Reconhecimento de padrões em séries temporais de ECG

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INTRODUCTION

Introduction

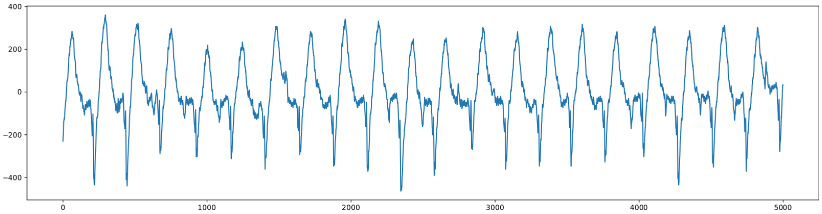
- The electrocardiogram (ECG) is a technology that is capable of recording the electrical activity of the heart.
- If the ECG exhibits adverse behavior, there is a sign of a cardiac problem.
- One of the most common heart diseases is the cardiac arrhythmia, which is characterized by the occurrence of irregular heartbeat.
- A considerable amount of data is produced, and solutions to automate this classification process are so important.

Introduction

- Cardiovascular diseases (CVDs) are the leading cause of death globally [1].
- An estimated 17.9 million people died from CVDs in 2019, representing 32% of all global deaths. Of these deaths, 85% were due to heart attack and stroke.
- Over three quarters of CVD deaths take place in low- and middle-income countries.
- By 2030, the number of CVD deaths is expected to increase to 23 million.
- It is important to detect cardiovascular disease as early as possible so that management with counselling and medicines can begin.

[1] World Health Organization

Figura 1: Real signal ECG



Introduction

Figura 2: Features of a signal ECG (CLIFFORD et al., 2006)

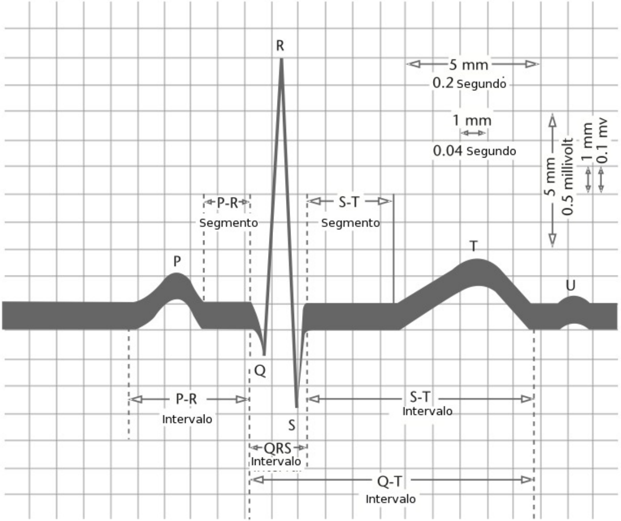
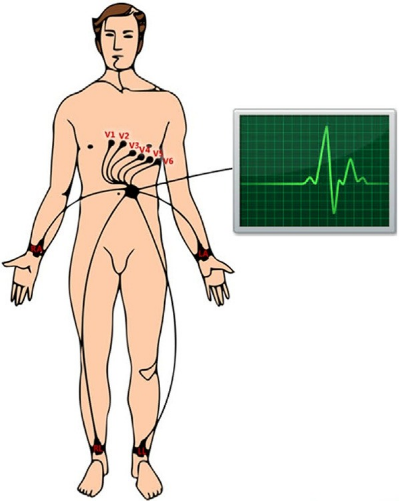
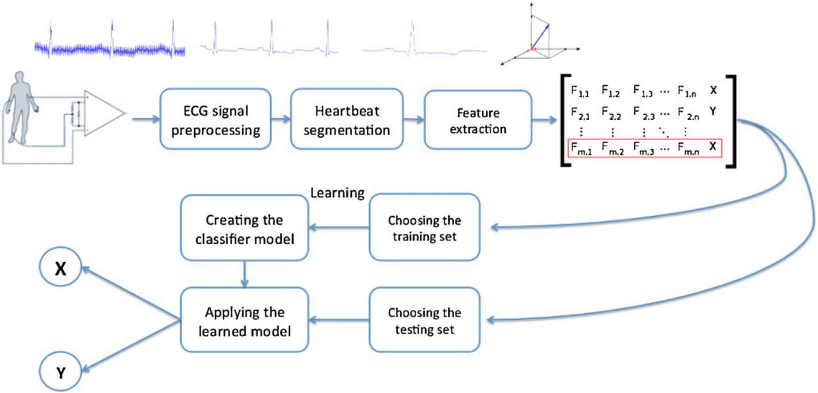


Figura 3: Typical 10 electrodes (leads) configuration (LUZ et al., 2016)



Introduction

Figura 4: A diagram of the arrhythmia classification system (LUZ et al., 2016)



Introduction

- Automatic ECG classification systems has two main paradigms: *intra-patient* and *inter-patient*.
  - *Intra-patient* a subject's heartbeat is used both for building the classification system and for testing.
  - *Inter-patient* used a separate set of subjects for building the classification system, and another for testing.

