# Framework for ECG analysis*

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**Abstract.** Currently, Point-of-Care (POC) ECG monitoring works either as plot devices or alarms for abnormal cardiac rhythms using predefined normal trigger ranges and some rhythm analysis, which raises the problem of false alarms. In comparison, complex 12-derivation ECG machines are not suitable to use as simple monitors, and are used with strict techniques for formal diagnostics. We aim to identify, on streaming data, life-threatening hearth electric patterns to reduce the number of false alarms, using low CPU and memory maintaining robustness. The study design is comparable to a diagnostic study, where high accuracy is essential. Physionet's 2015 challenge yielded very good algorithms for reducing false alarms. However, none of the authors reported benchmarks, memory usage, robustness test, or context invariance that could assure its implementation on real monitors to reduce alarm fatigue indeed. We expect to identify the obstacles of detecting life-threatening ECG changes within memory, space, and CPU constraints and to reduce ECG monitor's false alarms using the proposed methodology, and assess the feasibility of implementing the algorithm in the real world and other settings than ICU monitors.

**Keywords:** anomaly detection · ECG · fading factors · matrix profile · time series · point-of-care

## 1 Introduction

Point-of-Care (POC) ECG monitoring works either as plot devices or alarms for abnormal cardiac rhythms using predefined normal trigger ranges. Modern devices also incorporate algorithms to analyze arrhythmias improving their specificity. On the other hand, full 12-derivation ECG machines are complex, are not suited to use as simple monitors, and are used with strict techniques for formal diagnostics of hearth electric conduction pathologies. The automatic diagnostics are derived from a complete analysis of the 12-dimension data after fully and well

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collected. Both systems do not handle disconnected leads and patient's motions, being strictly necessary to have a good and stable signal to allow proper diagnosis. These interferences with the data collection frequently originate false alarms increasing both patient and staff's stress; depending on how it is measured, the rate of false alarms (overall) in ICU is estimated at 65 to 95%[11].

Alarm fatigue is a well-known problem that consists of a sensory overload of nurses and clinicians, resulting in desensitization to alarms and missed alarms (the "crying wolf" situation). Patient deaths have been attributed to alarm fatigue[23]. In 1982 it was recognized the increase in alarms with "no end in sight"; studies have demonstrated that most alarm signals have no clinical relevance and lead to clinical personnel's delayed response. Ultimately patient deaths were reported related to inappropriate responses to alarms[23].

In April of 2013, The Joint Commission[4] issued the Sentinel Event Alert[16], establishing alarm system safety as a top hospital priority in the National Patient Safety Goal. Nowadays (2021), this subject is still on their list, in fourth place of importance[5].

In February 2015, the CinC/Physionet Challenge 2015 was about "Reducing False Arrhythmia Alarms in the ICU[19].

Due to this matter's importance, this research aims to identify abnormal hearth electric patterns using streaming data, specifically those who are life-threatening, reducing the false alarms, being a reliable signal for Intensive Care Units to respond quickly to those situations.

## 2 Objectives and the research question

This research aims to identify, on streaming data, abnormal hearth electric patterns, specifically those which are life-threatening, to be a reliable signal for Intensive Care Units to respond quickly to those situations. It also may be able to continuously analyze new data and correct itself shutting off false alarms.

As it is known, this goal is not a new problem, so the main questions to solve are: (1) Can we reduce the number of false alarms in the ICU setting? (2) Can we accomplish this objective using a minimalist approach (low CPU, low memory) while maintaining robustness? (3) Can this approach be used in other health domains other than ICU or ECG?

## 3 Related Works

The CinC/Physionet Challenge 2015 produced several papers aiming to reduce false alarms on their dataset. In Table 1 it is listed the five life-threatening alarms present in their dataset.

