A Robust Approach for a Real-time Accurate Screening of ST Segment Anomalies

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

Università degli Studi del Molise

ASREM

HEALTHINF 2022
15TH INTERNATIONAL CONFERENCE ON HEALTH INFORMATICS

Decision Support Systems

126 **million**

ischemic heart disease
(wordlwide)

Ischemia

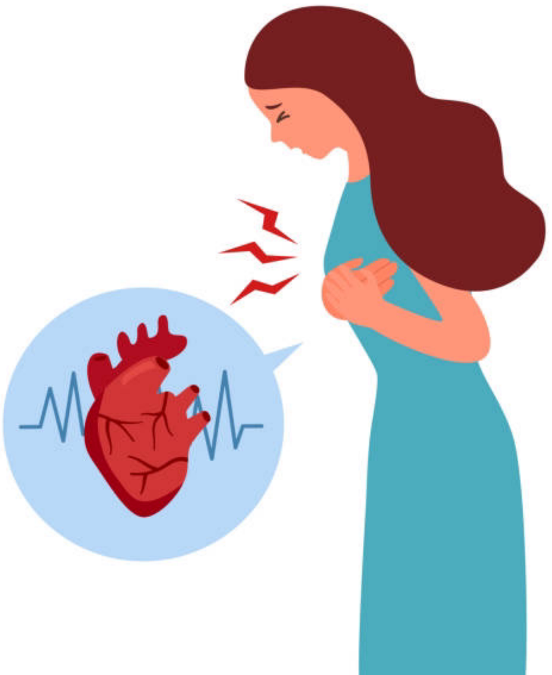
Myocardial Infarction

1.5 million

instances of myocardial infarction (US)

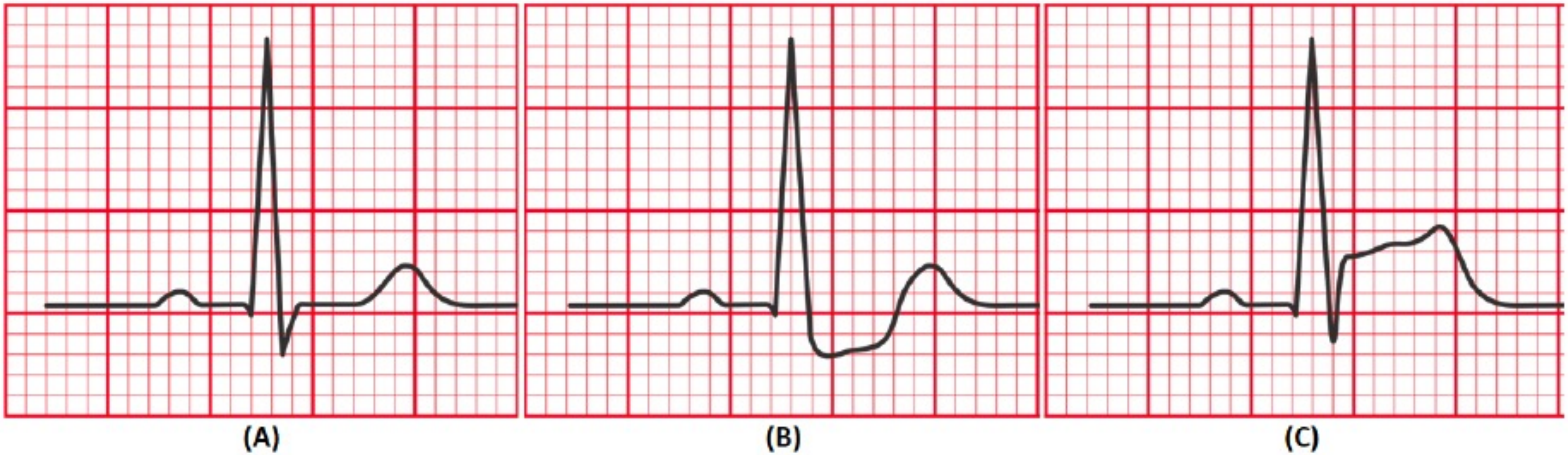
Changes in ST segment

Ischemia



Myocardial Infarction

ST segment sloping



ST normal　　ST depression　　ST elevation

An Adaptive Backpropagation Neural Network for Real-Time Ischemia Episodes Detection: Development and Performance Analysis Using the European ST-T Database

Nicos Maglaveras,* *Member, IEEE,* Telemachos Stamkopoulos, Costas Pappas, and Michael Gerassimos Strintzis, *Senior Member, IEEE*

***Abstract*—A supervised neural network (NN)-based algorithm was used for automated detection of ischemic episodes resulting from ST segment elevation or depression. The performance of the method was measured using the European ST-T database. In particular, the performance was measured in terms of beat-by-beat ischemia detection and in terms of the detection of ischemic episodes. The algorithm used to train the NN was an adaptive backpropagation (BP) algorithm. This algorithm drastically reduces training time (tenfold decrease in our case) when compared to the classical BP algorithm. The recall phase of the NN is then extremely fast, a fact that makes it appropriate for real-time detection of ischemic episodes. The resulting NN is capable of detecting ischemia independent of the lead used. It was found that the average ischemia episode detection sensitivity is 88.62% while the ischemia duration sensitivity is 72.22%. The results show that NN can be used in electrocardiogram (ECG) processing in cases where fast and reliable detection of ischemic episodes is desired as in the case of critical care units (CCU's).**

***Index Terms*—Adaptive backpropagation, ischemia, neural networks, ST segment depression, training.**

I. Introduction

ISCHEMIA is considered to be a major complication of the cardiac function, and a prime cause for the occurrence of cardiac infarction and dangerous cardiac arrhythmias [1]. The main characteristic of ischemia at the cellular level is the depolarization of the cellular resting membrane potential. This causes a potential difference between the normal and ischemic tissue which, in turn, causes the flow of an "injury current" [2]. This "injury current" is manifested in the electrocardiogram (ECG) by an ST depression or elevation, depending on the anatomical position of the heart and the dipole's position with respect to the recording electrodes [3]. Thus, there are cases in the 12-lead standard electrode system where the ST depression is not evident in ischemic beats, while ST depression may exist when ischemia is not present such as can happen with leads III and a VF due to patient position [4]. Ischemic episodes could be acute ones that should be detected immediately when the patient is in a critical care unit (CCU) environment, but also in a Holter database ischemic episodes should be reliably and correctly detected. Although ischemia detection from ST analysis alone is difficult to accomplish, and has to be accompanied by a number of biochemical and other examinations, ECG still remains one of the basic biosignals for aiding the clinical staff in a CCU environment.

Major problems contributing to poor detection of the ST segment in the ECG can be identified as follows: 1) slow baseline drift, 2) noise, 3) sloped ST changes, 4) patient-dependent abnormal ST depression levels, and 5) varying ST-T patterns in the ECG of the same patient. A number of methods have been proposed in the literature for ST detection based on digital filtering, time analysis of the signal first derivative, and syntactic methods [5]–[7]. None of these methods, however, was tested on an annotated database, so as to obtain a reliable evaluation of their ability to detect ST depression. Furthermore, these methods tend to measure specific parameters (such as degree of depression, ST-T duration, etc.) in ways critically dependent upon the correct detection of the J-point on the ECG. Uncertainty regarding the J-point position, may lead to inaccurate estimation of the ECG parameters related to the ST-T segment.

Recently, a new annotated database was developed, containing recordings with annotated ischemic episodes based on two-lead ECG's [8]. A number of new algorithms were developed to identify ischemia using this database. Jager *et al.* [9], [10] used information from both leads to improve sensitivity of ischemic episode detection and to correctly classify ST depression resulting from axis shifts due to body position. Laguna *et al.* [11] used a Karhunen–Loeve transform for the analysis of ventricular depolarization, but not for ischemic episode detection.

