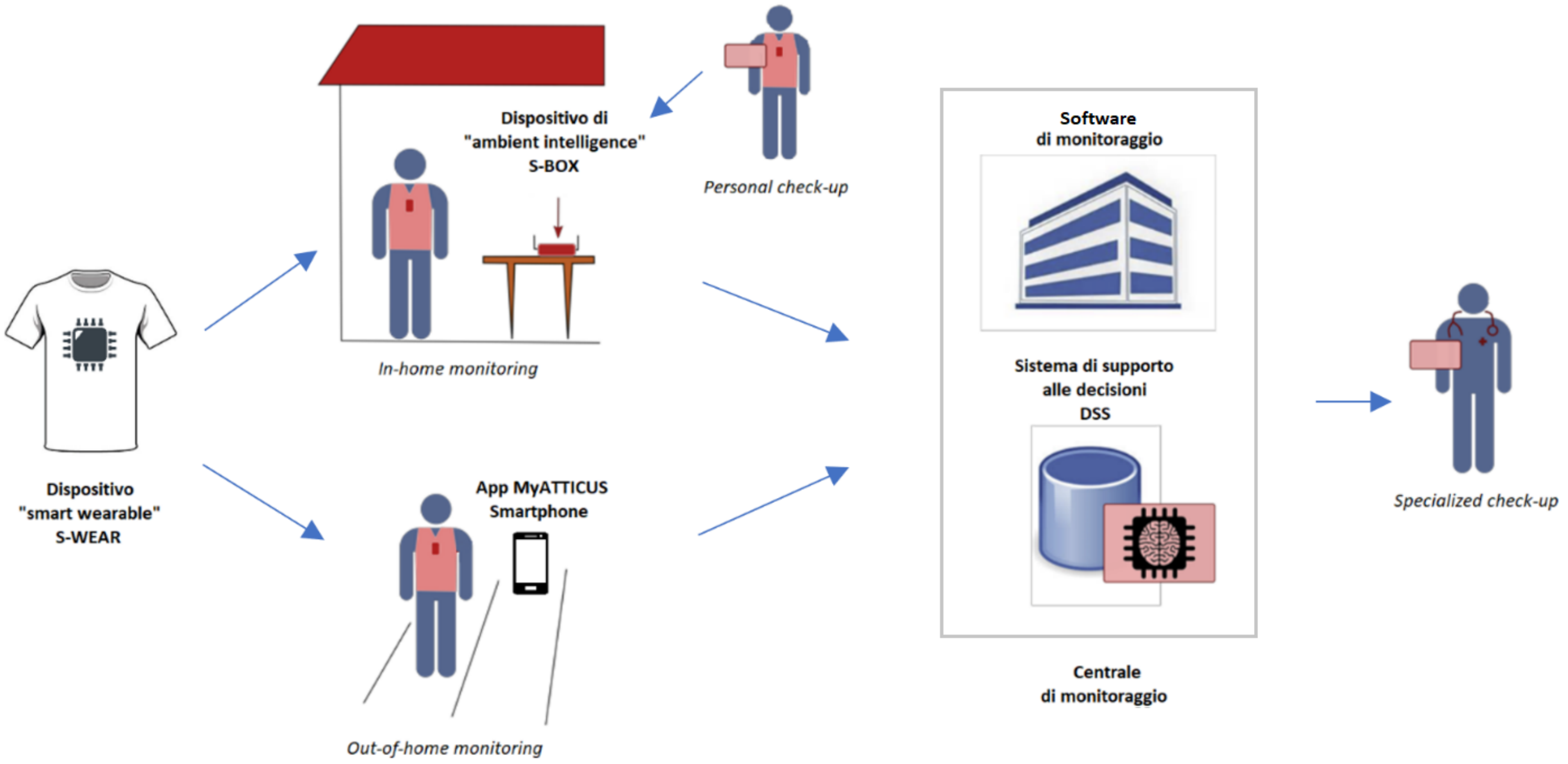
Overall Results

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

PON
RICERCA
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2014 - 2020

Summary

Internet of Medical Things

Preventive care

Long-term care and chronic diseases

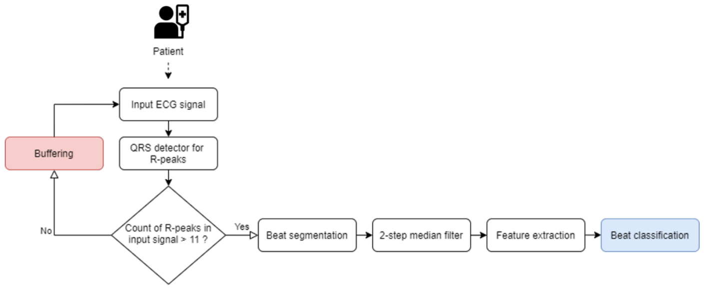
Zhao et al. (2005)

Haque et al. (2009)

Leonarduzzi et al. (2010)

Li et al. (2016)

NEAPOLIS in a nutshell



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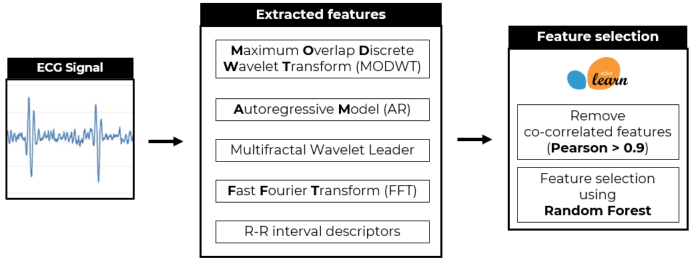

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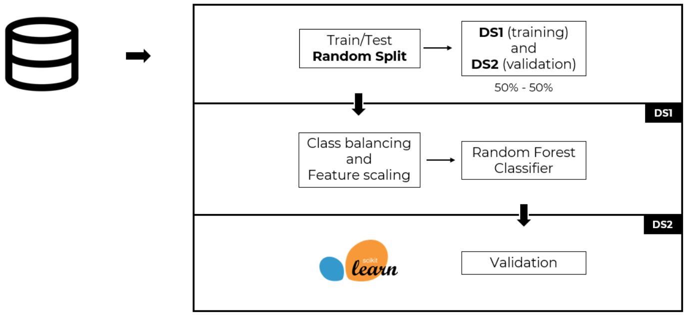

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