They used as score the following formula, which penalizes five times the false negatives (since we do not want to miss any real event):

$$Score = \frac{TP + TN}{TP + TN + FP + 5 * FN}$$

**Table 1.** Definition of the 5 alarm types used in CinC/Physionet Challenge 2015 challenge.

| Alarm | Definition |
|---|---|
| Asystole | No QRS for at least 4 seconds |
| Extreme Bradycardia | Heart rate lower than 40 bpm for 5 consecutive beats |
| Extreme Tachycardia | Heart rate higher than 140 bpm for 17 consecutive beats |
| Ventricular Tachycardia | 5 or more ventricular beats with heart rate higher than 100 bpm |
| Ventricular Flutter/Fibrillation | Fibrillatory, flutter, or oscillatory waveform for at least 4 seconds |

The five-best scores in this challenge are presented on Table 2[10, 12, 15, 17, 21].

**Table 2.** Challenge Results on Streaming

| Score | Authors |
|---|---|
| 81.39 | Filip Plesinger, Petr Klimes, Josef Halamek, Pavel Jurak |
| 79.44 | Vignesh Kalidas |
| 79.02 | Paula Couto, Ruben Ramalho, Rui Rodrigues |
| 76.11 | Sibylle Fallet, Sasan Yazdani, Jean-Marc Vesin |
| 75.55 | Christoph Hoog Antink, Steffen Leonhardt |

Their algorithm did a pretty good job on the Physionet test set. However, independently of their approach to this problem, none of the authors reported benchmarks, memory usage, robustness test, or context invariance that could assure its implementation on real monitors to reduce alarm fatigue indeed.

There are other arrhythmias that this challenge did not assess, like atrial standstill (hyperkalemia), third-degree atrioventricular block, and others that may be life-threatening in some settings. Pulseless electrical activity is a frequent condition in cardiac arrest but cannot be identified without blood pressure information. This information is usually present in ICU settings but not in other locations.

## 4 The planned approach and methods for solving the problem

### 4.1 State of the art

A literature review of the last ten years is being conducted to assess state of the art for ECG automatic processing collecting the following points if available :

(1) The memory and space used to perform the primary goal of the algorithm (sound an alarm, for ex.). (2) The type of algorithms used to identify ECG anomalies. (3) The type of algorithms used to identify specific diagnoses (like a flutter, hyperkalemia, and others). (4) Their performance (accuracy, ROC, etc.)

A broad search will be conducted on Pubmed, Scopus, Google Scholar, device manuals, and other specific sources.

Keywords:

- ECG AND monitoring AND ICU
- ECG AND [ time series ]
- ECG AND automatic AND interpretation

Articles published after "The PhysioNet/Computing in Cardiology Challenge 2015: Reducing False Arrhythmia Alarms in the ICU" will also be analyzed.

### 4.2 Research plan and methods

This research is being conducted using the Research Compendium principles[3]:

1. Stick with the convention of your peers;
2. Keep data, methods, and output separated;
3. Specify your computational environment as clearly as you can.

Data management follows the FAIR principle (findable, accessible, interoperable, reusable)[24].

Currently, the dataset used is stored on a public repository[6], the source code is publicly open and stored on Github[1], while the reports and reproducibility information on each step is found on a public website[2]. The current dataset and further collected data will be publicly available following the FAIR principle.

**Type of study** This thesis will be a diagnostic study as the algorithm must classify the change in pattern as positive or negative for life-threatening.

**The data** Initially, we will use the CinC/Physionet Challenge 2015 dataset that is publicly available on Physionet. This dataset is a good start for exploring the primary goal of reducing false alarms. This dataset has been curated for this challenge, and the events were labeled by experts, so it is not raw data. All signals have been resampled (using anti-alias filters) to 12 bits, 250 Hz, and have had FIR band-pass [0.05 to 40Hz] and mains notch filters applied to remove noise. Pacemaker and other artifacts may be present on the ECG[9]. Furthermore, this dataset contains at least two ECG derivations and one or more variables like arterial blood pressure, photoplethysmograph readings, and respiration movements.

These variables may or may not be helpful for increasing the sensitivity or specificity of the algorithm. We plan to use the minimum set of variables as it is known in multi-dimensional analysis that using just two (or some small subset) of all the dimensions can be much more accurate than using all dimensions or a single dimension[14].