RELATED WORKS

Related Works

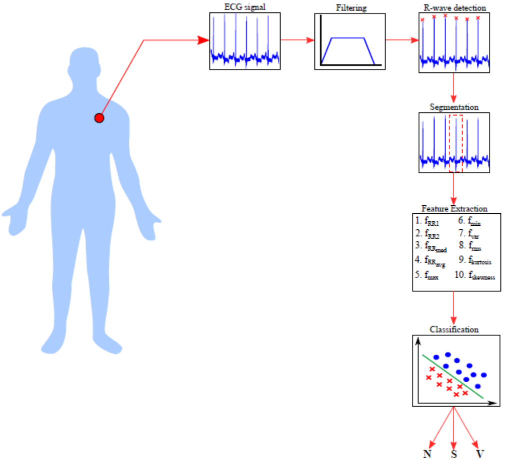
Arrhythmia classification from single-lead ECG signals using the inter-patient paradigm

- **Proposed work** (DIAS et al., 2021):
  - Single-lead ECG signals.
  - MIT-BIH Arrhythmia database.
  - Inter-patient paradigm.
  - Group of features: RR intervals, morphological values, and high order statistics.
  - Segmentation errors was tested by adding jitter (δ) to the R-wave positions.
  - Linear Discriminant classifier (LD).
  - Publication: Computer Methods and Programs in Biomedicine

Related Works

Arrhythmia classification from single-lead ECG signals using the inter-patient paradigm

Figura 5: Arrhythmia classification system



Related Works

Arrhythmia classification from single-lead ECG signals using the inter-patient paradigm

Tabela 1: Mapping between MIT-BIH and AAMI labels

MIT-BIH class	AAMI class	Number of events
Normal beat (N or .) Left bundle branch block beat (L) Right bundle branch block beat (R) Atrial escape beat (e) Nodal (junctional) escape beat (j)	Normal (N)	90125
Atrial premature beat (A) Aberrated atrial premature beat (a) Nodal (junctional) premature beat (J) Supraventricular premature beat (S)	Supraventricular ectopic beat (S)	2781
Premature ventricular contraction (V) Ventricular escape beat (E)	Ventricular ectopic beat (V)	7009
Fusion of ventricular and normal beat (F)	Fusion beat (F)*	803
Paced beat (P or /) Fusion of paced and normal beat (f) Unclassified beat (U)	Unknown beat (Q)*	15

*Classes F ad Q were excluded from the work because of the small sample number.

Inter-patient Paradigm proposed by (CHAZAL; O'DWYER; REILLY, 2004)

Dataset	Recordings
DS1 (Training)	101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, and 230.
DS2 (Testing)	100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, and 234.

Tabela 2: Distribution of the MIT-BIH recordings between training and testing

Related Works

Arrhythmia classification from single-lead ECG signals using the inter-patient paradigm

Figura 6: Comparison between the proposed methodology and diferent state-of-the-art methods that uses four classes: N, S, V, and F.

Work	Class (N)			Class (S)			Class (V)		
	Se^N	$+P^N$	F_s^N	Se^S	$+P^S$	F_s^S	Se^V	$+P^V$	F_s^V
Proposed ($\delta = 0$)	94.5	**99.4**	**96.9**	**92.5**	39.9	55.8	**88.6**	**94.6**	**91.5**
Proposed ($\delta = 18$)	93.7	99.2	96.4	89.7	36.8	52.2	87.9	93.9	90.8
Lin and Yang (2014) [12]	91.6	99.3	95.3	81.4	31.6	45.5	86.2	73.7	79.5
Garcia et. al (2016) [31]	**95.0**	96.5	95.7	29.6	26.4	27.9	85.1	66.3	74.5
Garcia et. al (2017) [32]	94.0	98.0	96.0	62.0	**53.0**	**57.1**	87.3	59.4	70.7

* Values in bold indicate the best result.

Related Works

A 12-lead electrocardiogram database for arrhythmia research covering more than 10,000 patients

- **Proposed work** (ZHENG et al., 2020):
  - 12-lead ECG signals.
  - Chinese Arrhythmia database (10,646 records).
  - Denoising methods (NLM, LOESS, Butterworth low pass filters)
  - ECG measurement:
    - lead II = lead I + lead II
    - lead aVR + aVL + aVF = 0
  - Extreme gradient boosting tree
  - Publication: Nature Scientific Data

Related Works

A 12-lead electrocardiogram database for arrhythmia research covering more than 10,000 patients

