

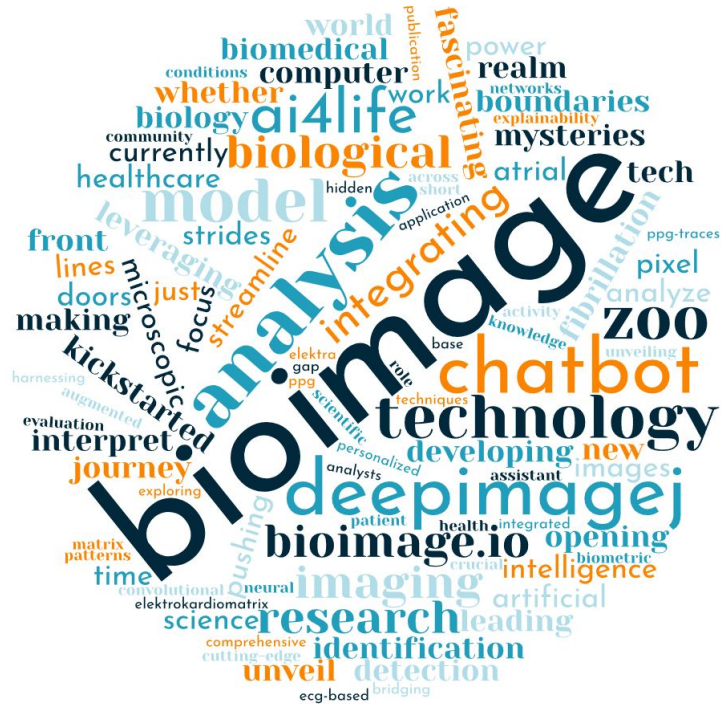
ECG and PPG applications in healthcare

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me

- **Telematics Engineering** at Universitat de les Illes Balears
- **Master in Cybersecurity** at Universidad Carlos III de Madrid
- **PhD in Computer Science and Technology** at UC3M
- **Post-doc in a Bioengineering Department** at UC3M



Content

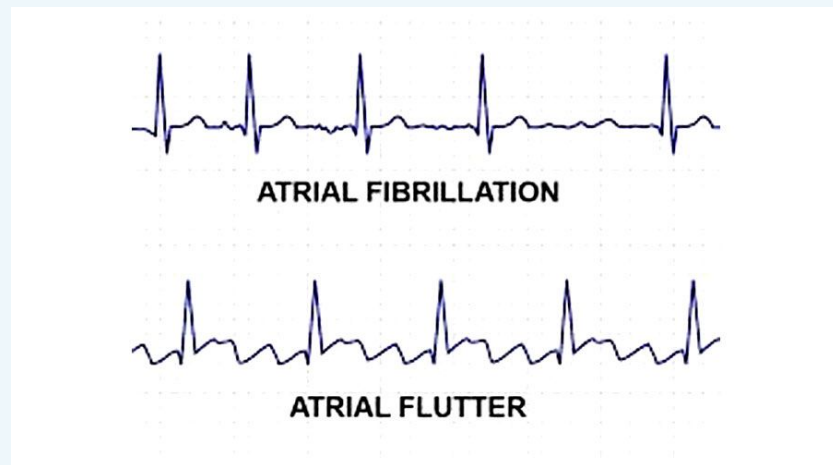
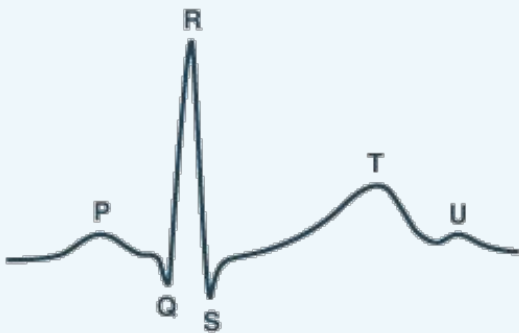
1. Cardiology Background
2. The Biometric Application on ECGs
3. From ECGs to ECMs: The Methodology
4. ECM for Patient Identification
5. Extending the methodology to PPG Signals
6. Summary and Conclusions

Background on Visualization in Cardiology

Introduction to ECGs and their medical importance

Cardiac Arrhythmias:

- Atrial Fibrillation (AF)
- Atrial Flutter (AFL)



Challenges of Interpreting Long-Term ECG Recordings

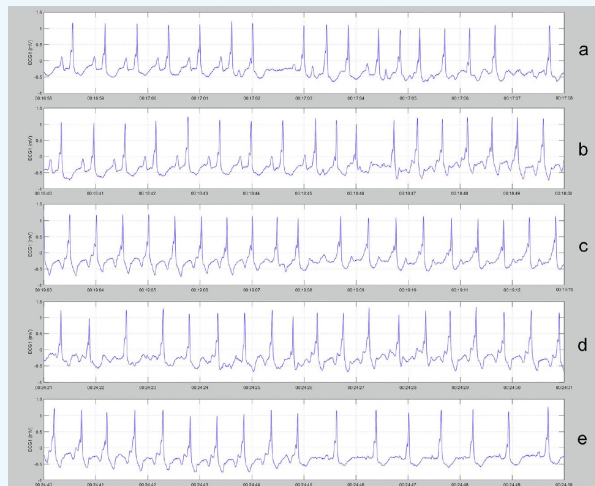
Key Challenges

- Volume of data → *hours/days*
- Time-consuming → *labour-intensive*
- Subtle features overlooked
- Context missing → *rhythm and morphology*

