Workshop on TinyML for Sustainable Development

TinyMLedu

Classification of electrocardiogram signals (ECG) using TinyML: Sinus Rate and Atrial Fibrillation.

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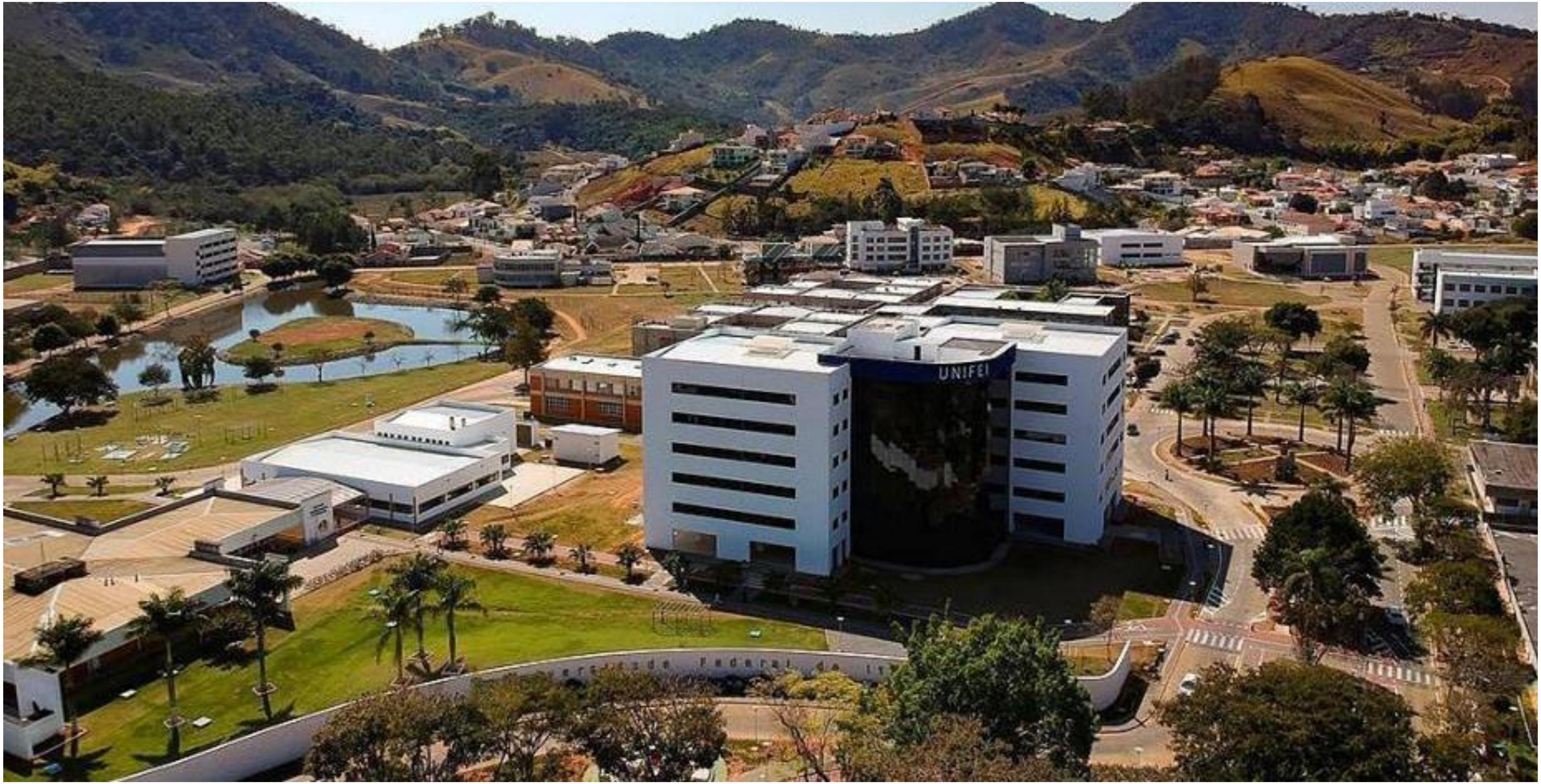
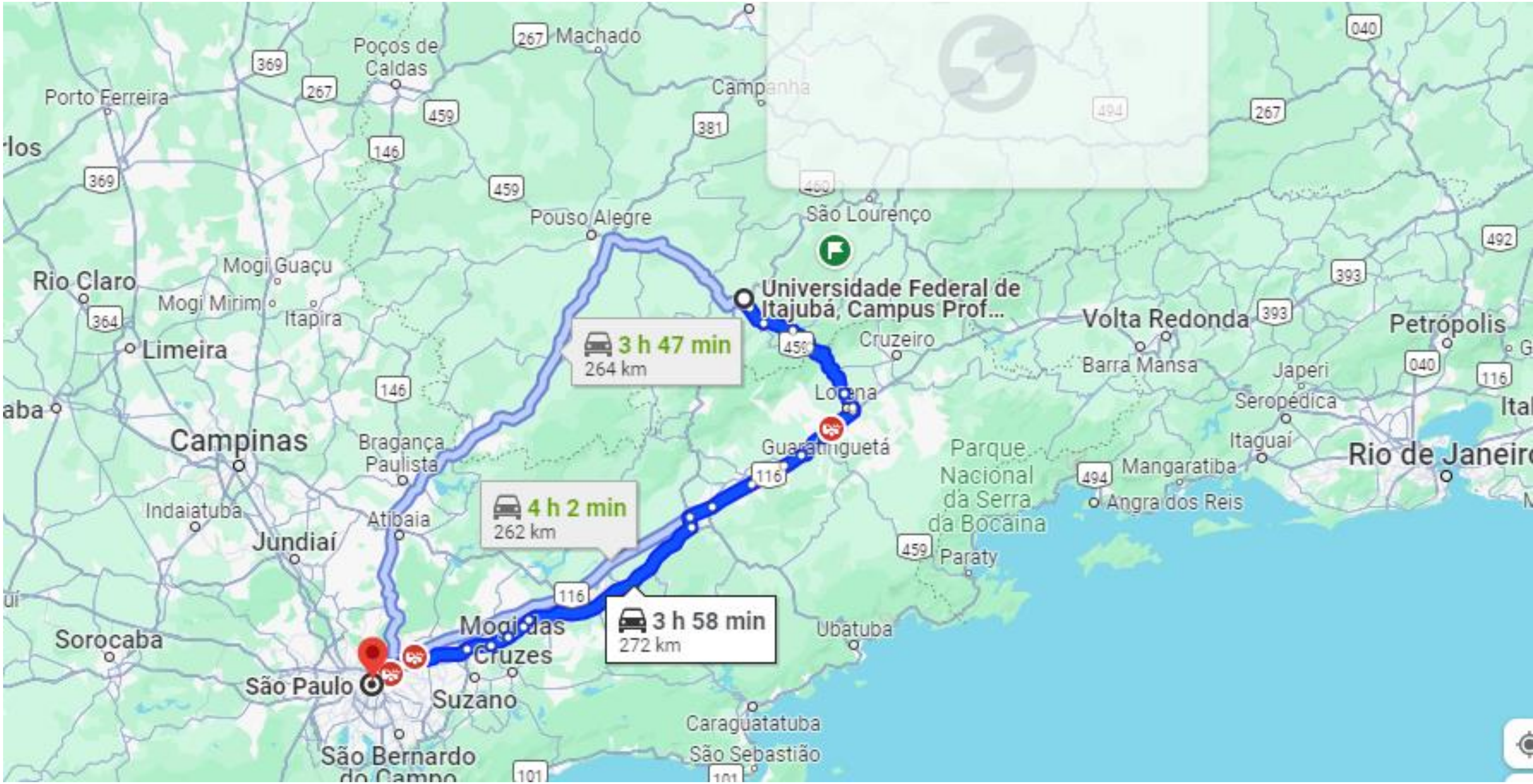
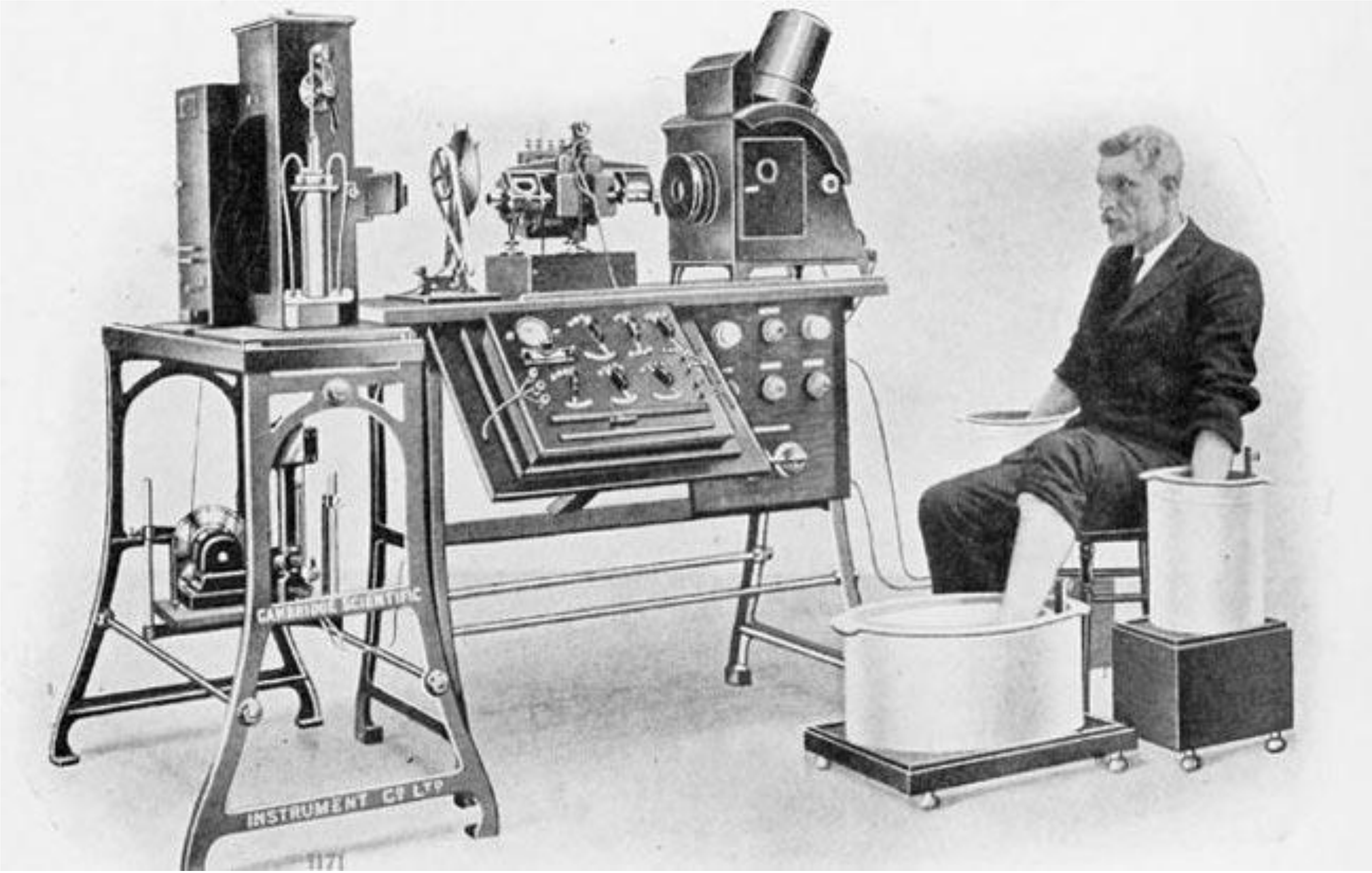
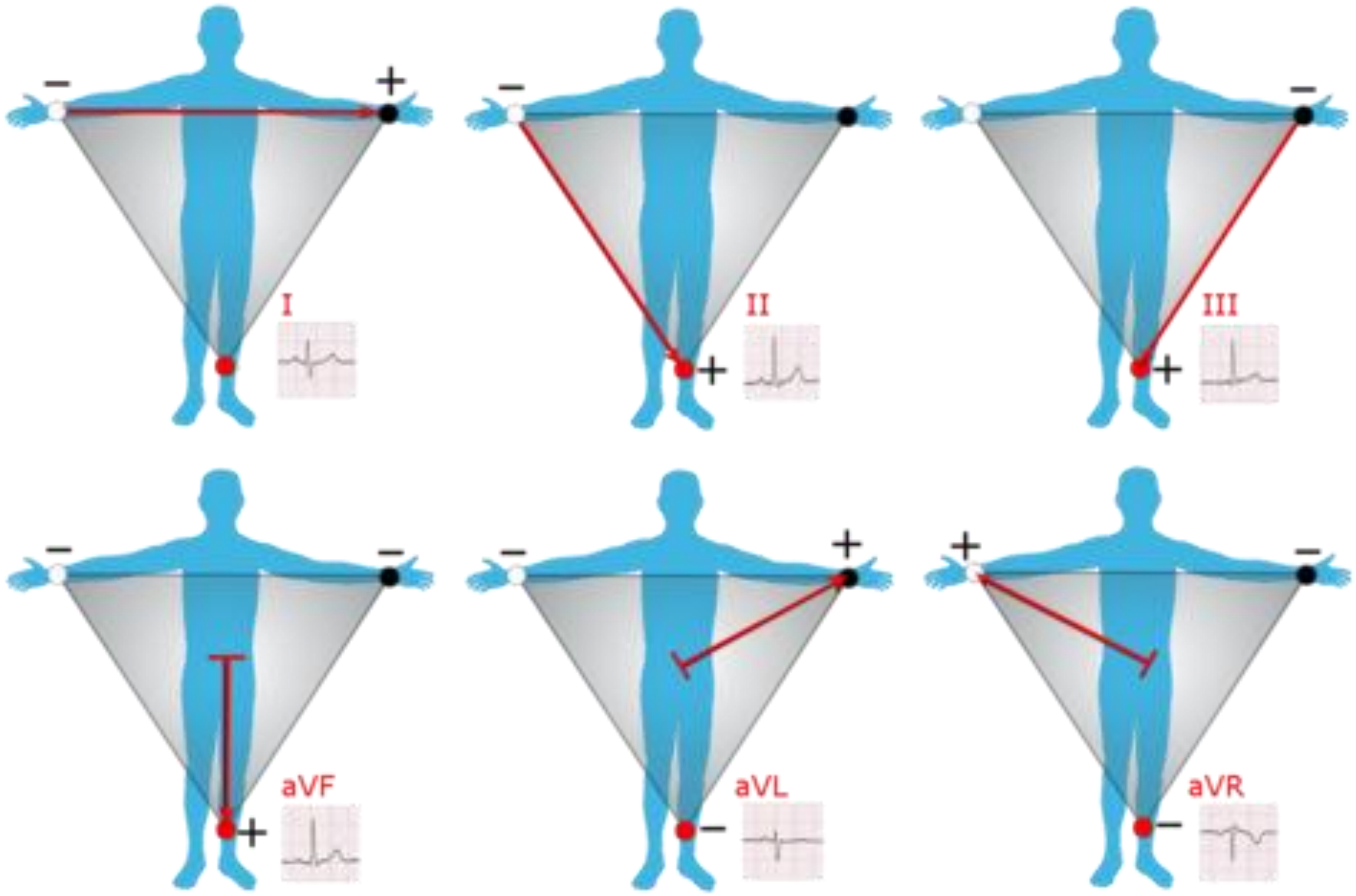