Neural networks (NN's) have been widely used over the past few years as pattern and statistical classifiers [12], [13] in many application areas including medicine [14]. For example, NN's were used for QRS/PVC classification [15], [16], or for

Manuscript received March 15, 1996; revised January 20, 1998. This work was supported in part by the Commission of the European Communities (CEC) under Project HC-1024 I4C. *Asterisk indicates corresponding author.*

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T. Stamkopoulos and C. Pappas are with the Lab of Medical Informatics, The Medical School, Aristotelian University, 54006 Thessaloniki, Macedonia, Greece.

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Maglaveras et al. (1998)

IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 45, NO. 7, JULY 1998 805

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Maglaveras et al. (1998)

A Deep Learning Approach to Examine Ischemic ST Changes in Ambulatory ECG Recordings

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Abstract

Patients with suspected acute coronary syndrome (ACS) are at risk of transient myocardial ischemia (TMI), which could lead to serious morbidity or even mortality. Early detection of myocardial ischemia can reduce damage to heart tissues and improve patient condition. Significant ST change in the electrocardiogram (ECG) is an important marker for detecting myocardial ischemia during the rule-out phase of potential ACS. However, current ECG monitoring software is vastly underused due to excessive false alarms. The present study aims to tackle this problem by combining a novel image-based approach with deep learning techniques to improve the detection accuracy of significant ST depression change. The obtained convolutional neural network (CNN) model yields an average area under the curve (AUC) at 89.6% from an independent testing set. At selected optimal cutoff thresholds, the proposed model yields a mean sensitivity at 84.4% while maintaining specificity at 84.9%.

1. Introduction

Patients with acute coronary syndrome (ACS) are at risk of transient myocardial ischemia (TMI), which can lead to serious medical complications. It has been found that more occurrence of myocardial infarction after admission, acute pulmonary edema and unplanned transfer from telemetry unit to the intensive care unit associated with patients with TMI compared to those without TMI[1]. As a critical step in identifying ACS, the early detection of myocardial ischemia helps reduce irreversible damage to heart tissues and prevent patient deterioration. Several deployed methods in detecting myocardial ischemia, such as coronary angiography and echocardiogram, are either invasive and/or resource demanding, or only able to access a brief time period, making them unsuitable for initial rule-out phase for ACS. On the other hand, continuous electrocardiography (ECG) provides an economical alternative and additional diagnostic values for early transient ischemia detection. It measures the electrophysiological activities of the heart in real time and noninvasively, together with other benefits including easy setup and long-term monitoring.

ECG is an important risk stratification tool in the immediate phase of ACS. ST (i.e. the isoelectric section in ECG waveform between J point and the beginning of T wave) elevation on the ECG is presented in up to 25% of ACS patients (i.e., ST elevation myocardial infarction (STEMI)), whereas the rest (non-ST elevation-ACS (NSTE-ACS) or unstable angina (UA)) show non-specific ECG changes[2,3]. This 75% of ACS patients is at risk for TMI, which can be detected with continuous ECG monitoring. However, current ECG monitoring software is underutilized due to excessive false alarms[4]. This further contributes to alarm fatigue, which is ranked as the top technology hazard in 2014 by the Emergency Care Research Institute (ECRI)[5].

In contrary to current monitoring software, expert clinicians are capable of detecting true ST changes even if the ECG is moderately contaminated (i.e., motion artifact, patient movement, etc.) and are able to differentiate between ischemic and non-ischemic changes, by examining ECG waveforms screen by screen. Therefore, representing ECG tracings as images could provide valuable discriminative features about ST change. Meanwhile, the rapid developing approach of deep learning techniques, especially the convolutional neural network (CNN), has been constantly pushing the performance boundary of image recognition by computer algorithms[6]. A well-designed CNN model has even surpassed human benchmarks in a visual recognition challenge[7]. Some pioneer studies have adopted deep learning techniques in mining ECG features to tackle challenging medical problems related to the heart. In one study, CNN was adopted to detect various types of arrhythmia in ECG[8]. In another study, CNN was utilized to learn ECG features for screening paroxysmal atrial fibrillation patients[9].

256

Xiao et al. (2018)

IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 45, NO. 7, JULY 1998

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[1]Department of Physiological Nursing, University of California, San Francisco, CA; [2]Department of Neurological Surgery, University of California, San Francisco, CA; [3]Institute for Computational Health Sciences, University of California, San Francisco, CA; [4]Core Faculty, UCB/UCSF Graduate Group in Bioengineering, University of California, San Francisco, CA

Abstract

1. Introduction

256

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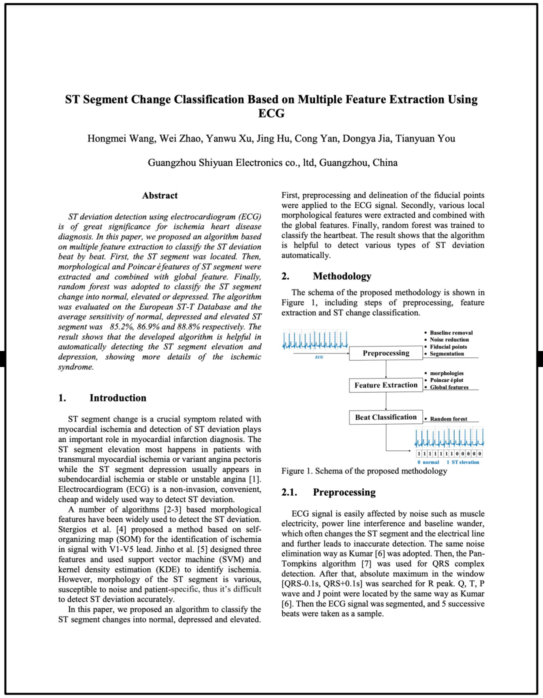


ST Segment Change Classification Based on Multiple Feature Extraction Using ECG

Hongmei Wang, Wei Zhao, Yanwu Xu, Jing Hu, Cong Yan, Dongya Jia, Tianyuan You

Guangzhou Shiyuan Electronics co., ltd, Guangzhou, China

Abstract

1. Introduction

2. Methodology

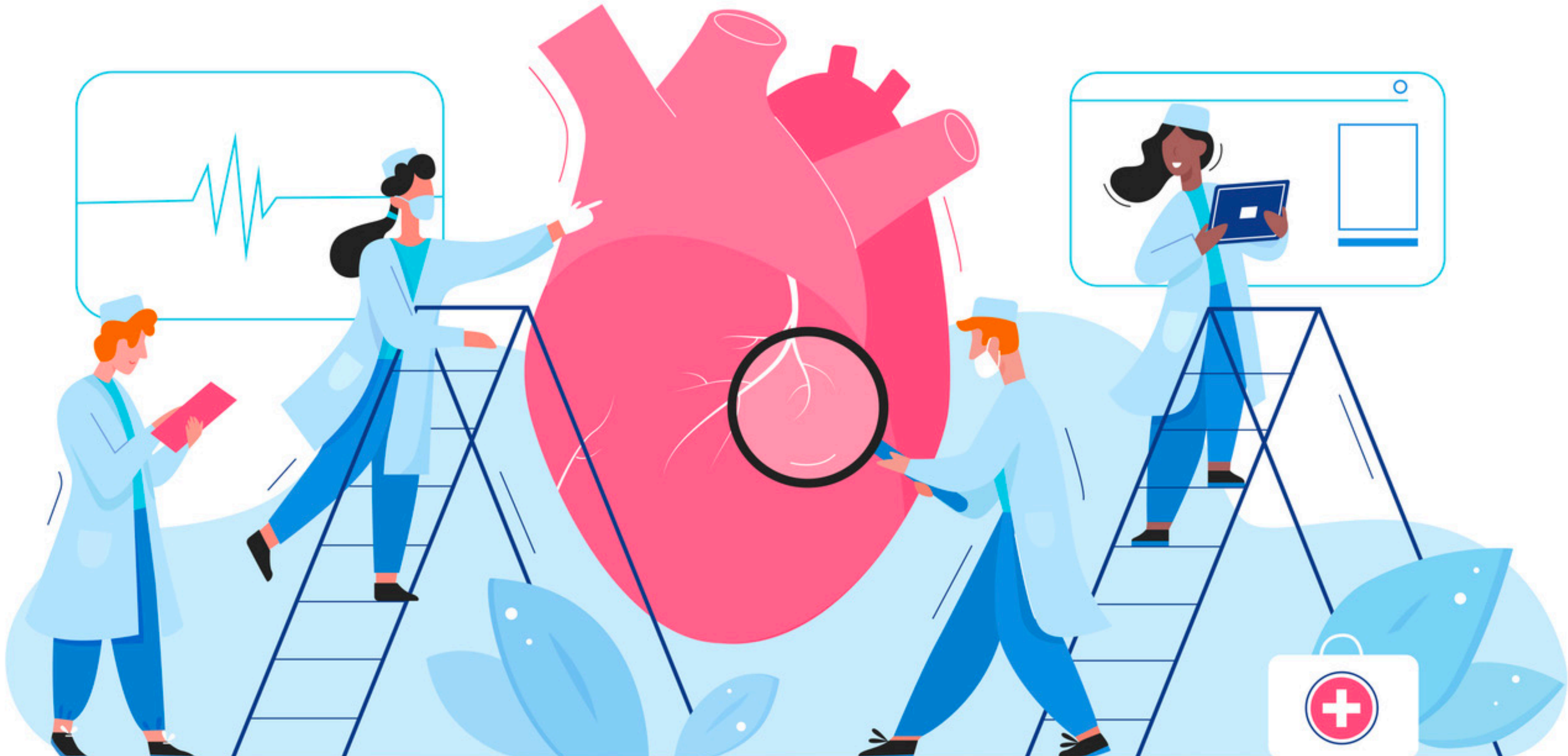
Figure 1. Schema of the proposed methodology