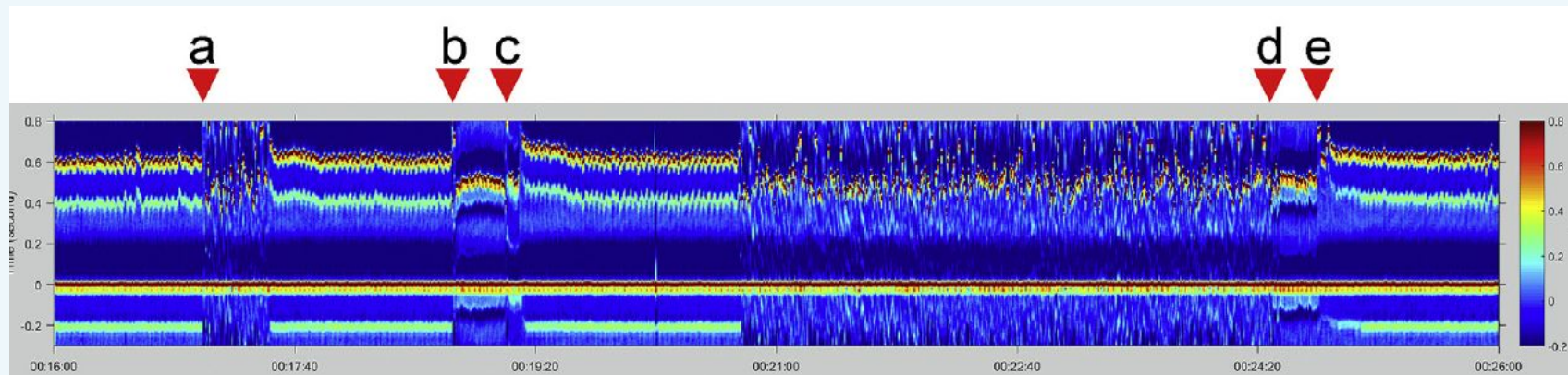
Motivation for visualization

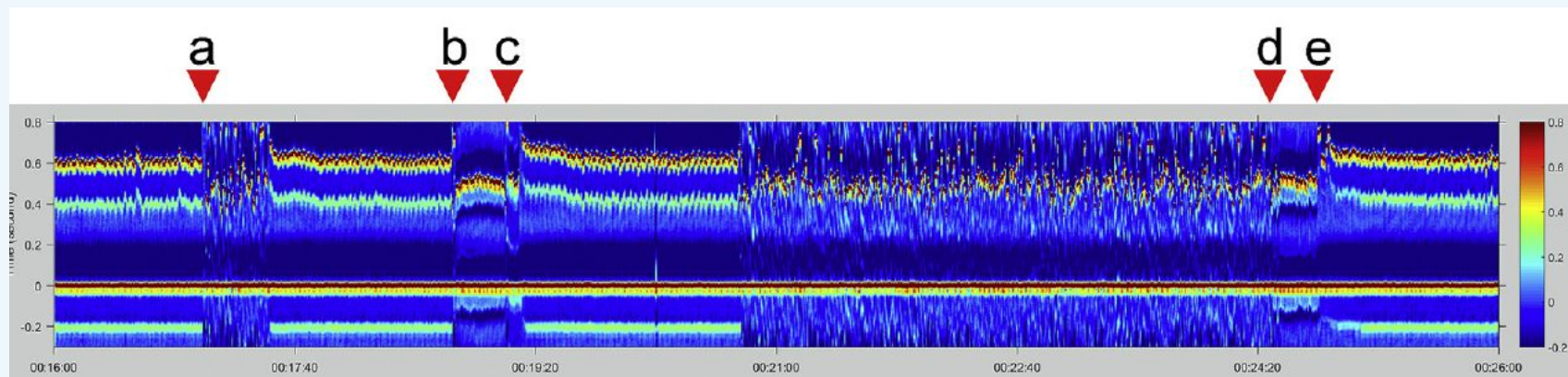
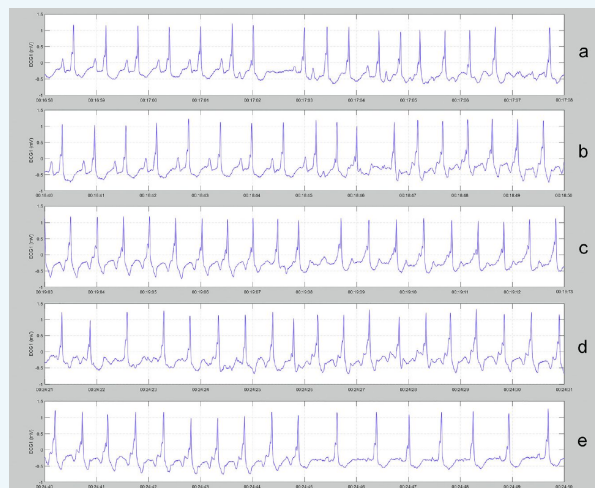
- Clear identification of **irregular** or **absent** P-waves and irregular R-R intervals
- More **interpretable** format for **long** recordings
- Display **beat-to-beat** changes for rapid detection

What a medical professional receives



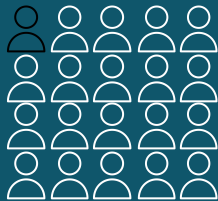
What they should receive

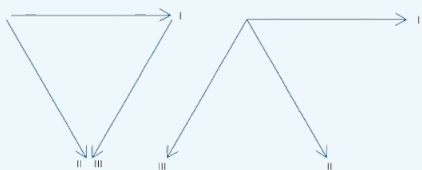




The Biometric Application on ECGs

ECGs are unique and enough to identify individuals



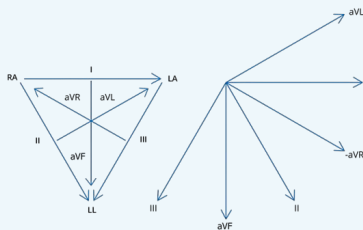


A. Goldberg
presented a new
lead configuration
for EKG.
1942

"ECG Analysis: a
new approach in
human
identification"
by L. Biel
2001

"Electrocardiomatrix: a
new method for
beat-by-beat visualisation
and inspection of cardiac
signals"
by Duan Li
2015

1902
The EKG was
first recorded
by
W. Eithoven



1981
A book wrote by
A. Goldberg of how
to read an EKG.

2002
"One-lead ECG for
identity verification"
by T. W. Shen



ECGs as a biometric system



Non-invasive



Liveliness



Inclusivity



Diagnosis

The process of ECG identification





The problem with datasets:

Privacy and Reproducibility

30% **70%**
Public Datasets Private Datasets
from a pool of 21

Diab, Mohamad O., et al. "A review on ecg-based biometric authentication systems." Hidden Biometrics (2020)



Pan-and-Tompkins

Pan, Jiapu, and Willis J. Tompkins. "A real-time QRS detection algorithm." IEEE transactions on biomedical engineering 3 (1985): 230-236.

Wavelet Transform

Alduwaile, Dalal, and Md Saiful Islam. "Single heartbeat ECG biometric recognition using convolutional neural network." 2020 International Conference on Advanced Science and Engineering (ICOASE). IEEE, 2020.

Adaptative Filtering

Widrow, Bernard, et al. "Adaptive noise cancelling: Principles and applications." Proceedings of the IEEE 63.12 (1975): 1692-1716.

Singular Value Decomposition (SVD)

Liu, Fang, et al. "The ECG identification based on GRNN." 2018 IEEE International Conference on Communication Systems (ICCS). IEEE, 2018.

Independent Component Analysis (ICA)

Yang, Weiyi, et al. "A novel method for identifying electrocardiograms using an independent component analysis and principal component analysis network." Measurement 152 (2020): 107363.



Handcrafted

Non-handcrafted

Fiducial

Non-fiducial

Fiducial

Non-fiducial

Lifting scheme

Wavelet Transform

-

CNN

Wavelet Transform

RNN

"Electrocardiogram signals de-noising using lifting-based discrete wavelet transform." Computers in Biology and Medicine (2004)

"Toward improving electrocardiogram biometric verification using mobile sensors: A two-stage classifier approach." Sensors (2017)

"Deep-ECG: Convolutional neural networks for ECG biometric recognition." Pattern Recognition Letters (2019)

"A deep bidirectional GRU network model for biometric ECG classification based on RNN." IEEE Access (2019)

FIDUCIAL ANALYSIS



NON-FIDUCIAL ANALYSIS

- Similar to the one conducted by medical professionals
- Used as features for user identification
- Computationally costly

- Focus on the whole signal, not specific points
- The EKG can be processed in time, frequency, time-frequency or as an image
- Less costly through a NN



Handcrafted

Non-handcrafted

Fiducial

Non-fiducial

Fiducial

Non-fiducial

Lifting scheme

Wavelet Transform

-

CNN

Wavelet Transform

RNN

"Electrocardiogram signals de-noising using lifting-based discrete wavelet transform." Computers in Biology and Medicine (2004)

"Toward improving electrocardiogram biometric verification using mobile sensors: A two-stage classifier approach." Sensors (2017)

"Deep-ECG: Convolutional neural networks for ECG biometric recognition." Pattern Recognition Letters (2019)

"A deep bidirectional GRU network model for biometric ECG classification based on RNN." IEEE Access (2019)



Template Matching (TM)

Liu, Jikui, et al. "A multiscale autoregressive model-based electrocardiogram identification method." IEEE Access 6 (2018): 18251-18263.