At first, we will assemble a workflow to explore the Physionet's dataset and find a suitable solution for detecting regime changes and verify if these changes are, in fact, clinical changes or just artifacts. At this stage, the aim is to build a classifier for the "simplest" type of change: Asystole. While one may think detecting the "absence" of heartbeats may be trivial, this will set the grounds for distinguishing patient data from artifacts.

It is desirable that real data extracted from Portuguese ICU could be used in a further stage to assess the validity of the model in real settings and robustness (using raw data instead of filtered data). The variables available on Physionet's dataset are commonly available on Portuguese ICUs. However, this real data also need to go through several stages, including manual labeling, which can hold back this project. In addition to the dataset used on Challenge 2015, Physionet has a vast collection of ECG recordings well labeled and reviewed by cardiologists. Therefore, these data can be used as a final test for the resulting model.

**Workflow management** All steps of the process will be managed using the R package `targets`[18] from data extraction to the final report, as shown in Fig. 1.

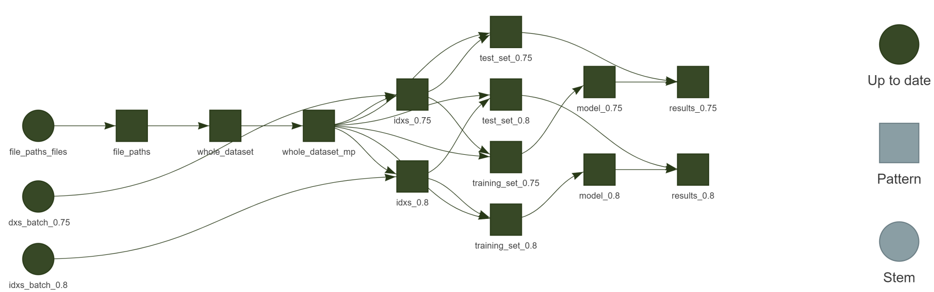


**Fig. 1.** Reprodutible research workflow using 'targets'.

The report will then be available on the main webpage[2], allowing inspection of previous versions managed by the R package `workflowr`[7], as we can see in Fig. 2.

**Proposed approach** The proposed approach is depicted in Fig. 3. That is only a draft of the final workflow. The algorithm for the classification of the regime changes is still to be defined. However, the main innovation resides in the correct regime detection. Also, to achieve the goal of low CPU and memory usage, the

Summary | Checks ✔ | Past versions

These are the previous versions of the repository in which changes were made to the R Markdown ( `analysis/index.Rmd` ) and HTML ( `docs/index.html` ) files. If you've configured a remote Git repository (see `?wflow_git_remote` ), click on the hyperlinks in the table below to view the files as they were in that past version.

| File | Version | Author | Date | Message |
|---|---|---|---|---|
| Rmd | b869025 | Francisco Bischoff | 2021-03-24 | targets and workflowr |
| html | 52e7f0b | GitHub Actions | 2021-03-24 | Build site. |
| Rmd | c87e8e1 | Francisco Bischoff | 2021-03-24 | targets and workflowr |
| Rmd | 7c3cc31 | Francisco Bischoff | 2021-03-23 | Targets |
| html | 7c3cc31 | Francisco Bischoff | 2021-03-23 | Targets |
| html | 01a7ace | Francisco Bischoff | 2020-07-23 | Refactor |
| html | 5f450d2 | Francisco Bischoff | 2020-05-05 | gh-pages placeholder |

**Fig. 2.** Reprodutible reports using 'workflowr.'

strategy will be to combine fading factors[13, 22] to reduce computation in online settings like in this research.

**Statistical analysis** The Statistical analysis will be performed using R language v4.1.1 or greater, and it will be computed the ROC curve for the algorithm.

The experiment will be conducted using the Matrix Profile concept[25], the state-of-the-art for time series analysis. It will be conducted several experiments to identify the best algorithm for this task. One of such algorithms is the online semantic segmentation for multi-dimensional time series[14].