2.1. Preprocessing

Wang et al. (2020)

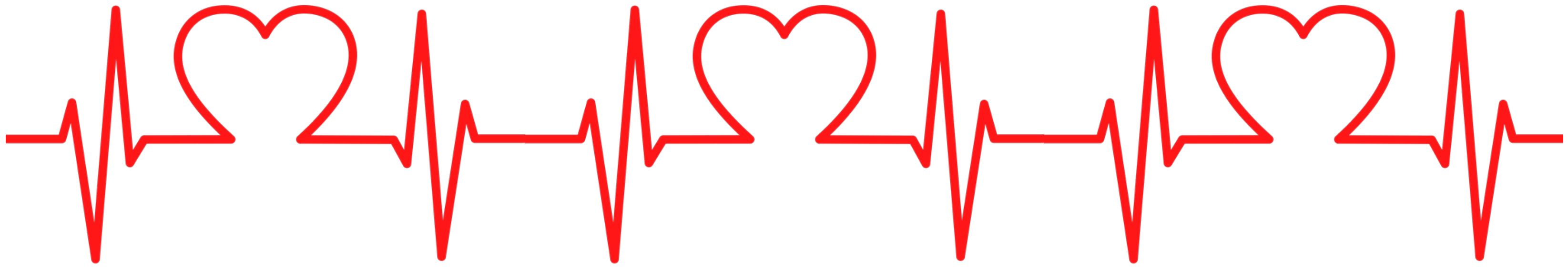
Maglaveras et al. (1998) | Xiao et al. (2018) | Wang et al. (2020) | **Harun-Ar-Rashid et al. (2020)**

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

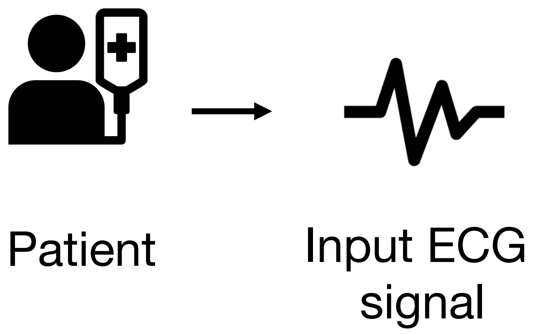


RAST

a robust approach
for a **R**eal-time **A**ccurate screening
of **ST** segment anomalies



RAST in a nutshell



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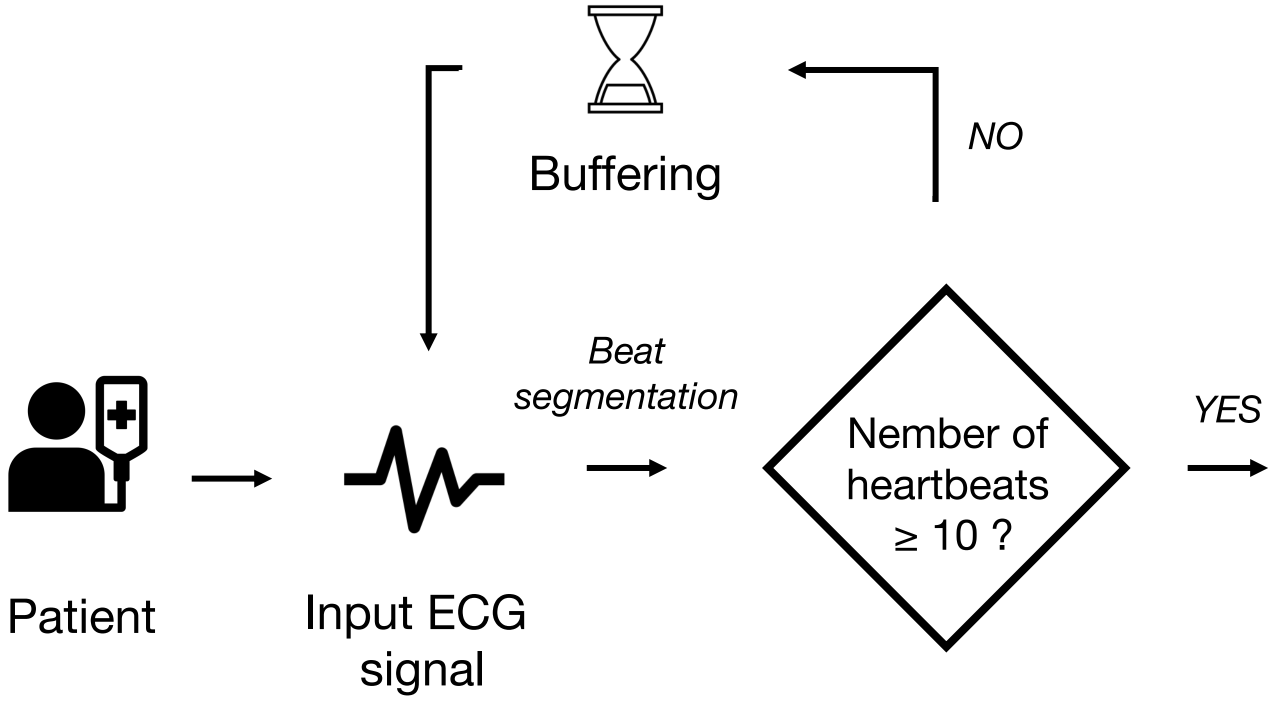