Figura 7: Rhythm information and baseline characteristics of participants

Acronym Name	Full Name	Frequency, n(%)	Age, Mean $\pm$ SD	Male, n(%)
SB	Sinus Bradycardia	3,889 (36.53)	58.34 ± 13.95	2,481 (58.48%)
SR	Sinus Rhythm	1,826 (17.15)	54.35 ± 16.33	1,024 (56.08%)
AFIB	Atrial Fibrillation	1,780 (16.72)	73.36 ± 11.14	1,041 (58.48%)
ST	Sinus Tachycardia	1,568 (14.73)	54.57 ± 21.06	799 (50.96%)
AF	Atrial Flutter	445 (4.18)	71.07 ± 13.5	257 (57.75%)
SI	Sinus Irregularity	399 (3.75)	34.75 ± 23.03	223 (55.89%)
SVT	Supraventricular Tachycardia	587 (5.51)	55.62 ± 18.53	308 (52.47%)
AT	Atrial Tachycardia	121 (1.14)	65.72 ± 19.3	64 (52.89%)
AVNRT	Atrioventricular Node Reentrant Tachycardia	16 (0.15)	57.88 ± 17.34	12 (75%)
AVRT	Atrioventricular Reentrant Tachycardia	8 (0.07)	57.5 ± 16.84	5 (62.5%)
SAAWR	Sinus Atrium to Atrial Wandering Rhythm	7 (0.07)	51.14 ± 31.83	6 (85.71%)
All	All	10,646 (100)	51.19 ± 18.03	5,956 (55.95%)

Figura 8: Performance report of gradient boosting tree model.

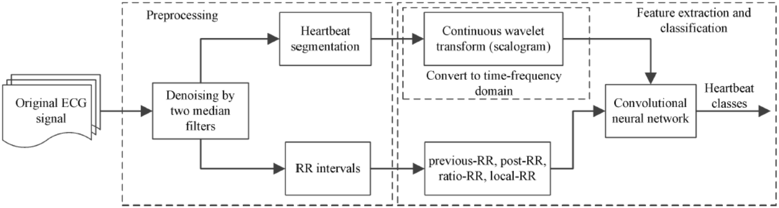
Rhythm group	F1-score	Precision	Recall
AFIB	0.941	0.938	0.944
GSVT	0.949	0.953	0.944
SB	0.993	0.990	0.996
SR	0.977	0.982	0.972
macro avg	0.965	0.966	0.964
micro avg	0.970	0.970	0.970
weighted avg	0.970	0.971	0.970

- **Proposed work** (WANG et al., 2021):
  - Single-lead ECG signals.
  - MIT-BIH Arrhythmia database.
  - Inter-patient paradigm
  - Continuous Wavelet Transform (CWT) e Convolutional Neural Network (CNN)
  - Publication: Entropy Journal

Related Works

Automatic ECG Classification Using Continuous Wavelet Transform and Convolutional Neural Network

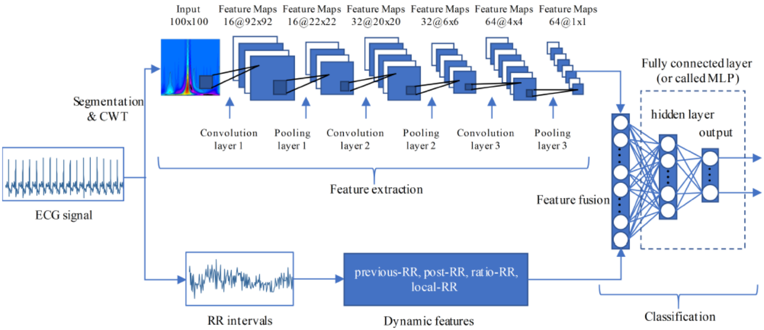
Figura 9: Flowchart of authors' proposed method



Related Works

Automatic ECG Classification Using Continuous Wavelet Transform and Convolutional Neural Network

Figura 10: CNN architecture



Related Works

Automatic ECG Classification Using Continuous Wavelet Transform and Convolutional Neural Network

Figura 11: Classification performance

Classes	Metrics	Methods					
		Liu et al.	Chen et al.	Zhang et al.	Ye et al.	Garcia et al.	Our Method
N	Positive predictive value	96.66%	95.42%	98.98%	97.55%	98.00%	98.17%
	Sensitivity	94.06%	98.42%	88.94%	88.61%	94.00%	99.42%
	F1-score	95.34%	96.90%	93.69%	92.87%	95.96%	98.79%
SVEB	Positive predictive value	39.87%	38.40%	35.98%	52.34%	53.00%	89.54%
	Sensitivity	33.12%	29.50%	79.06%	61.02%	62.00%	74.56%
	F1-score	36.18%	33.36%	49.46%	56.34%	57.15%	81.37%
VEB	Positive predictive value	76.51%	85.25%	92.75%	61.45%	59.40%	93.25%
	Sensitivity	90.20%	70.85%	85.48%	81.82%	87.30%	95.65%
	F1-score	82.79%	77.38%	88.96%	70.19%	70.70%	94.43%
F	Positive predictive value	12.99%	0.00%	13.73%	2.50%	-	2.04%
	Sensitivity	40.72%	0.00%	93.81%	19.69%	-	0.26%
	F1-score	19.70%	0.00%	23.96%	4.43%	-	0.46%
Average	Positive predictive value	56.51%	54.77%	60.36%	53.46%	52.60%	70.75%
	Sensitivity	63.53%	49.69%	86.82%	62.79%	60.83%	67.47%
	F1-score	58.50%	51.91%	64.02%	55.96%	55.95%	68.76%

PROPOSED WORK

Proposed Work

- MIT-BIH database
- Inter-patient paradigm
- Wavelet transform (coeficients), duration, RR interval, amplitude, and others features
- Classification: SVM and neural network

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