UNIFEI



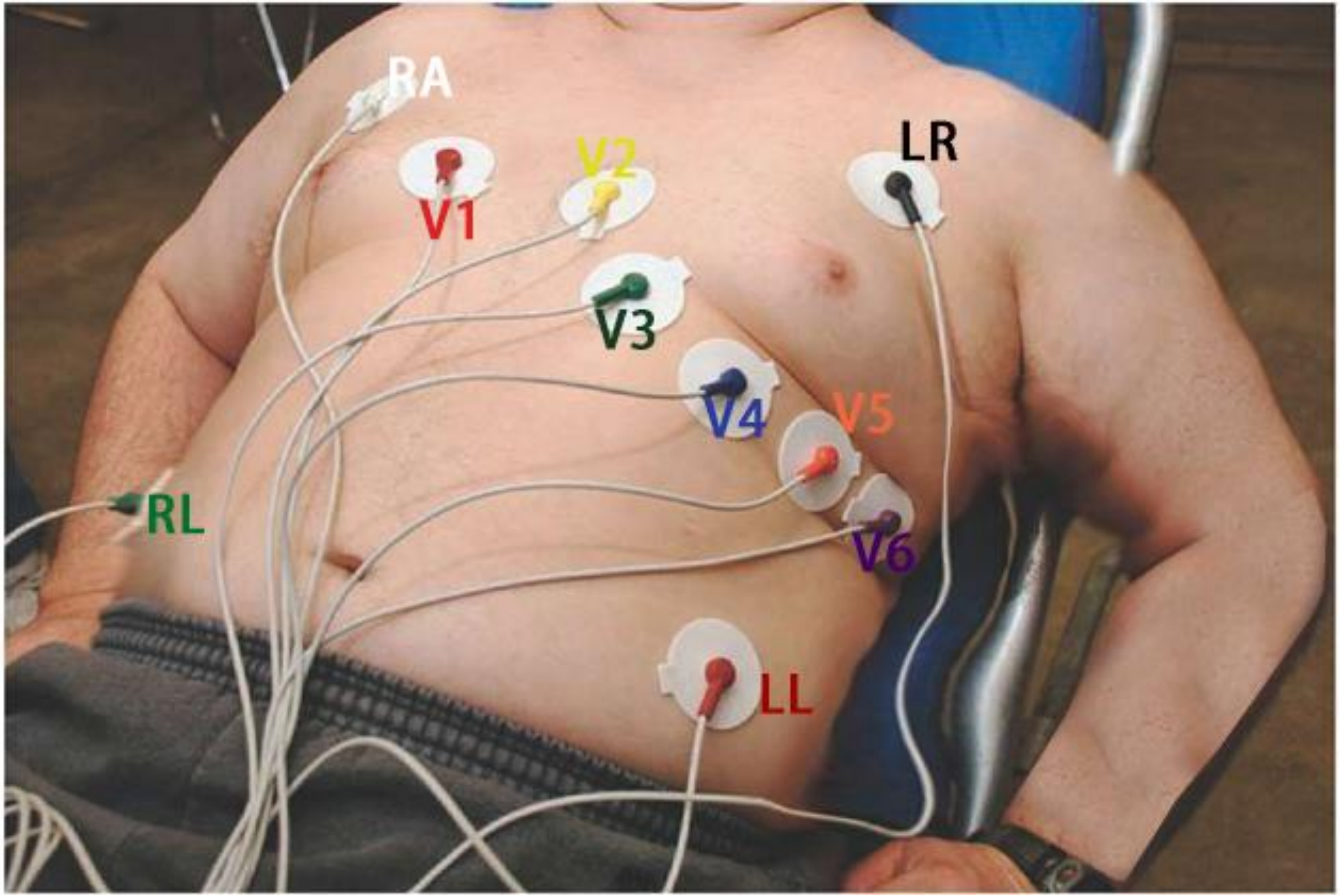
Machado
Poços de Caldas
Campanha
Porto Ferreira
Pouso Alegre
São Lourenço
Mogi Guaçu
Rio Claro
Mogi Mirim
Itapira
Universidade Federal de Itajubá, Campus Prof...
Volta Redonda
Petrópolis
Limeira
3 h 47 min
264 km
Cruzeiro
Barra Mansa
Japeri
Seropédica
Campinas
Bragança Paulista
Guaratinguetá
Parque Nacional da Serra da Bocaina
Itaguaí
Mangaratiba
Rio de Janeiro
Indaiatuba
Atibaia
4 h 2 min
262 km
Angra dos Reis
Jundiaí
Paraty
3 h 58 min
272 km
Sorocaba
Ubatuba
São Paulo
Suzano
Caraguatatuba
São Sebastião
São Bernardo do Campo



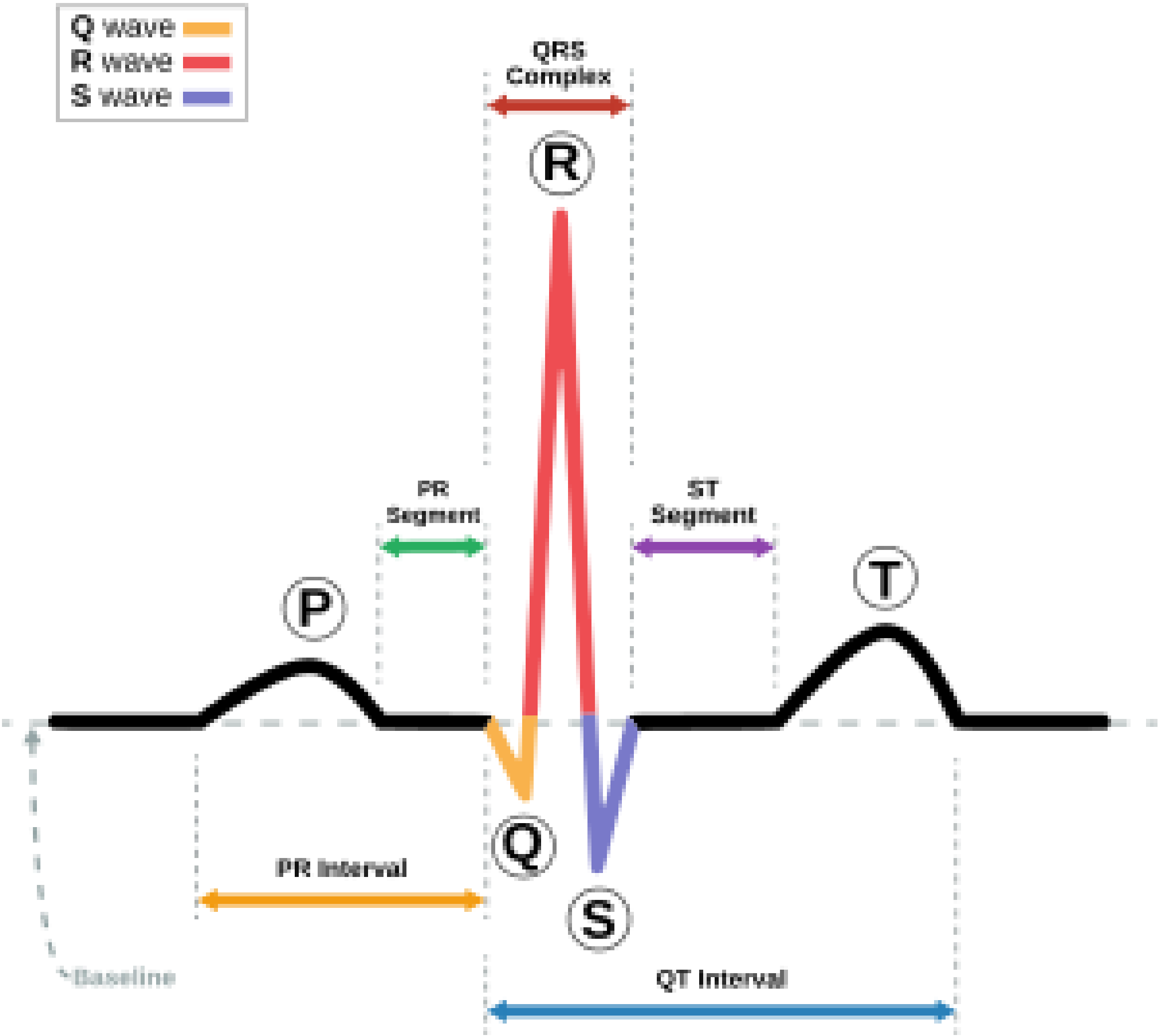
https://www.pastmedicalhistory.co.uk/willem-einthoven-and-the-electrocardiogram/



https://en.wikipedia.org/wiki/Electrocardiography



https://www.conectmed.com/12-leads-ecg-ekg-placement-with-10-leads-ecg-cable.html



Schematic representation of normal sinus rhythm showing standard wave, segments, and intervals

https://en.wikipedia.org/wiki/Sinus_rhythm

ECG Features of Atrial Fibrillation

- Irregularly irregular rhythm
- No P waves
- Absence of an isoelectric baseline
- Variable ventricular rate
- QRS complexes usually < 120ms, unless pre-existing bundle branch block, accessory pathway, or rate-related aberrant conduction
- Fibrillatory waves may be present and can be either fine (amplitude < 0.5mm) or coarse (amplitude > 0.5mm)
- Fibrillatory waves may mimic P waves leading to misdiagnosis

https://litfl.com/atrial-fibrillation-ecg-library/

Atrial fibrillation: Irregularly irregular ventricular rate without visible P waves

https://litfl.com/atrial-fibrillation-ecg-library/

THE DATASET

PTB-XL, a large publicly available electrocardiography dataset

Patrick Wagner, **Nils Strodthoff**, **Ralf-Dieter Bousseljot**, **Wojciech Samek**, **Tobias Schaeffter**

Published: Nov. 9, 2022. Version: 1.0.3

Abstract

Electrocardiography (ECG) is a key diagnostic tool to assess the cardiac condition of a patient. Automatic ECG interpretation algorithms as diagnosis support systems promise large reliefs for the medical personnel - only on the basis of the number of ECGs that are routinely taken. However, the development of such algorithms requires large training datasets and clear benchmark procedures. In our opinion, both aspects are not covered satisfactorily by existing freely accessible ECG datasets.