Support Vector Machine (SVM)

Aziz, Sumair, et al. "ECG-based biometric authentication using empirical mode decomposition and support vector machines." 2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON). IEEE, 2019.

Random Forest (RF)

Tan, Robin, and Marek Perkowski. "ECG biometric identification using wavelet analysis coupled with probabilistic random forest." 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA). IEEE, 2016.

Logistic Regression (LR)

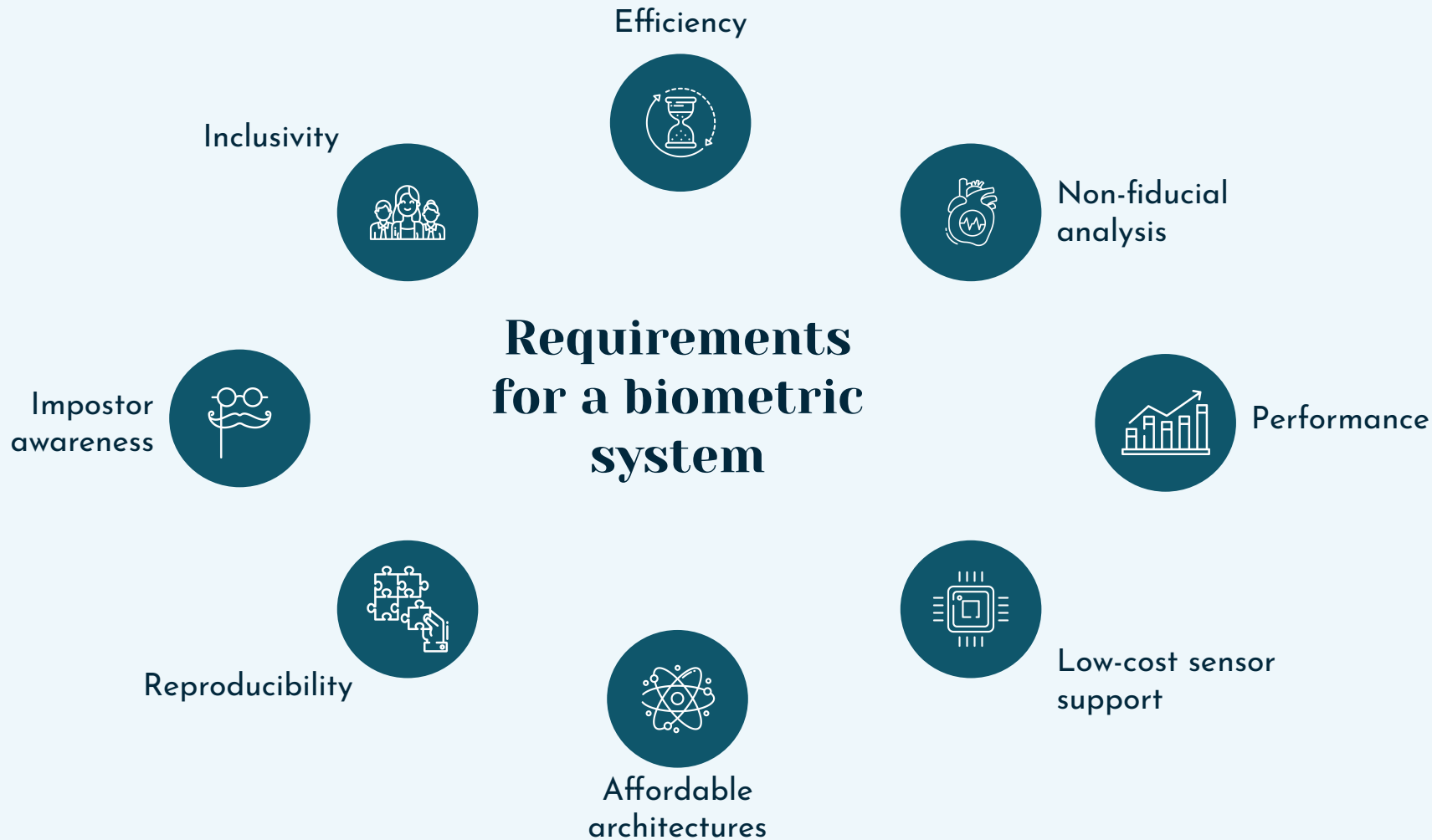
Chandrashekhar, Vishnu, et al. "Pulse id: the case for robustness of ecg as a biometric identifier." 2020 IEEE 30th International Workshop on Machine Learning for Signal Processing (MLSP). IEEE, 2020.

k-Nearest Neighbour (k-NN)

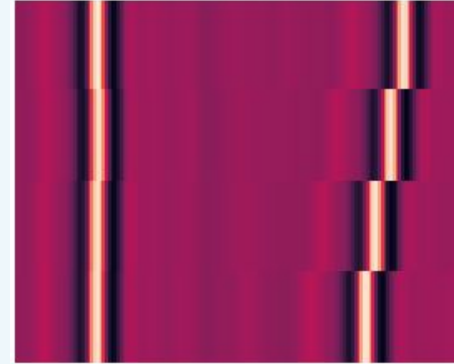
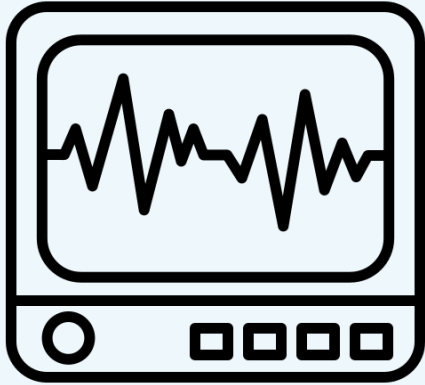
Wübbeler, Gerd, et al. "Verification of humans using the electrocardiogram." Pattern Recognition Letters 28.10 (2007): 1172-1175.