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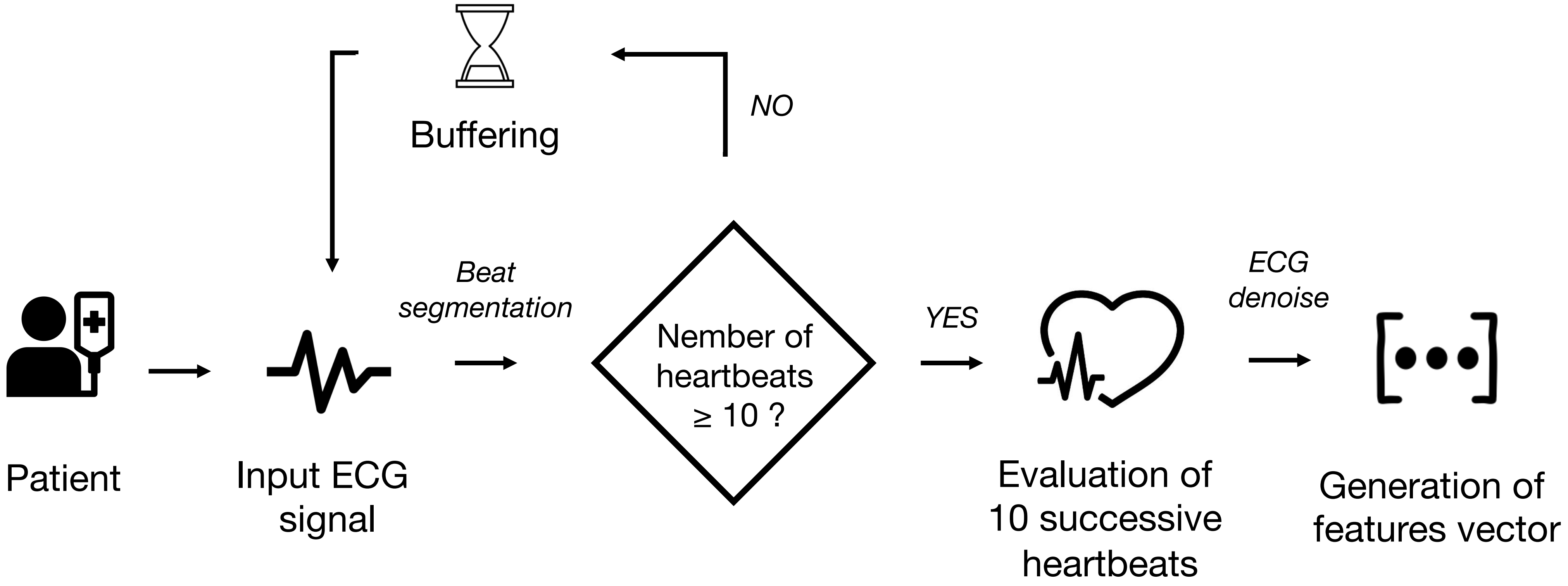

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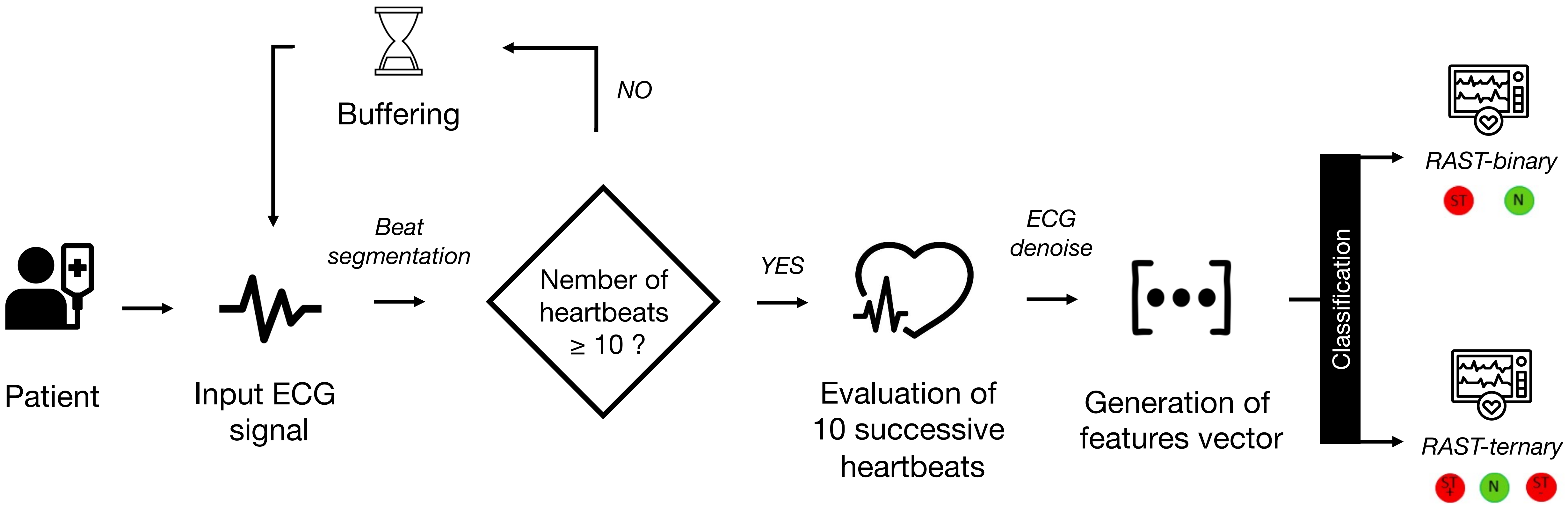
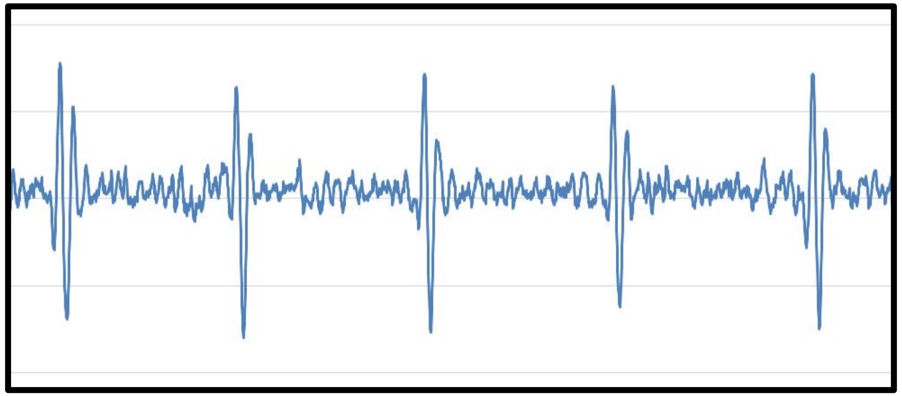


Generation of features vector



10 successive heartbeats

→

Energy of **M**aximal **O**verlap **D**iscrete **W**avelet **T**ransform (EMO-DWT)

Autoregressive **M**odel (AR)

Multifractal **W**avelet **L**eader (MWL)

Fast **F**ourier **T**ransform (FFT)

Experiment

European ST-T Database

90

ECG Recordings

~360

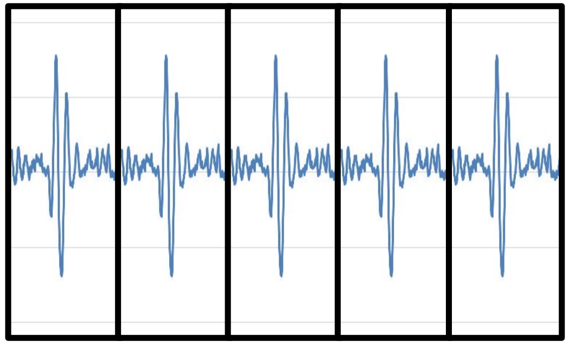
ST segment change

Goldberger et al. (2000); Taddei et al. (1992)

PhysioNet

The Research Resource for Complex Physiologic Signals

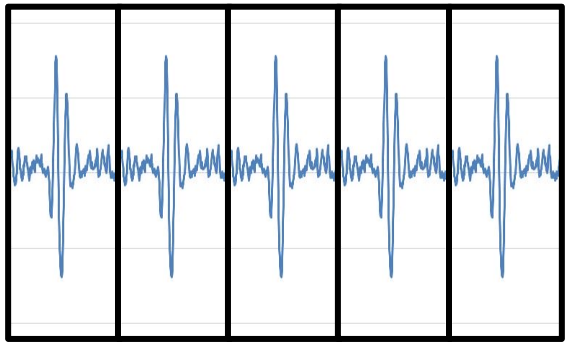
Parameters Tuning



n. of evaluated beats
[4, 6, 8, 10, 16, 32, 64]

Temporal Window for the Heartbeat Observation (TWHO)