The PTB-XL ECG dataset is a large dataset of 21799 clinical 12-lead ECGs from 18869 patients of 10 second length. The raw waveform data was annotated by up to two cardiologists, who assigned potentially multiple ECG statements to each record. The in total 71 different ECG statements conform to the SCP-ECG standard and cover diagnostic, form, and rhythm statements. To ensure comparability of machine learning algorithms trained on the dataset, we provide recommended splits into training and test sets. In combination with the extensive annotation, this turns the dataset into a rich resource for the training and the evaluation of automatic ECG interpretation algorithms. The dataset is complemented by extensive metadata on demographics, infarction characteristics, likelihoods for diagnostic ECG statements as well as annotated signal properties.

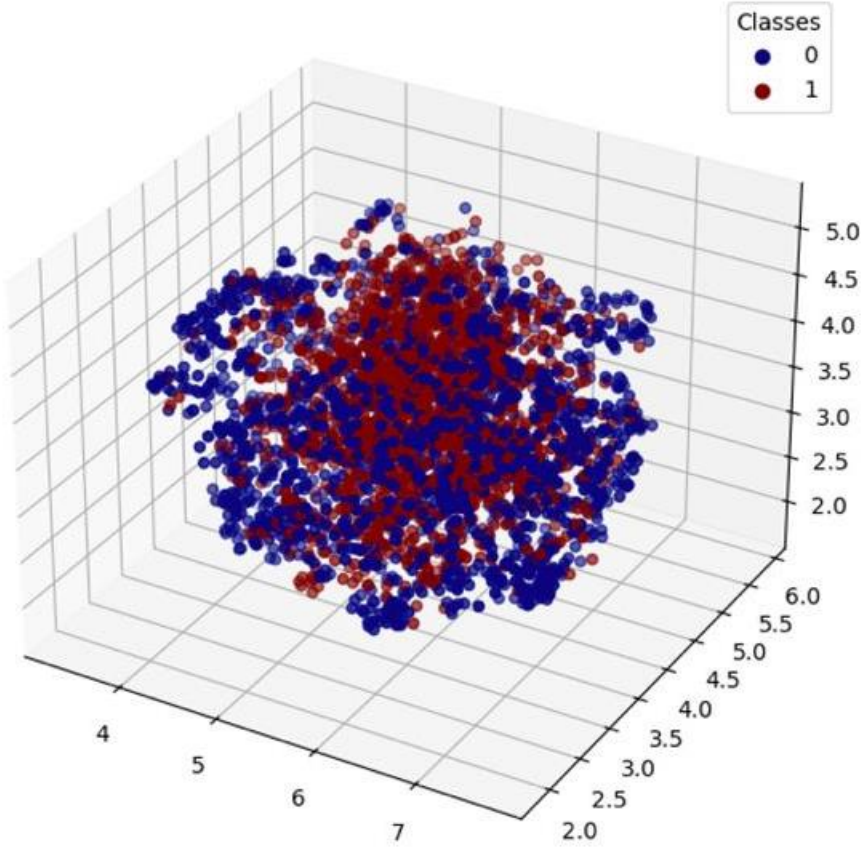
A large-scale multi-label 12-lead electrocardiogram database with standardized diagnostic statements

Liu Hui, Chen Dan, Chen Da, Zhang Xiyu, Li Huijie, Bian Lipan, Shu Minglei & Wang Yinglong

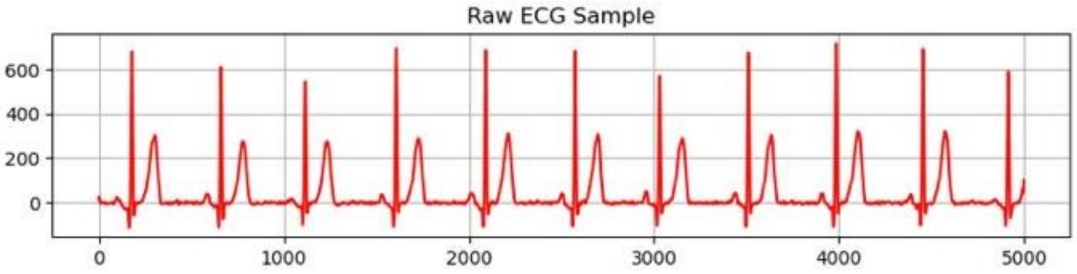
Scientific Data **9**, Article number: 272 (2022) | Cite this article

Abstract

Deep learning approaches have exhibited a great ability on automatic interpretation of the electrocardiogram (ECG). However, large-scale public 12-lead ECG data are still limited, and the diagnostic labels are not uniform, which increases the semantic gap between clinical practice. In this study, we present a large-scale multi-label 12-lead ECG database with standardized diagnostic statements. The dataset contains 25770 ECG records from 24666 patients, which were acquired from Shandong Provincial Hospital (SPH) between 2019/08 and 2020/08. The record length is between 10 and 60 seconds. The diagnostic statements of all ECG records are in full compliance with the AHA/ACC/HRS recommendations, which aims for the standardization and interpretation of the electrocardiogram, and consist of 44 primary statements and 15 modifiers as per the standard. 46.04% records in the dataset contain ECG abnormalities, and 14.45% records have multiple diagnostic statements. The dataset also contains additional patient demographics.



Classes
0
1
5.0
4.5
4.0
3.5
3.0
2.5
2.0
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0
4
5
6
7



Raw ECG Sample
600
400
200
0
0
1000
2000
3000
4000
5000

PRE-PROCESSING

FILTERS

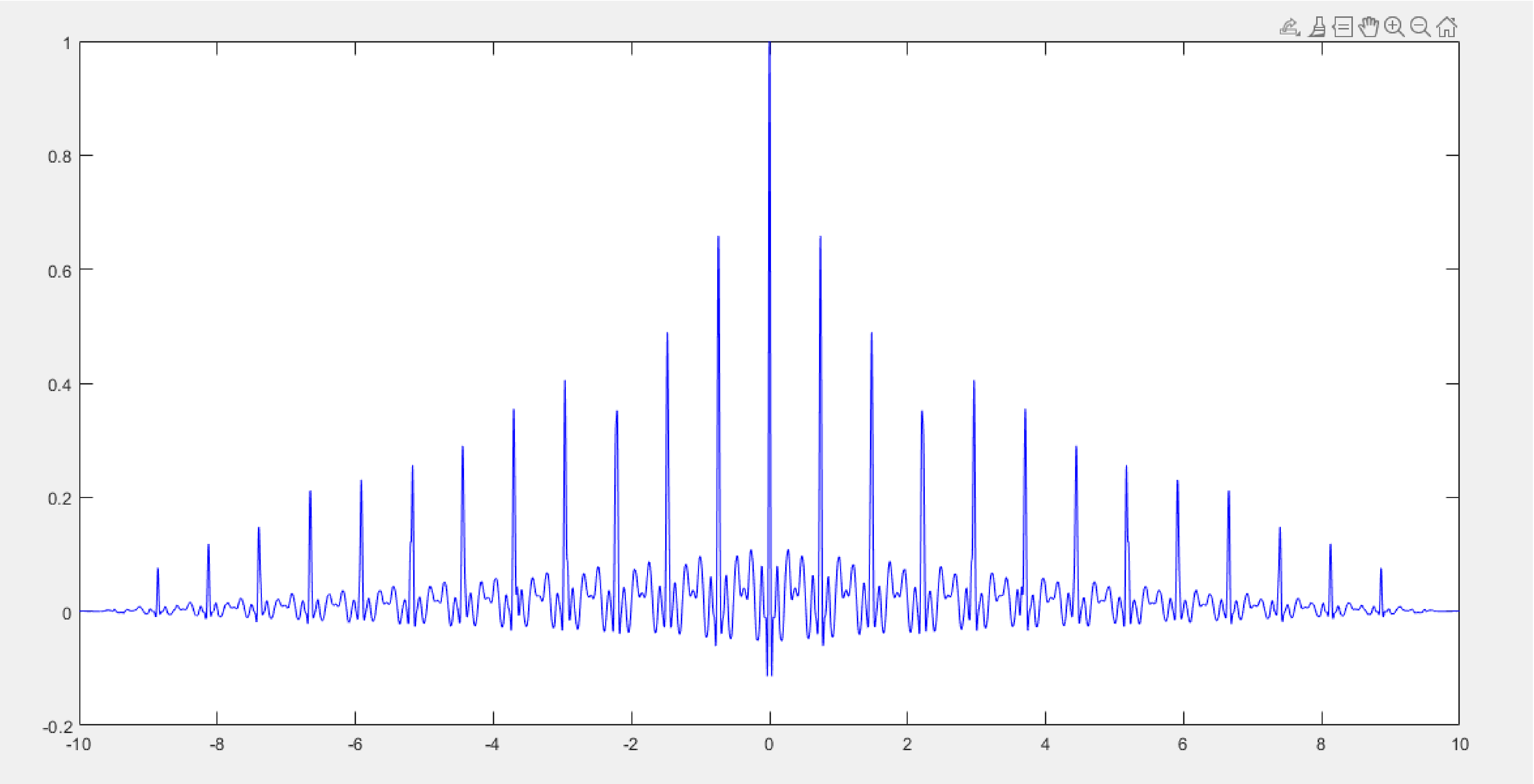
a) Butterworth low pass filter was used to remove the signal with a frequency above 50Hz. (2X)