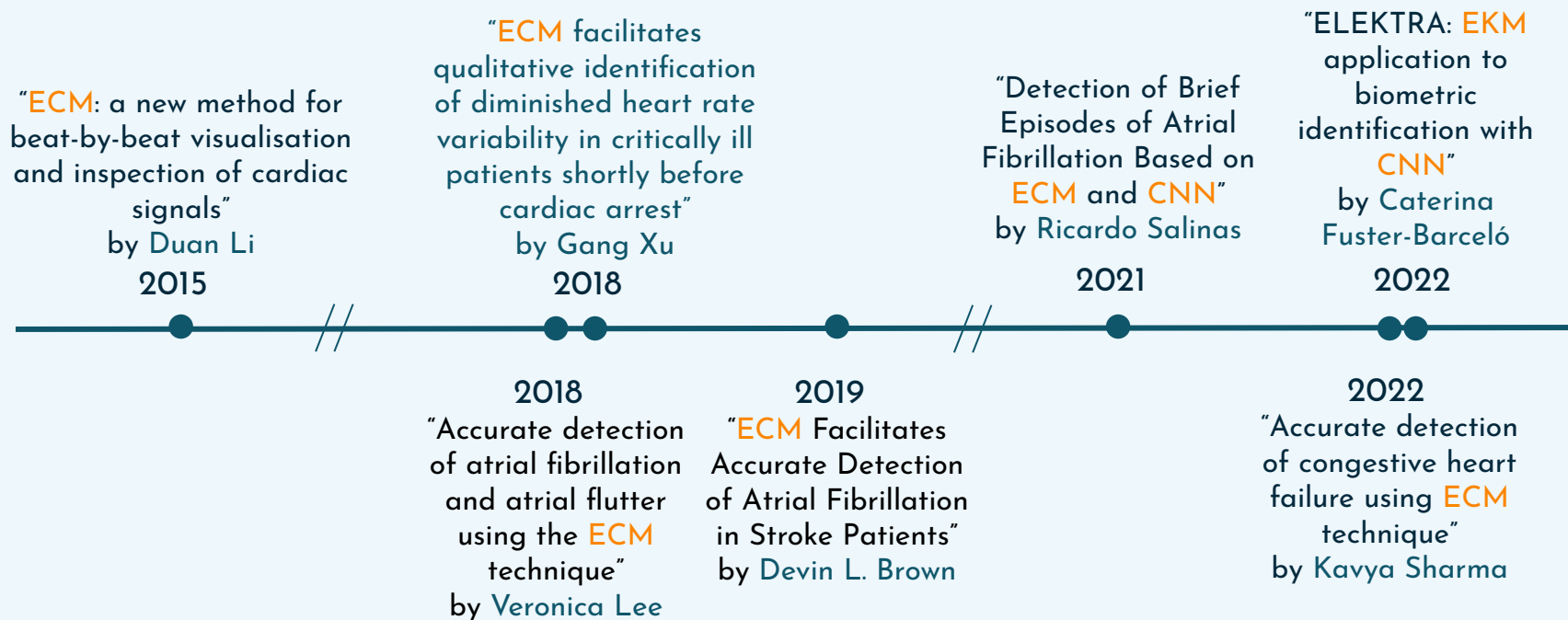
Convolutional Neural Networks (CNN)

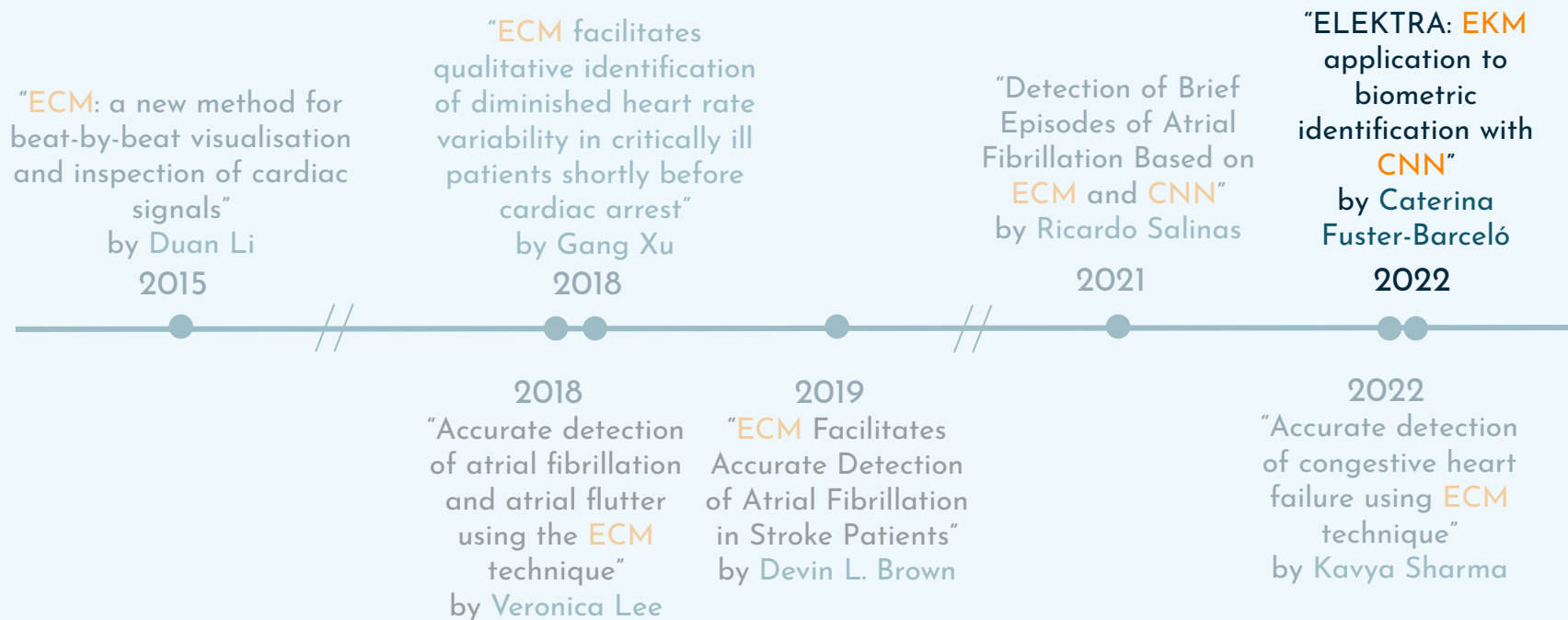
Li, Yazhao, et al. "Toward improving ECG biometric identification using cascaded convolutional neural networks." Neurocomputing 391 (2020): 83-95.