Parameters Tuning



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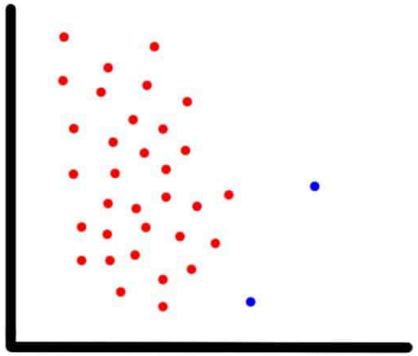
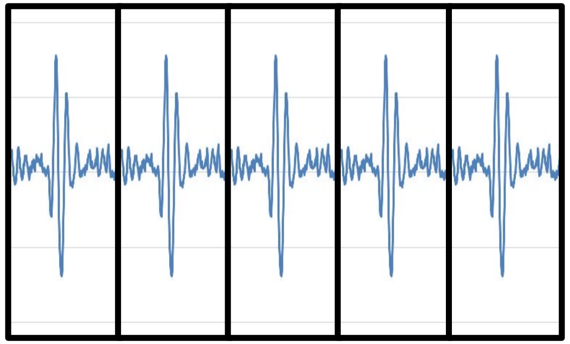


SMOTE

Sampling technique

Parameters Tuning



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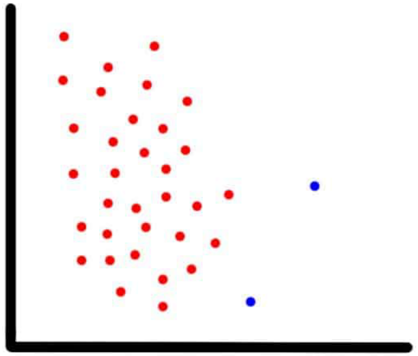
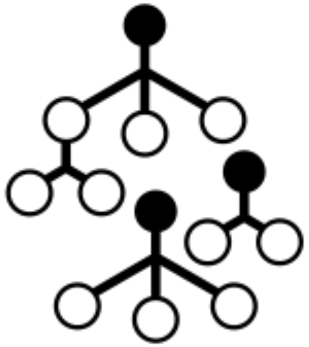


SMOTE

Sampling technique



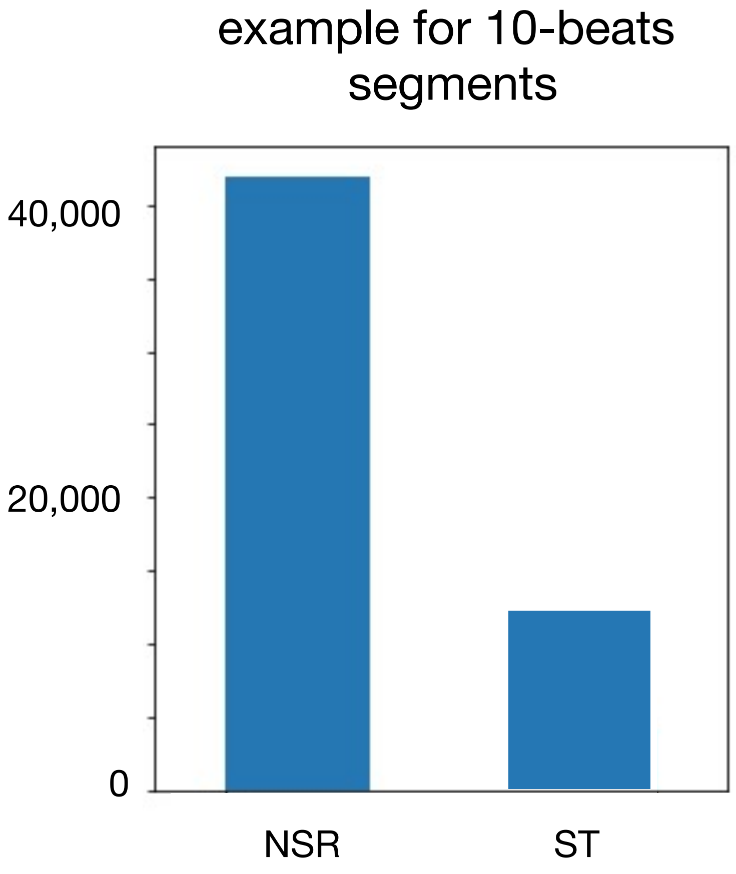
Random Forest

ML algorithm

RQ 1

To what extent does the accuracy of
a binary or ternary detector of ST-segment
anomalies vary?