b) LOESS smoother was utilized to clear the efects of baseline wandering.

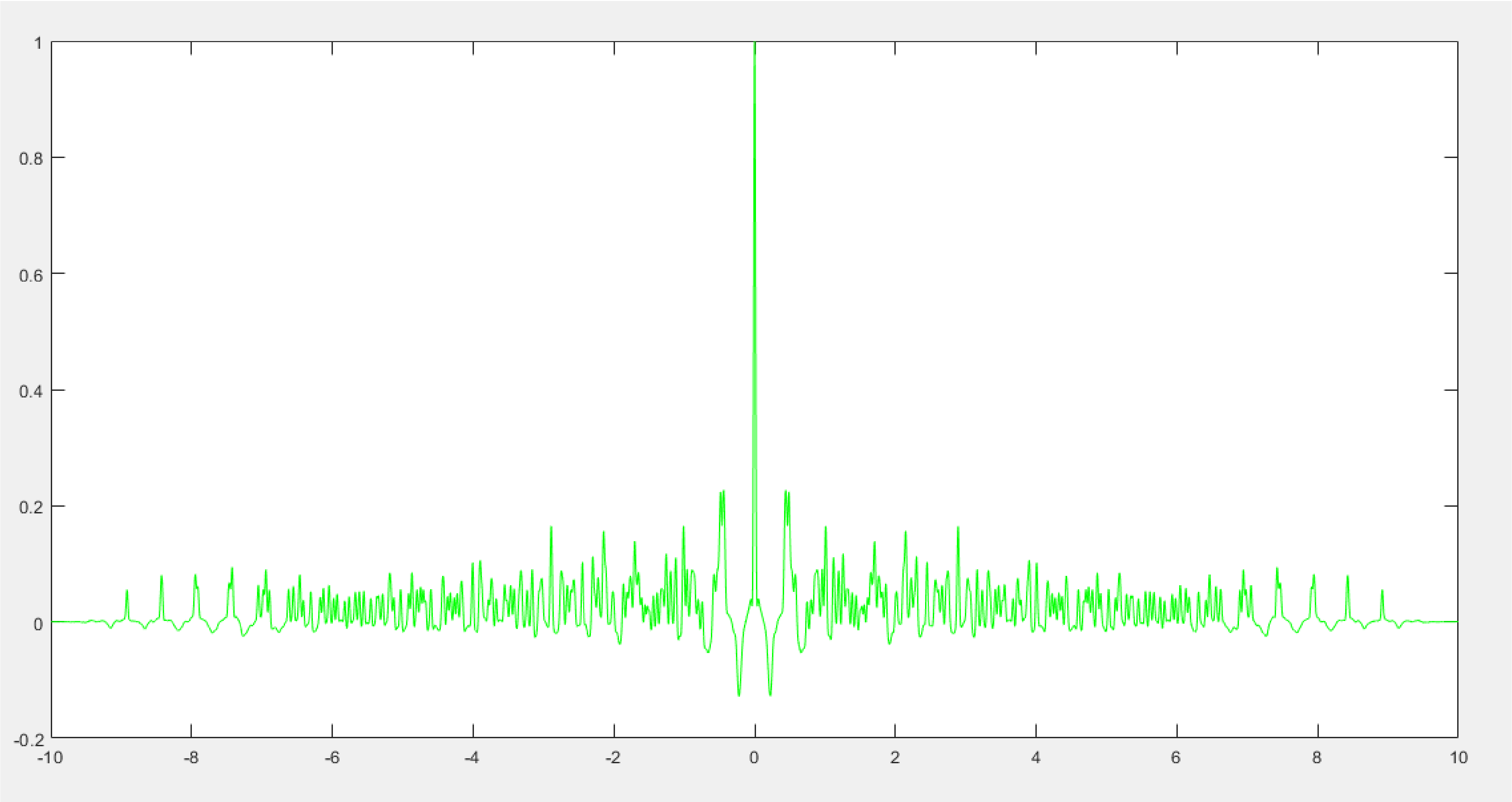
c) Non Local Means (NLM) technique was used to handle the remaining noise.