In addition, we will combine the fading factors[13, 22] strategy to minimize the memory and space consumption lowering the processor power needed, allowing this algorithm to be used in almost any device.

### Research Team

- Thesis Author: Francisco Bischoff
- Supervisor: Professor Pedro Pereira Rodrigues
- Co-supervisor: Professor Eamonn Keogh (UCR, Riverside)

### 4.3 Expected results and outcomes

We expect the following results: (1) Identify the obstacles of identifying life-threatening ECG changes within memory, space, and CPU constraints. (2) Be able to reduce ECG monitor's false alarms using the proposed methodology. (3) Assess the feasibility of implementing the algorithm in the real world and other settings than ICU monitors.

And outcomes: (1) To achieve a better score of false alarm reduction than the best on Physionet's 2015 challenge. (2) To push forward the state-of-the-art technology on false alarms reduction, maybe even being domain agnostic. (3) To

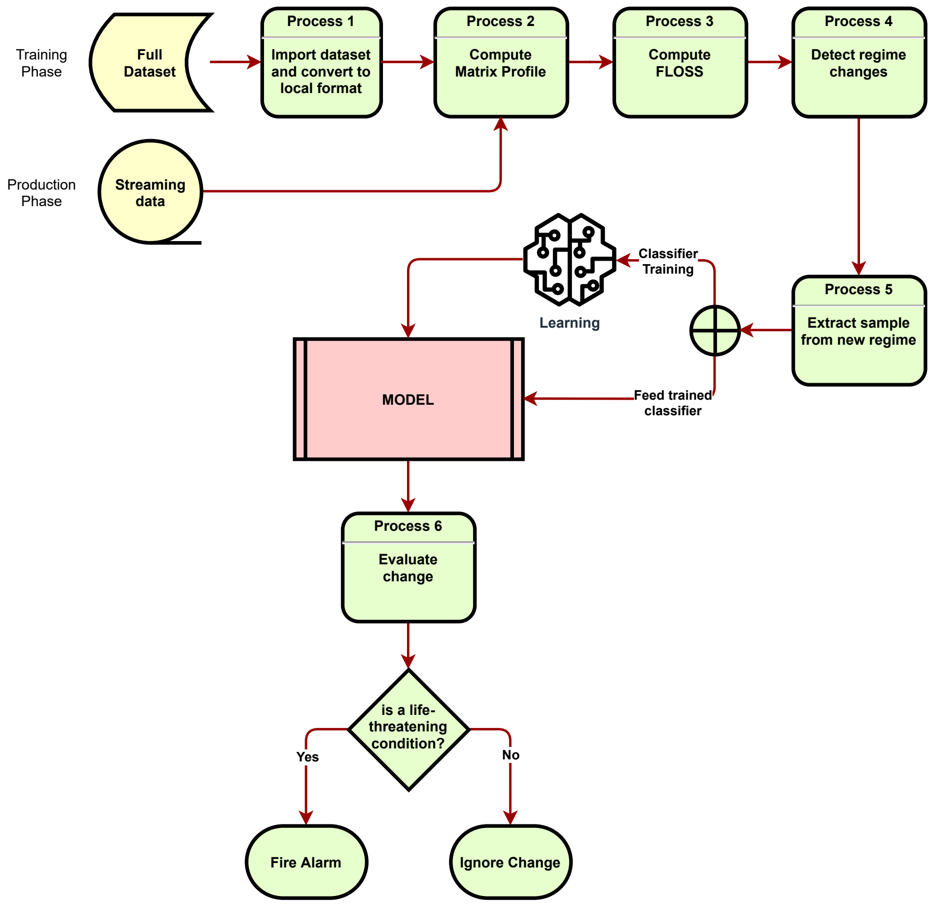


**Fig. 3.** Proposed approach to train the model for relevant patterns detection.

draw more attention to fading factors as a reliable, fast, and cheap approximation of the true value. (4) To draw more attention to the matrix profile concept as an efficient, agnostic, and almost parameter-free way to analyze time series. (5) To draw more attention of the Patient Monitorization industry on solving the false alarm problem.

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