Dataset for **RAST** binary



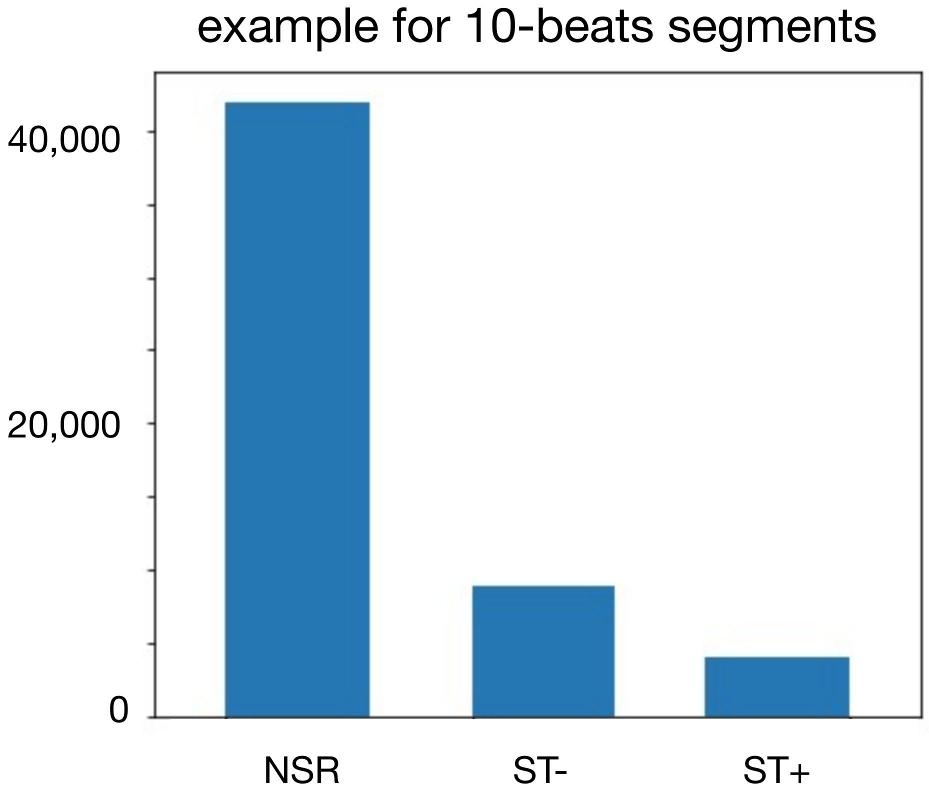
~40,000

NSR segments

~13,000

ST sloping

Dataset for **RAST** ternary



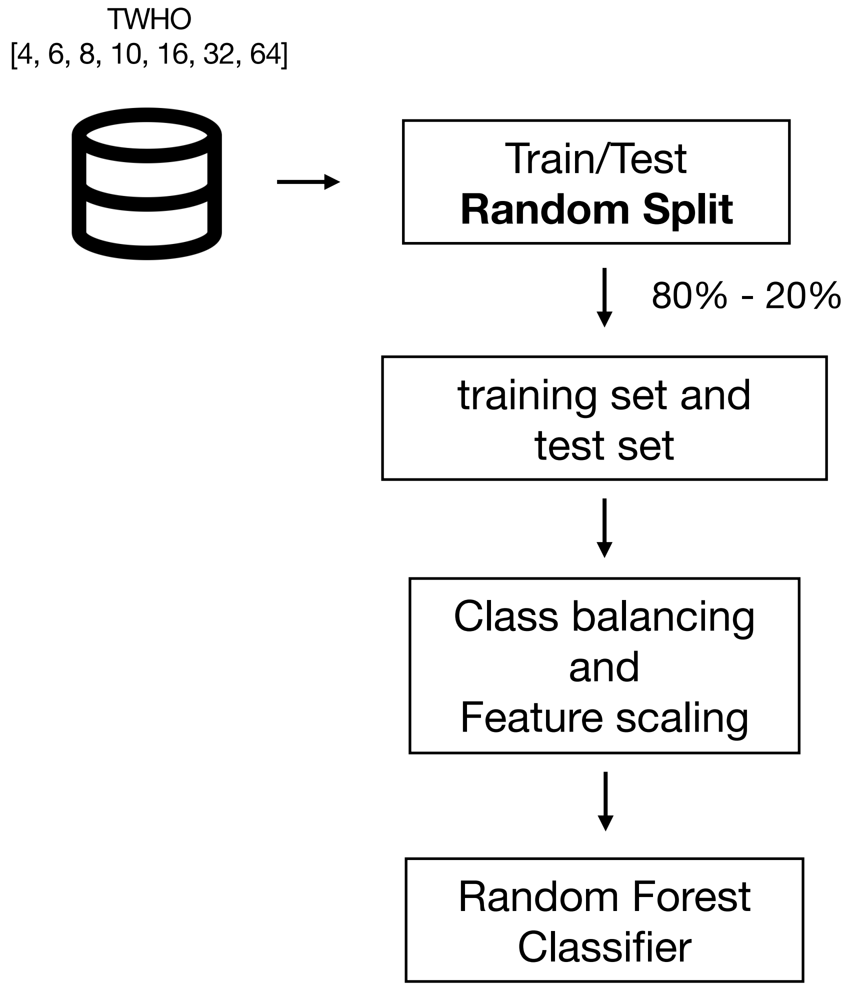
~9,000

ST depression

~4,000

ST elevation

RAST binary vs **RAST** ternary

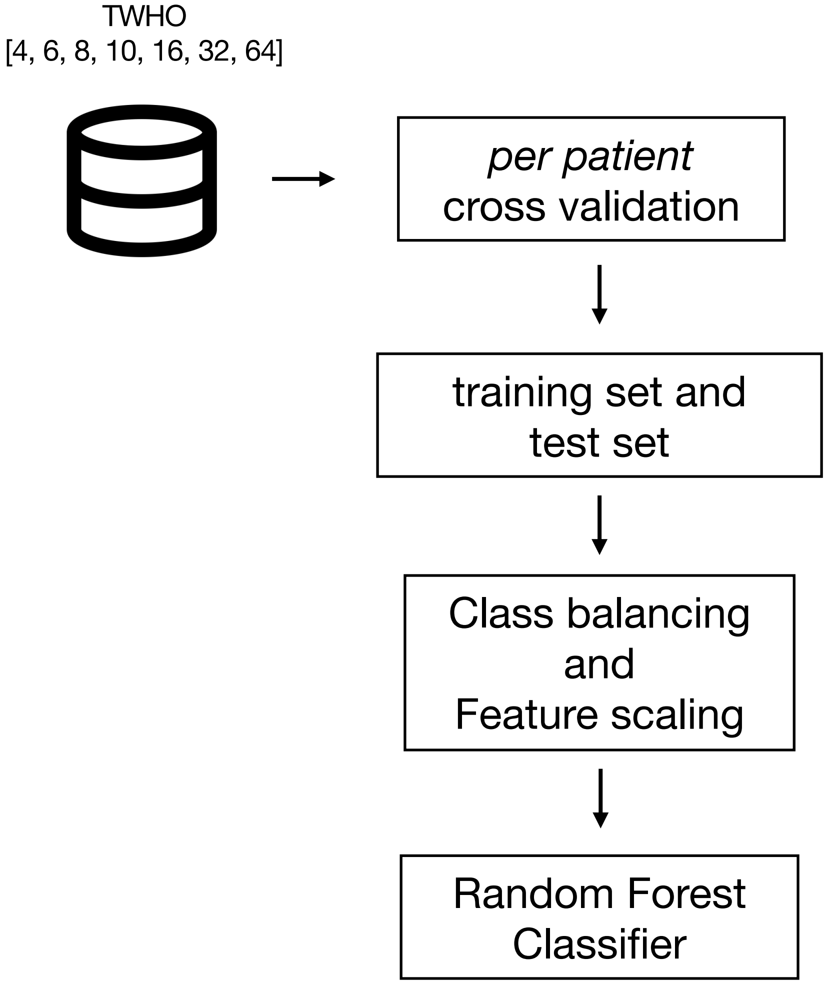


80/20
validation scheme

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

RAST binary vs **RAST** ternary

L1SO
validation scheme



80/20

Window	Acc	Spec	Prec	Recall	F1 Score
4 beats	**93,61**	**88,62**	**93,61**	**93,61**	**93,61**
6 beats	93,46	88,33	93,47	93,46	93,46
8 beats	92,73	88,60	92,88	92,73	92,79
10 beats	93,36	88,13	93,37	93,36	93,37
16 beats	93,13	87,79	93,14	93,13	93,14
32 beats	92,63	86,71	92,63	92,63	92,62
64 beats	92,21	85,63	92,19	92,21	92,19

Window	Acc	Spec	Prec	Recall	F1 Score
4 beats	**93,52**	**90,03**	**93,60**	**93,52**	**93,54**
6 beats	93,38	89,77	93,46	93,38	93,40
8 beats	92,47	90,00	92,74	92,47	92,56
10 beats	93,29	89,47	93,35	93,29	93,30
16 beats	92,99	89,02	93,07	92,99	93,01
32 beats	92,60	88,16	92,67	92,61	92,62
64 beats	92,26	86,54	92,26	92,26	92,22

L1SO

Window	Acc	Spec	Prec	Recall	F1 Score
4 beats	76,31	33,09	84,57	76,31	72,79
6 beats	75,98	32,88	84,63	75,98	72,47
8 beats	76,37	**33,33**	85,48	76,37	**72,78**
10 beats	75,11	31,57	84,66	75,11	71,09
16 beats	**76,49**	24,94	86,21	**76,49**	70,17
32 beats	76,11	23,57	**86,70**	76,11	69,73
64 beats	75,00	30,28	83,52	75,00	70,83

Window	Acc	Spec	Prec	Recall	F1 Score
4 beats	77,04	**31,79**	85,33	77,04	72,58
6 beats	76,70	30,82	84,90	76,70	71,90
8 beats	**77,35**	31,40	86,05	**77,35**	**72,83**
10 beats	76,24	29,69	**86,40**	76,24	70,95
16 beats	75,78	28,33	86,36	75,78	70,15
32 beats	76,28	27,49	86,33	76,28	70,75
64 beats	75,74	27,94	86,40	75,74	69,98

RAST binary

RAST ternary

80/20

Window	Acc	Spec	Prec	Recall	F1 Score
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8 beats	**77,35**	31,40	86,05	**77,35**	**72,83**
10 beats	76,24	29,69	**86,40**	76,24	70,95
16 beats	75,78	28,33	86,36	75,78	70,15
32 beats	76,28	27,49	86,33	76,28	70,75
64 beats	75,74	27,94	86,40	75,74	69,98