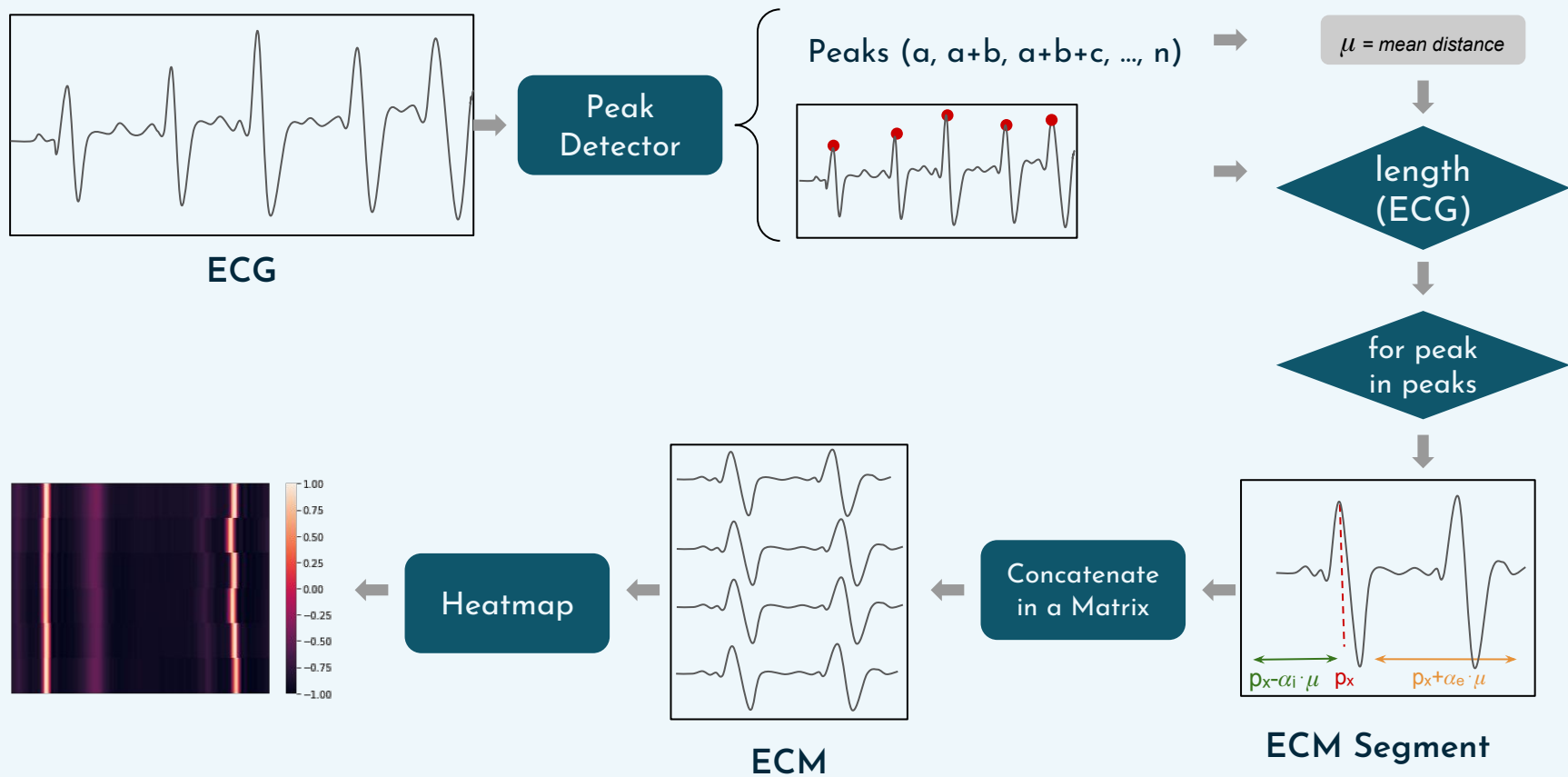


From Electrocardiograms to Electrocardiomatrix



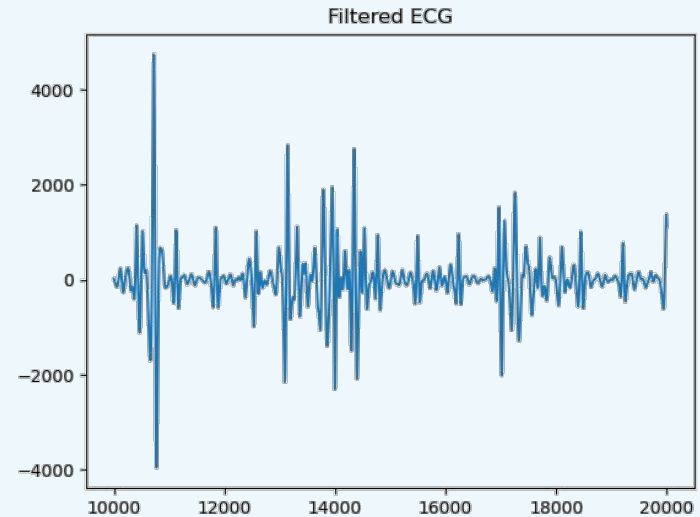
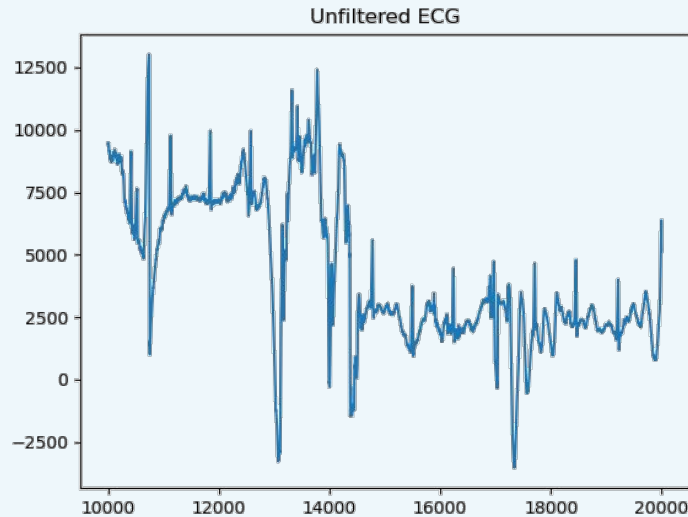






Signal Preprocessing

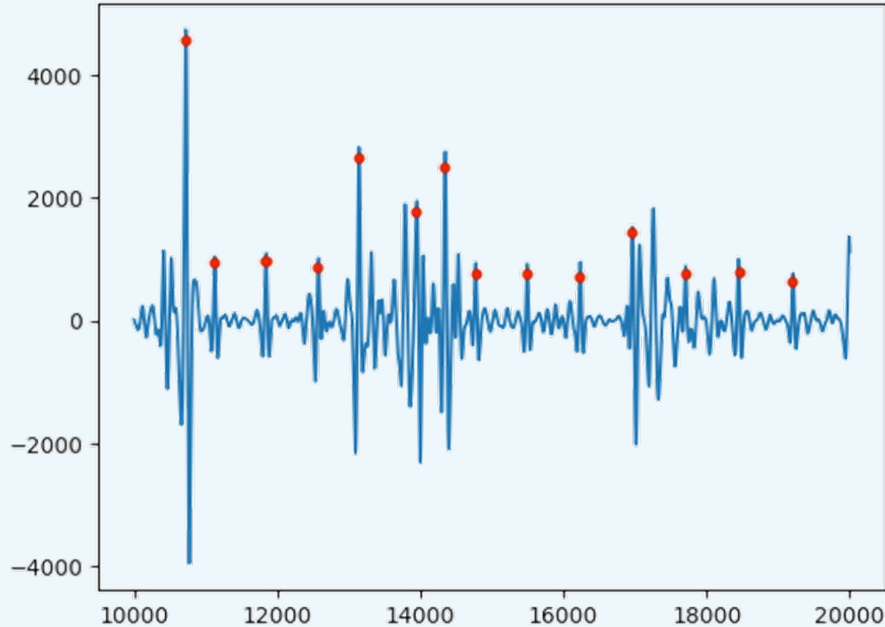
From a raw ECG signal to a processed and clean ECG signal with a list of its R-peaks with Pan and Tompkins