AUTOCORRELATION

$$y[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n] x[n+k]$$

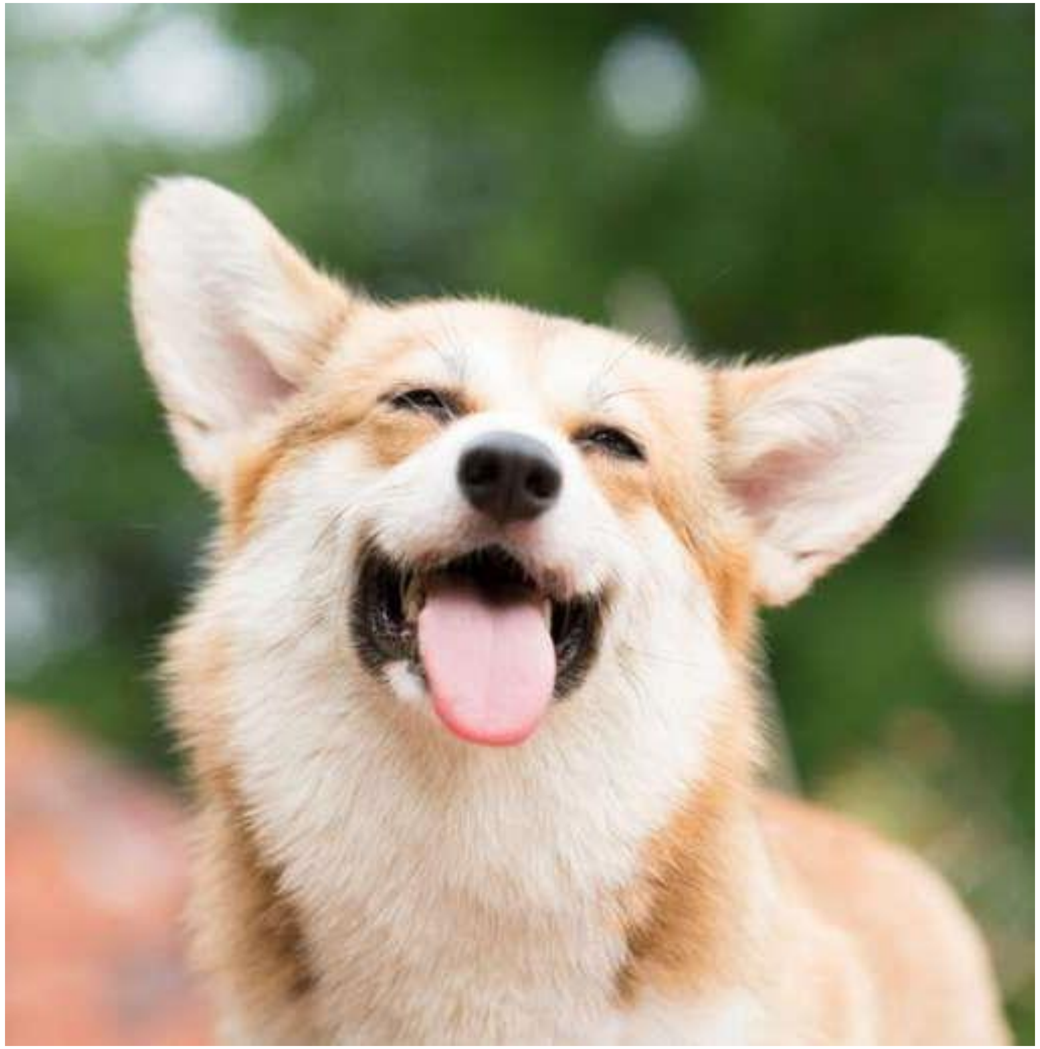


Autocorrelation – ECG SR

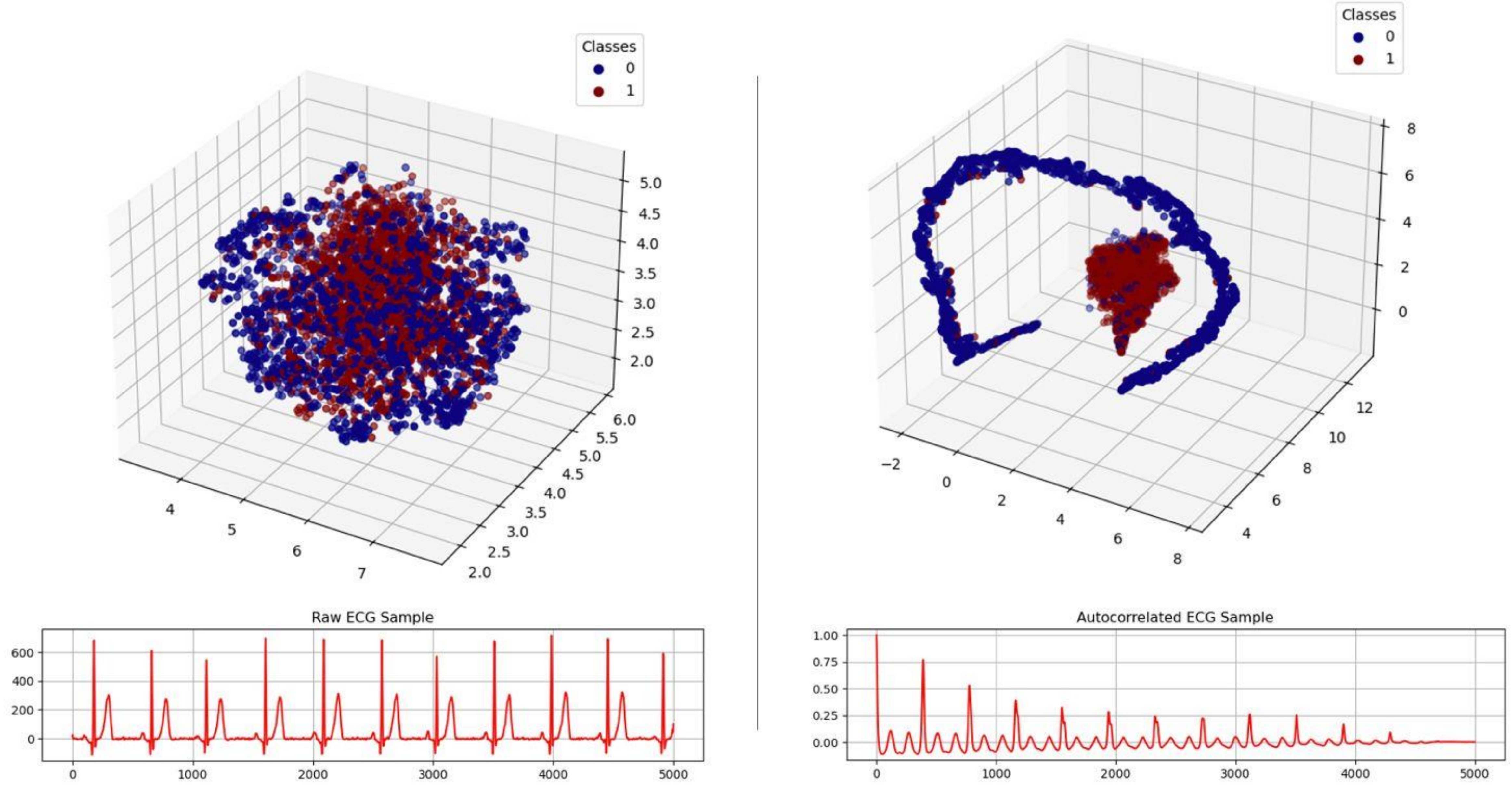


Autocorrelation – ECG AFIB

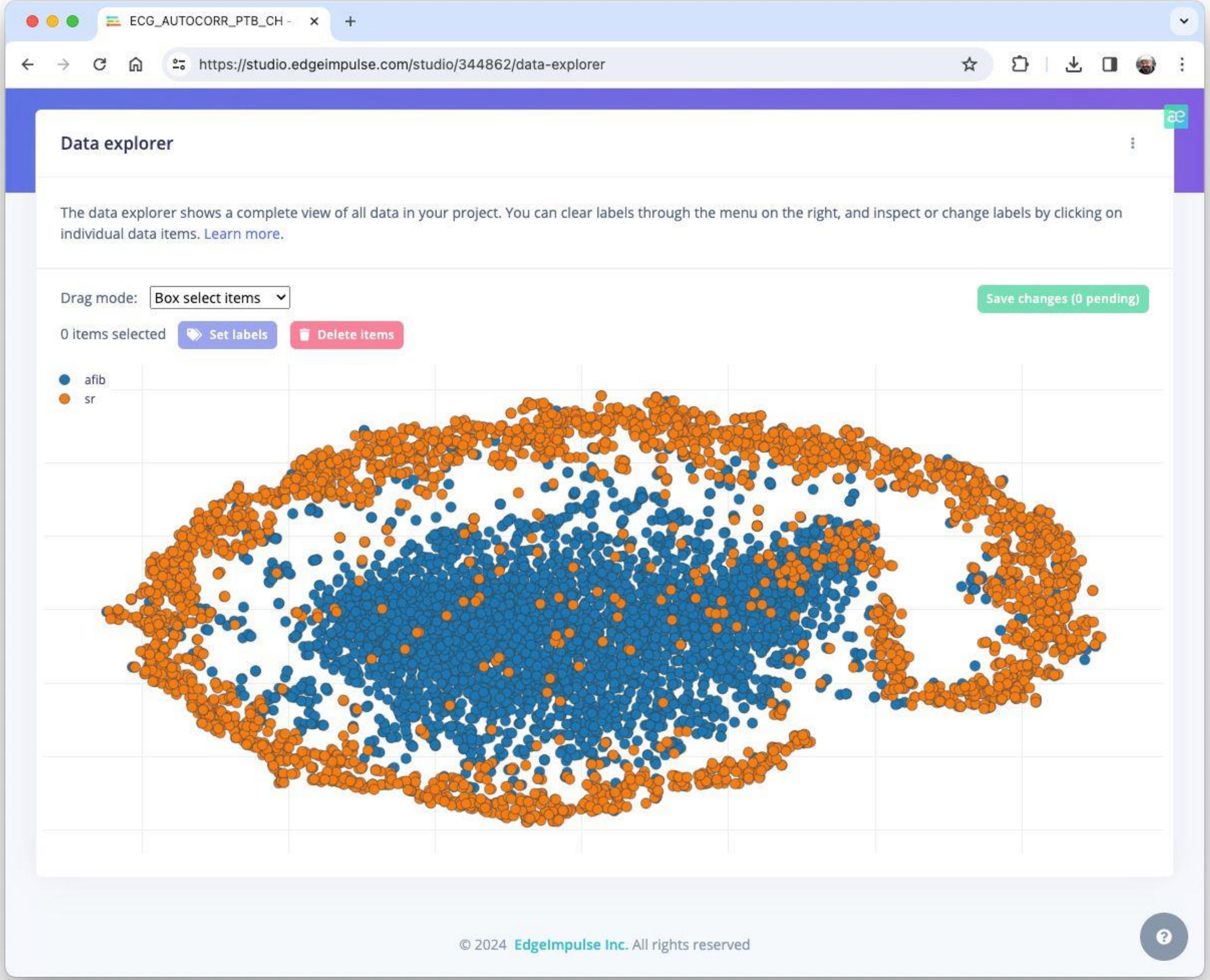
SR - Autocorrelation



AFIB - Autocorrelation



Denoised Chinese Dataset


ECG_AUTOCORR_PTB_CH -
https://studio.edgeimpulse.com/studio/344862/data-explorer
Data explorer
The data explorer shows a complete view of all data in your project. You can clear labels through the menu on the right, and inspect or change labels by clicking on individual data items. Learn more.
Drag mode:
Box select items
Save changes (0 pending)
0 items selected
Set labels
Delete items
afib
sr
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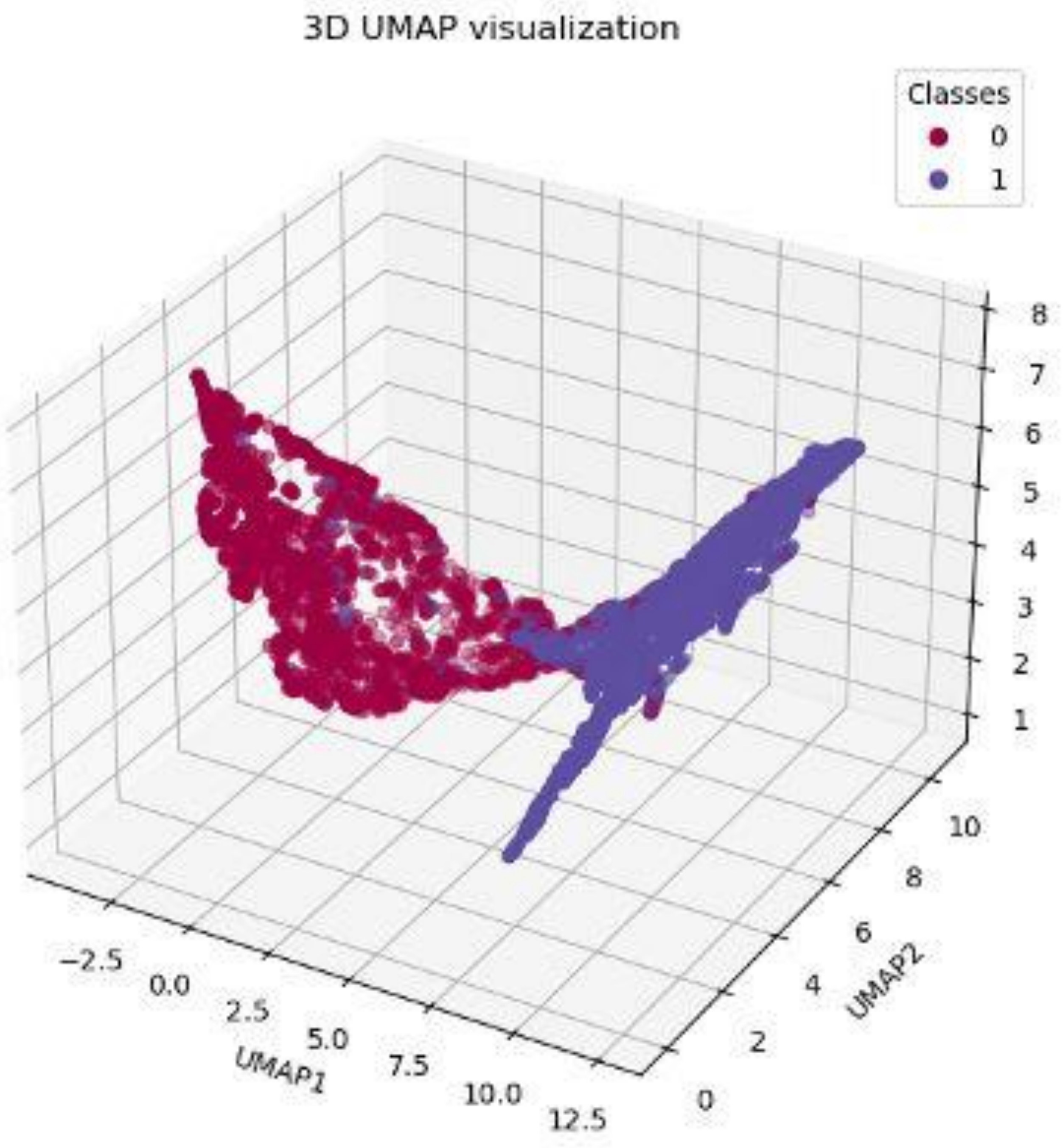


3D UMAP visualization
Classes
0
1
UMAP1
UMAP2
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
0
2
4
6
8
10
1
2
3
4
5
6
7
8

Model

Model version: Quantized (int8)

Last training performance (validation set)

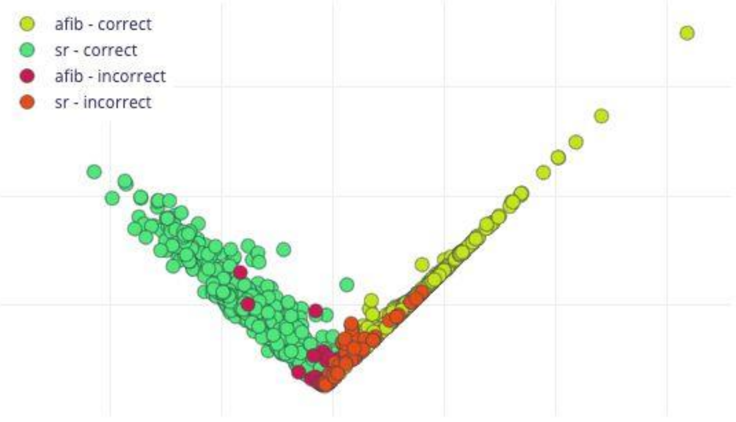
ACCURACY
95.2%

LOSS
0.24

Confusion matrix (validation set)

	AFIB	SR
AFIB	96.2%	3.8%
SR	6%	94%
F1 SCORE	0.95	0.95

Data explorer (full training set)



On-device performance

INFERENCIN...
65 ms.