RAST binary

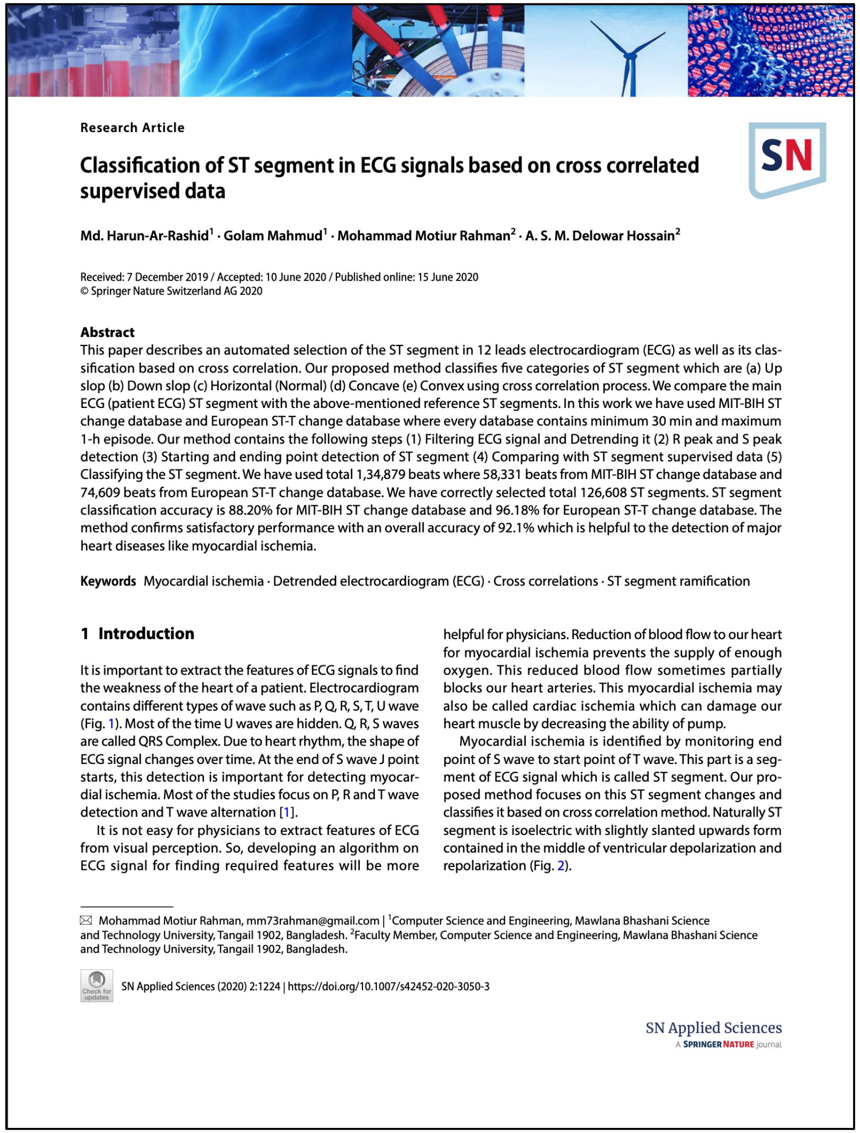
RAST ternary

RQ 2

Can a real-time and noise-robust approach outperform the accuracy of a state-of-the-art method?

Selected baseline

Classification of
5 types of ST segments



Research Article

Classification of ST segment in ECG signals based on cross correlated supervised data

Md. Harun-Ar-Rashid[1] · Golam Mahmud[1] · Mohammad Motiur Rahman[2] · A. S. M. Delowar Hossain[2]

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Abstract
This paper describes an automated selection of the ST segment in 12 leads electrocardiogram (ECG) as well as its classification based on cross correlation. Our proposed method classifies five categories of ST segment which are (a) Up slop (b) Down slop (c) Horizontal (Normal) (d) Concave (e) Convex using cross correlation process. We compare the main ECG (patient ECG) ST segment with the above-mentioned reference ST segments. In this work we have used MIT-BIH ST change database and European ST-T change database where every database contains minimum 30 min and maximum 1-h episode. Our method contains the following steps (1) Filtering ECG signal and Detrending it (2) R peak and S peak detection (3) Starting and ending point detection of ST segment (4) Comparing with ST segment supervised data (5) Classifying the ST segment. We have used total 1,34,879 beats where 58,331 beats from MIT-BIH ST change database and 74,609 beats from European ST-T change database. We have correctly selected total 126,608 ST segments. ST segment classification accuracy is 88.20% for MIT-BIH ST change database and 96.18% for European ST-T change database. The method confirms satisfactory performance with an overall accuracy of 92.1% which is helpful to the detection of major heart diseases like myocardial ischemia.

Keywords Myocardial ischemia · Detrended electrocardiogram (ECG) · Cross correlations · ST segment ramification

1 Introduction

It is important to extract the features of ECG signals to find the weakness of the heart of a patient. Electrocardiogram contains different types of wave such as P, Q, R, S, T, U wave (Fig. 1). Most of the time U waves are hidden. Q, R, S waves are called QRS Complex. Due to heart rhythm, the shape of ECG signal changes over time. At the end of S wave J point starts, this detection is important for detecting myocardial ischemia. Most of the studies focus on P, R and T wave detection and T wave alternation [1].

It is not easy for physicians to extract features of ECG from visual perception. So, developing an algorithm on ECG signal for finding required features will be more helpful for physicians. Reduction of blood flow to our heart for myocardial ischemia prevents the supply of enough oxygen. This reduced blood flow sometimes partially blocks our heart arteries. This myocardial ischemia may also be called cardiac ischemia which can damage our heart muscle by decreasing the ability of pump.

Myocardial ischemia is identified by monitoring end point of S wave to start point of T wave. This part is a segment of ECG signal which is called ST segment. Our proposed method focuses on this ST segment changes and classifies it based on cross correlation method. Naturally ST segment is isoelectric with slightly slanted upwards form contained in the middle of ventricular depolarization and repolarization (Fig. 2).

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SN Applied Sciences
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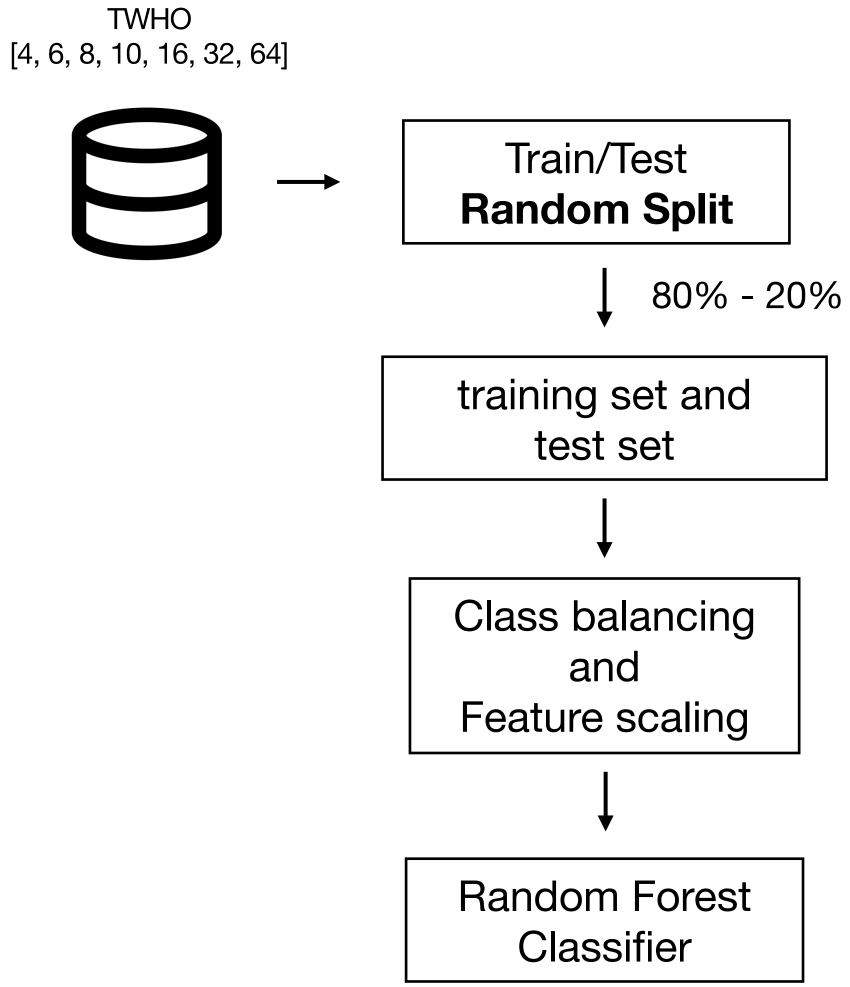
Harun-Ar-Rashid et al. (2020)