Pan, Jiapu, and Willis J. Tompkins. "A real-time QRS detection algorithm." IEEE transactions on biomedical engineering (1985)

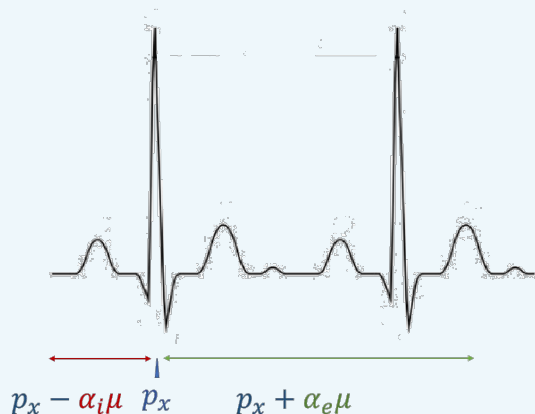
Signal Preprocessing

From a raw ECG signal to a processed and clean ECG signal with a list of its R-peaks with Pan and Tompkins



Construction of the ECM

Creating segments for each R-peak of the ECM



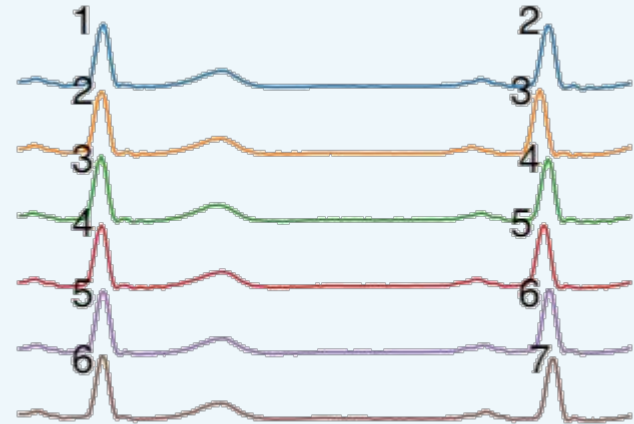
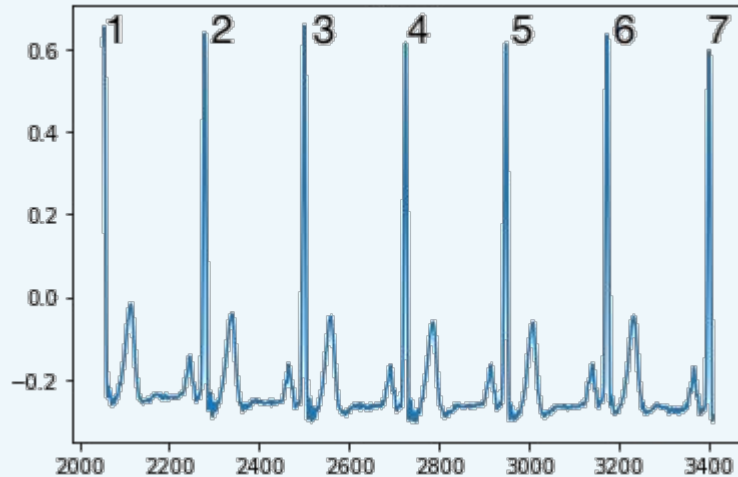
$$InitSegment = p_x - \alpha_i \mu$$

$$EndSegment = p_x + \alpha_e \mu$$

github.com/cfusterbarcelo/ELEKTRA-approach

Construction of the ECM

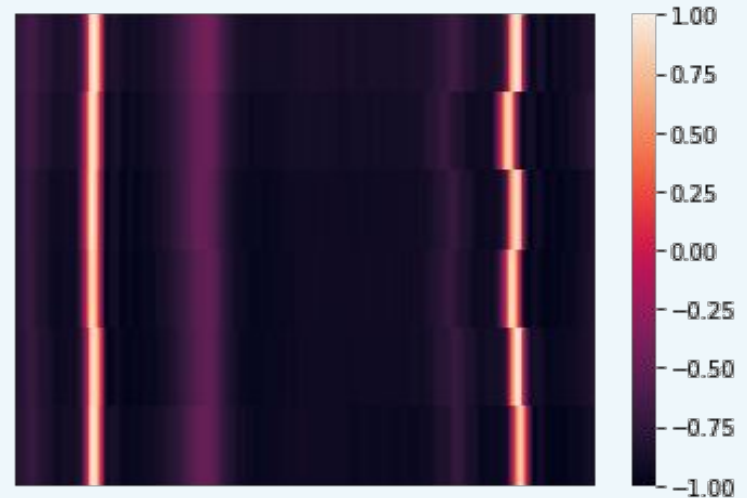
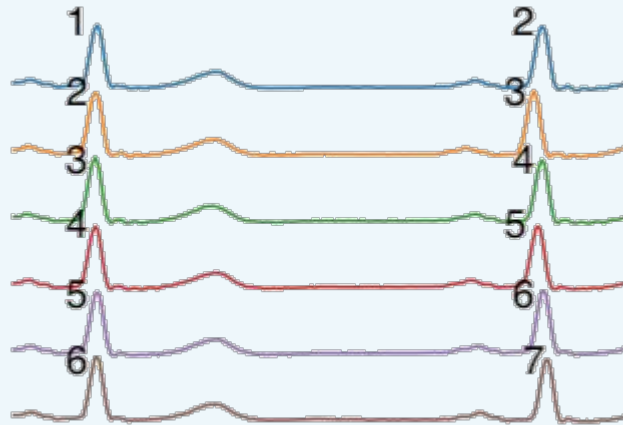
Converting the ECG signal into a matrix