PEAK RAM U...
81.0K

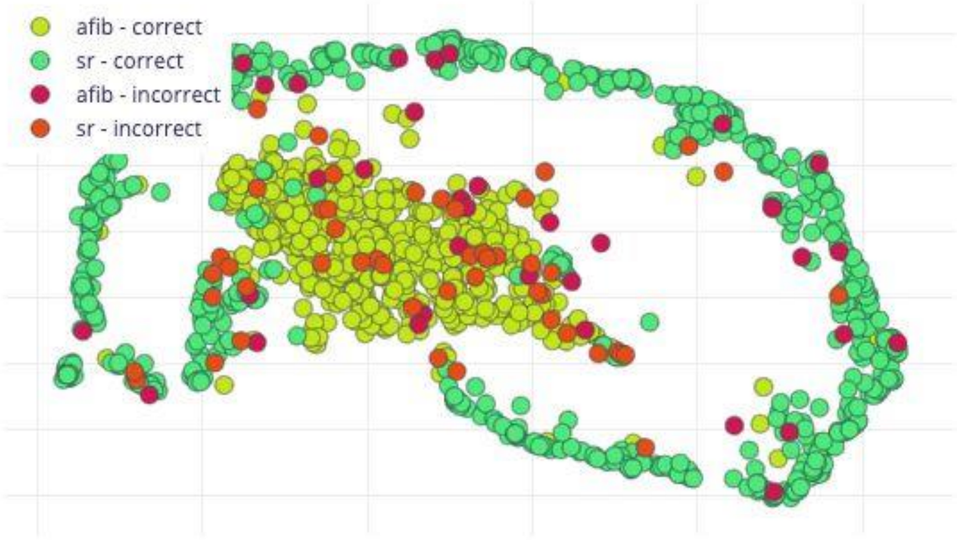
FLASH USAGE
1.3M

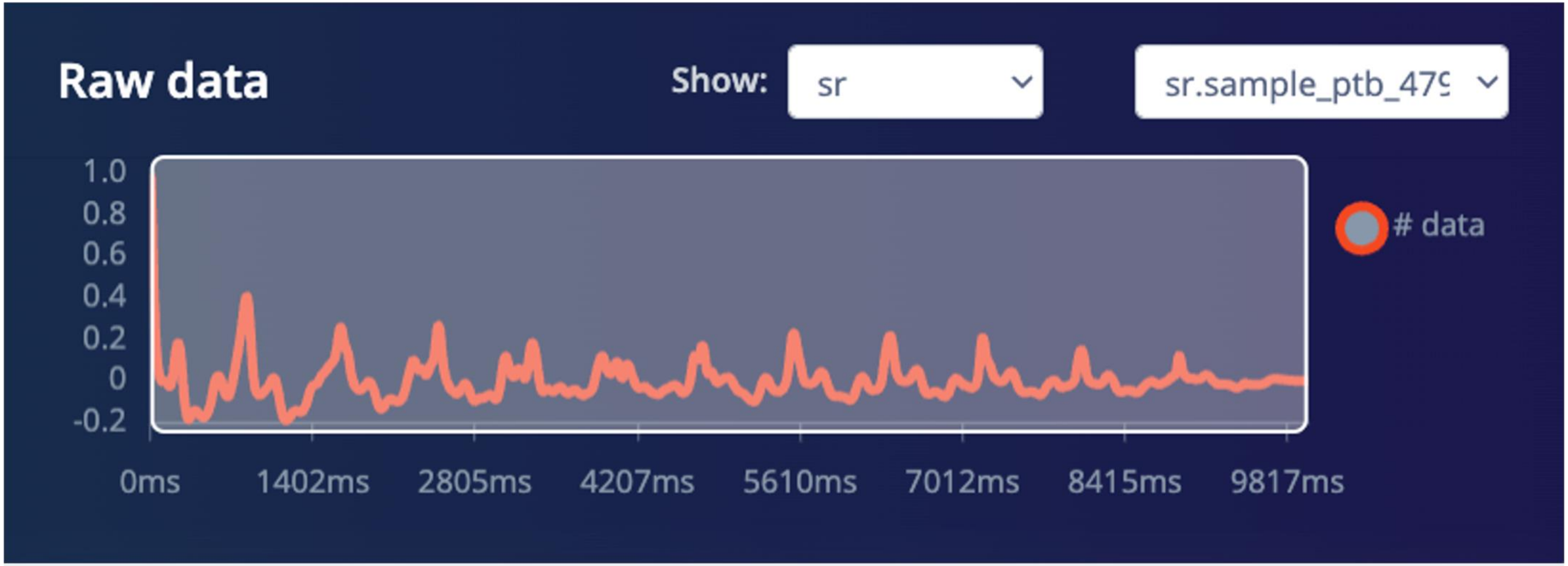
Model testing results

ACCURACY
93.49%

	AFIB	SR	UNCERTAIN
AFIB	94.0%	5.7%	0.3%
SR	6.8%	93.1%	0.1%
F1 SCORE	0.93	0.94	

Feature explorer

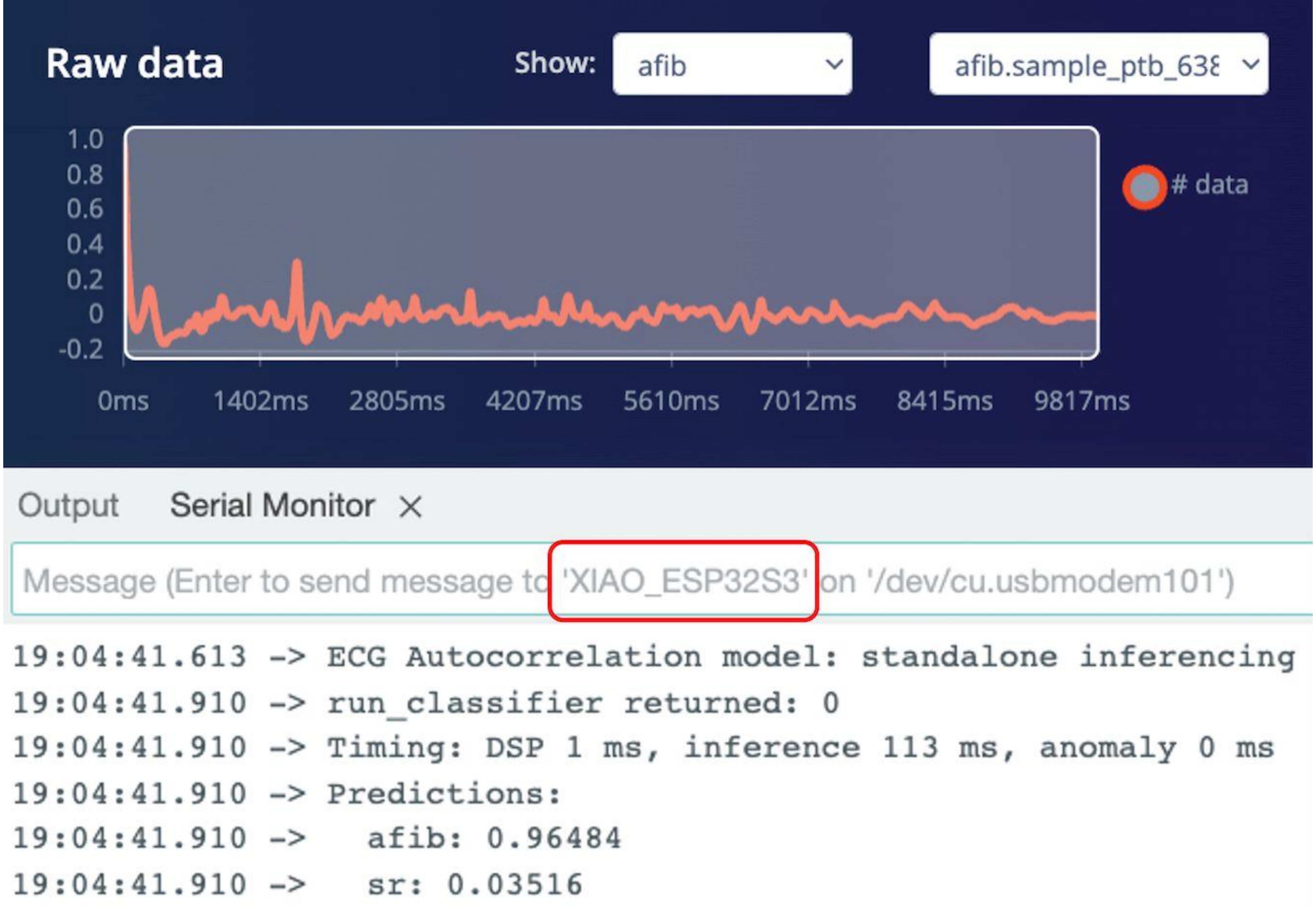




Output   Serial Monitor ×

Message (Enter to send message to 'Arduino Nicla Vision' on '/dev/cu.usbmodem101')

```
18:06:01.329 -> ECG Autocorrelation model: standalone inferencing (Arduino NiclaV)
18:06:01.362 -> run_classifier returned: 0
18:06:01.362 -> Timing: DSP 0 ms, inference 38 ms, anomaly 0 ms
18:06:01.362 -> Predictions:
18:06:01.362 ->   afib: 0.01172
18:06:01.362 ->   sr: 0.98828
```


Raw data
Show:
afib
afib.sample_ptb_638
1.0
0.8
0.6
0.4
0.2
0
-0.2
0ms
1402ms
2805ms
4207ms
5610ms
7012ms
8415ms
9817ms
data
Output
Serial Monitor
Message (Enter to send message to 'XIAO_ESP32S3' on '/dev/cu.usbmodem101')
19:04:41.613 -> ECG Autocorrelation model: standalone inferencing
19:04:41.910 -> run_classifier returned: 0
19:04:41.910 -> Timing: DSP 1 ms, inference 113 ms, anomaly 0 ms
19:04:41.910 -> Predictions:
19:04:41.910 -> afib: 0.96484
19:04:41.910 -> sr: 0.03516

Filters+Autoconvolution +Inference

PCB	TIME
XIAO ESP32-S3	8.0 s
Arduino Nicla Vision	0.5 s

TinyML: ML's Future is Tiny and Bright

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John A. Paulson School of Engineering and Applied Sciences | Harvard University |
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Be Tiny! Be Great!


DĚKUJI
OBRIGADO
ASANTE
MERCI
salamat
Shukran
TAK!
toda
Thank you
СПАСИБО
GRACIAS
ARIGATO
tack
TAKK
GRAZIE
DANKE
ДЯКУЮ