Classification

80/20

validation scheme

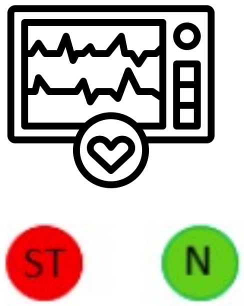


Repeated **1,000 times**, due to split randomness

RAST vs Baseline

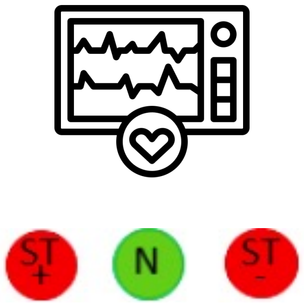
+1.51 (93.61)

overall accuracy score of **RAST** binary

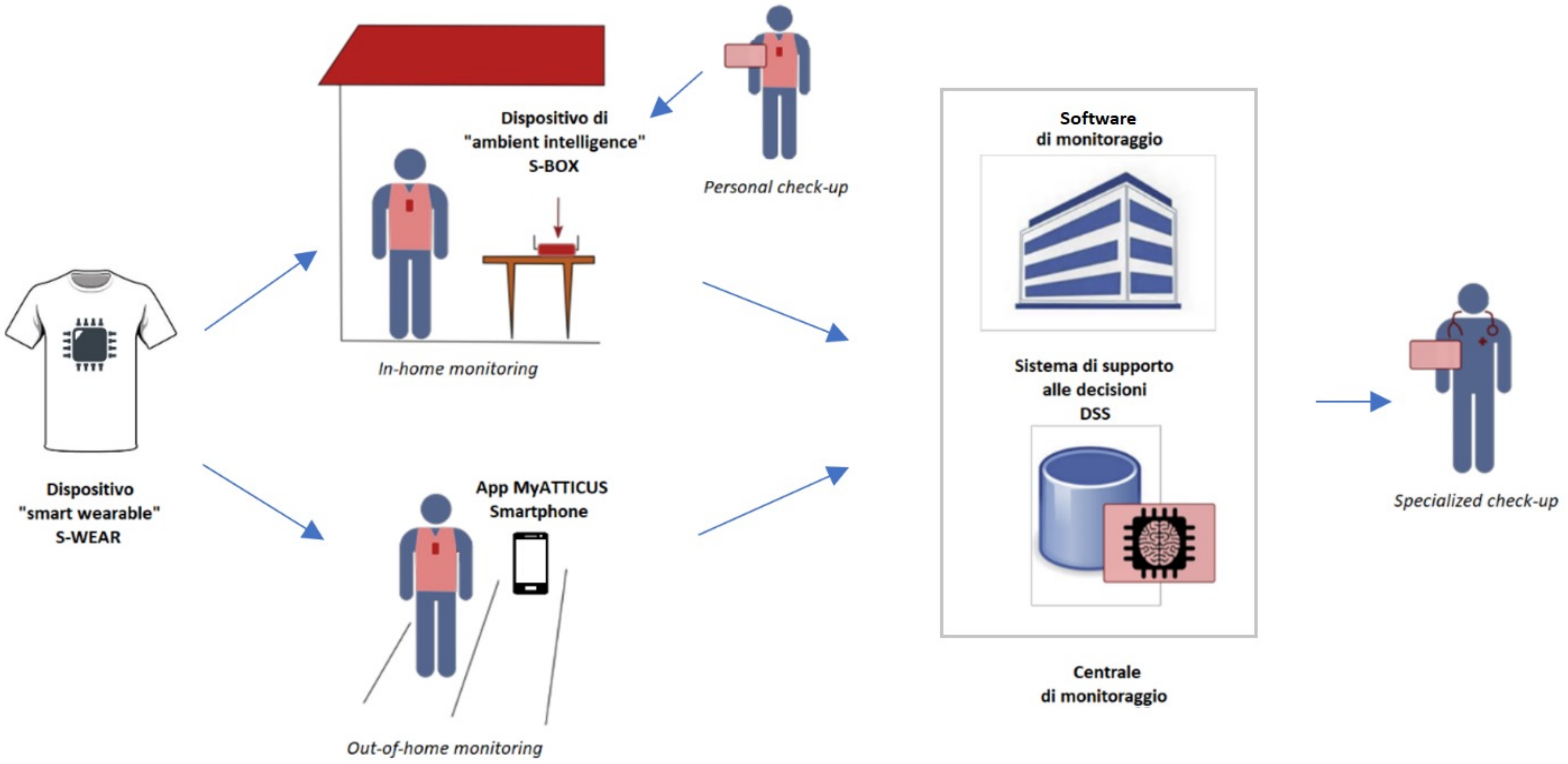


+1.42 (93.52)

overall accuracy score of **RAST** ternary



RAST is a part of a real IoMT system



ATTICUS
Ambient-intelligent Tele-monitoring System

PON
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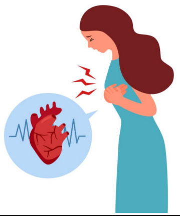
2014 - 2020

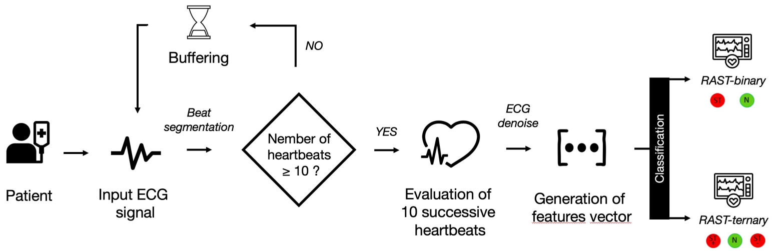
Summary

Changes in ST segment

Ischemia | **Myocardial Infarction**



RAST in a nutshell



RQ 1

To what extent does the accuracy of a binary or ternary detector of ST-segment anomalies vary?

80/20

Window	Acc	Spec	Prec	Recall	F1 Score
4 beats	**93,61**	**88,62**	**93,61**	**93,61**	**93,61**
6 beats	93,46	88,33	93,47	93,46	93,46
8 beats	92,73	88,60	92,88	92,73	92,79
10 beats	93,36	88,13	93,37	93,36	93,37
16 beats	93,13	87,79	93,14	93,13	93,14
32 beats	92,63	86,71	92,63	92,63	92,62
64 beats	92,21	85,63	92,19	92,21	92,19

Window	Acc	Spec	Prec	Recall	F1 Score
4 beats	**93,52**	**90,03**	**93,60**	**93,52**	**93,54**
6 beats	93,38	89,77	93,46	93,38	93,40
8 beats	92,47	90,00	92,74	92,47	92,56
10 beats	93,29	89,47	93,35	93,29	93,30
16 beats	92,99	89,02	93,07	92,99	93,01
32 beats	92,60	88,16	92,67	92,61	92,62
64 beats	92,26	86,54	92,26	92,26	92,22

L1SO

Window	Acc	Spec	Prec	Recall	F1 Score
4 beats	76,31	33,09	84,57	76,31	72,79
6 beats	75,98	32,88	84,63	75,98	72,47
8 beats	76,37	**33,33**	85,48	76,37	**72,78**
10 beats	75,11	31,57	84,66	75,11	71,09
16 beats	**76,49**	24,94	86,21	**76,49**	70,17
32 beats	76,11	23,57	**86,70**	76,11	69,73
64 beats	75,00	30,28	83,52	75,00	70,83

Window	Acc	Spec	Prec	Recall	F1 Score
4 beats	77,04	**31,79**	85,33	77,04	72,58
6 beats	76,70	30,82	84,90	76,70	71,90
8 beats	**77,35**	31,40	86,05	**77,35**	**72,83**
10 beats	76,24	29,69	**86,40**	76,24	70,95
16 beats	75,78	28,33	86,36	75,78	70,15
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RAST binary | **RAST** ternary

RQ 2

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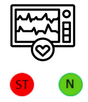
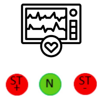
RAST vs Baseline

+1.51 (93.61)
overall accuracy score of **RAST** binary



+1.42 (93.52)
overall accuracy score of **RAST** ternary



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ATTICUS - RNA/COR 576347