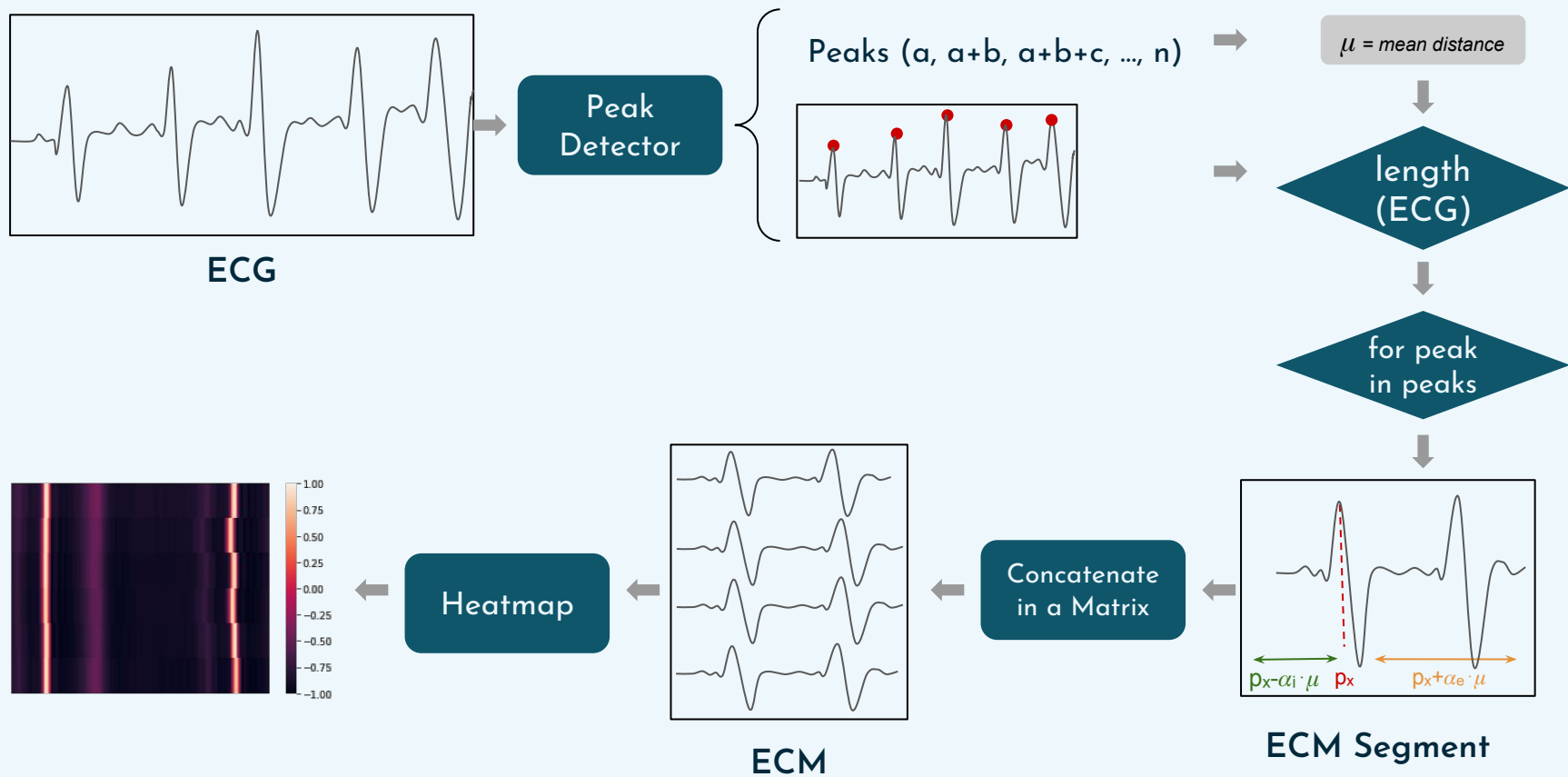
github.com/cfusterbarcelo/ELEKTRA-approach

Construction of the ECM

Converting the ECG signal into a matrix



github.com/cfusterbarcelo/ELEKTRA-approach



Beats per frame (bpf)

A hyperparameter that can be chosen according to each case



3bpf



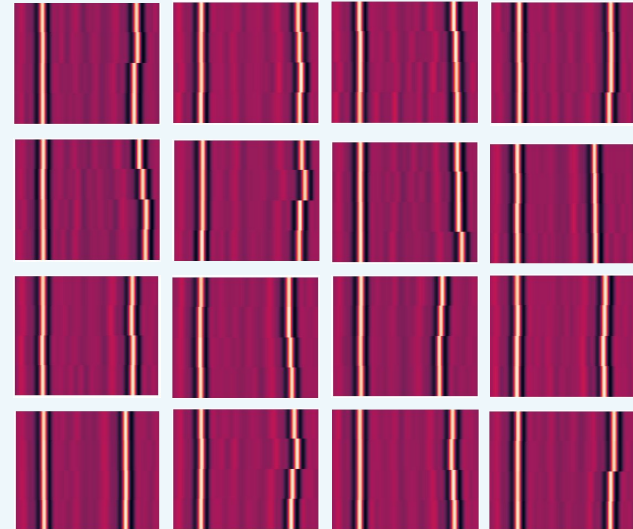
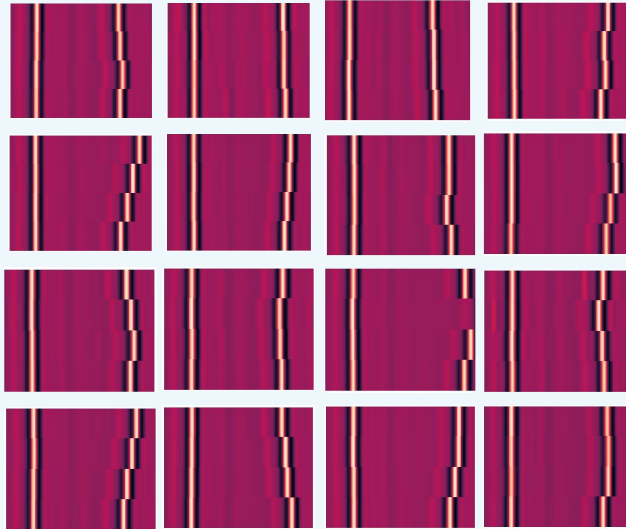
5bpf



7bpf

Construction of the ECM

Reproduce for each user and database



Electrocardiomatrix for Patient Identification

Patient identification in health care

- In 712 hospitals from USA, 2,463,727 wristbands were examined and 2.7% (67,289) errors were found in which the 49.5% were due to the absence of wristbands.
- A 2016 study classified 7,600/10,915 events as wrong-patient events involving patient identification such as patient misidentification, duplicate records and others.
- An international research with 181 health organisations reported 7,613 cases of misidentification of patients.



"Interventions to reduce patient identification errors in the hospital setting: a systematic review protocol" (2019)

"Patient Identification Techniques - Approaches, Implications, and Findings" (2020)

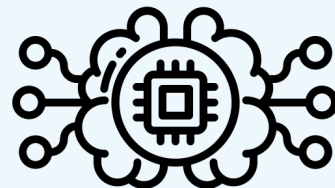
Patient identification in health care: **the proposal**

- **Unification** of health care system (Spain).
- Use ELEKTRA as a biometric system: **inclusive**, no need to be **awake**, possibility of **diagnosis**, accessible **acquisition** system...
- Previous **enrollment** of users
- Possible application in many **different situations**: unconscious or unresponsive patient, loose of wristband, avoid duplicates, etc



Convolutional Neural Networks

A Convolutional Neural Network (ConvNet/**CNN**) is a **Deep Learning algorithm** which can take in an input **image**, assign importance (learnable weights and biases) to various **aspects**/objects in the image and be able to **differentiate one from the other**.



Deep Neural Networks



Images

12.214, 45.600, 49.225, 56.318 ...
98.200, 1.253, 25.365, 12.549 ...
4.568, 83.106, 32.510, 11.258 ...

Numerical Data

Could you correct this email?

Yes. Here you have it: ...

Conversations

Others



Yes/No - {0, 1, ...N}

Classification

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua.

Text



Images

12.214, 45.600, 49.225, 56.318 ...
98.200, 1.253, 25.365, 12.549 ...
4.568, 83.106, 32.510, 11.258 ...

Numerical Data

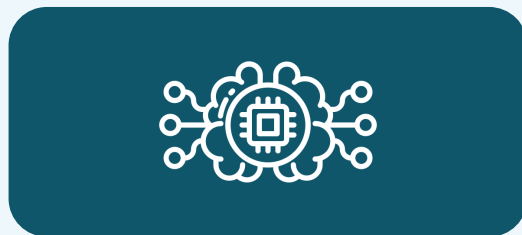
CNNs for Classification: Training



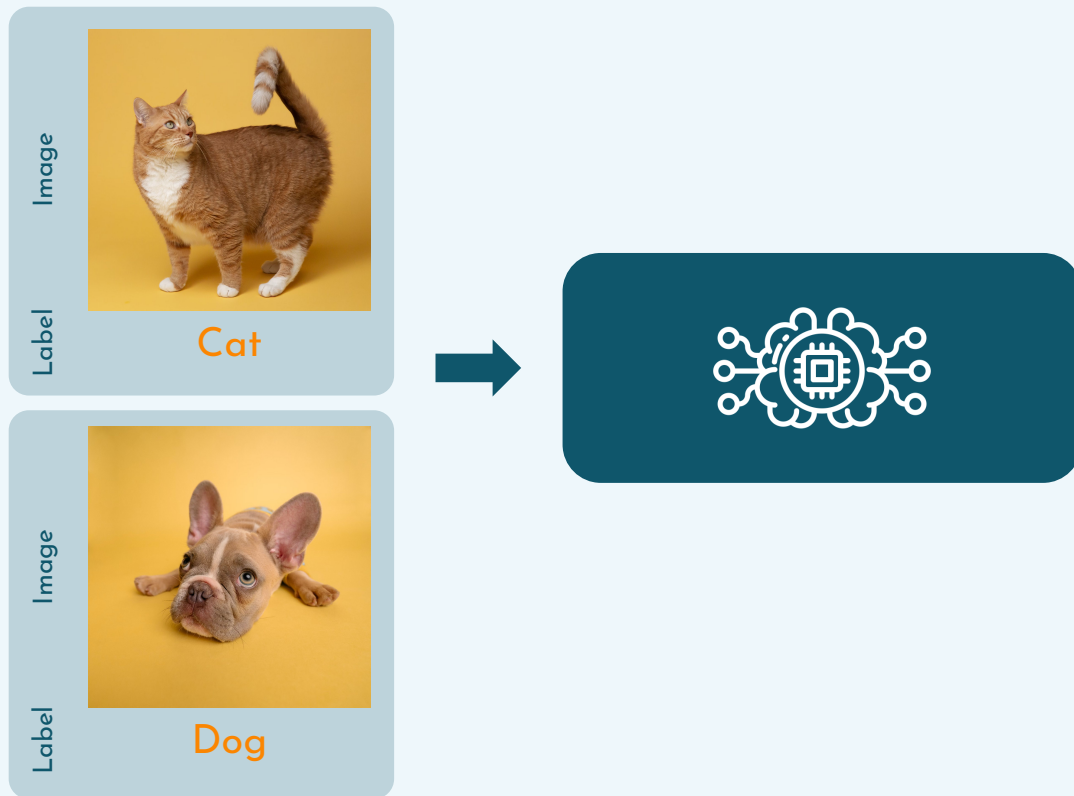
Cat



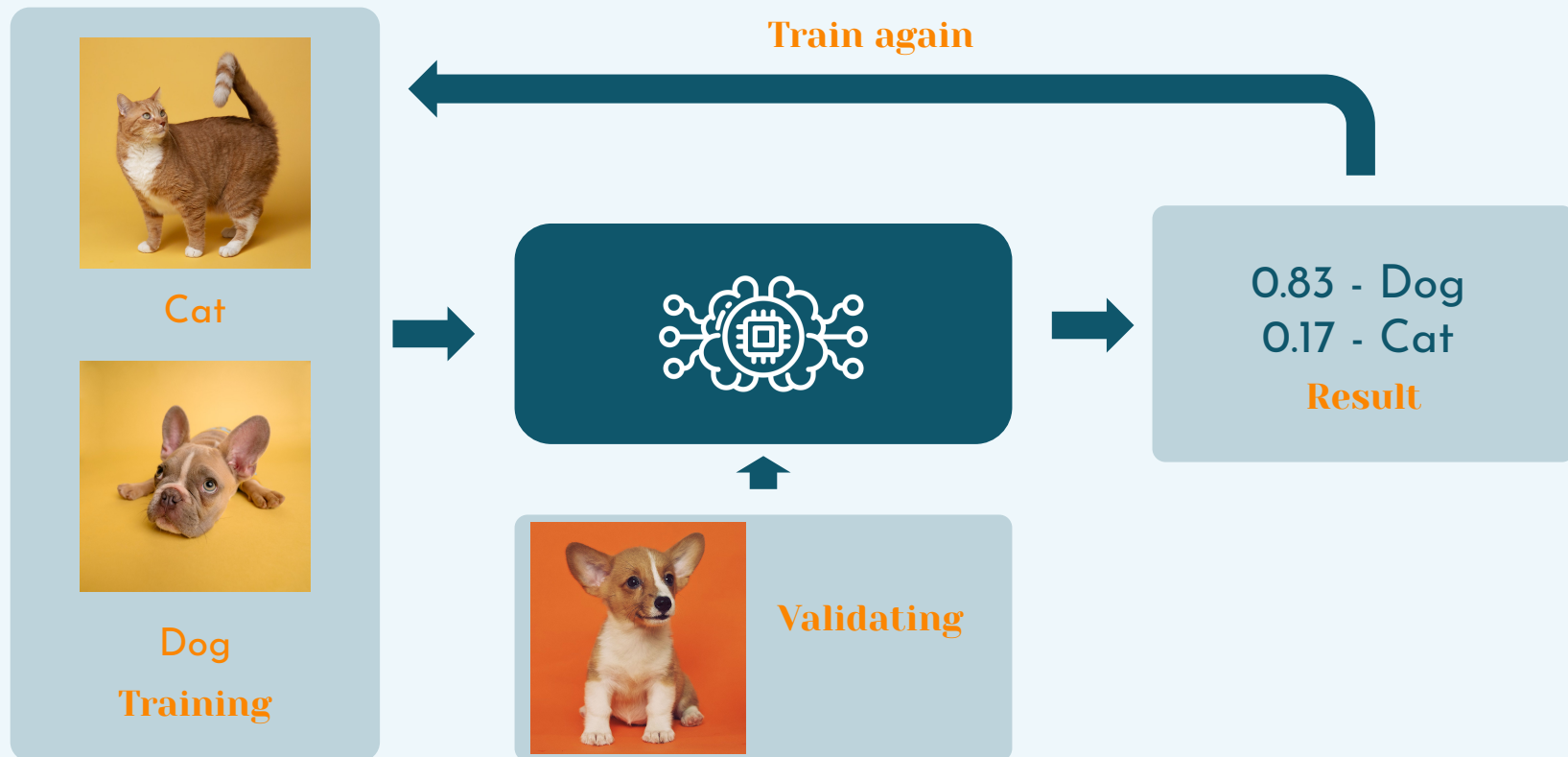
Dog



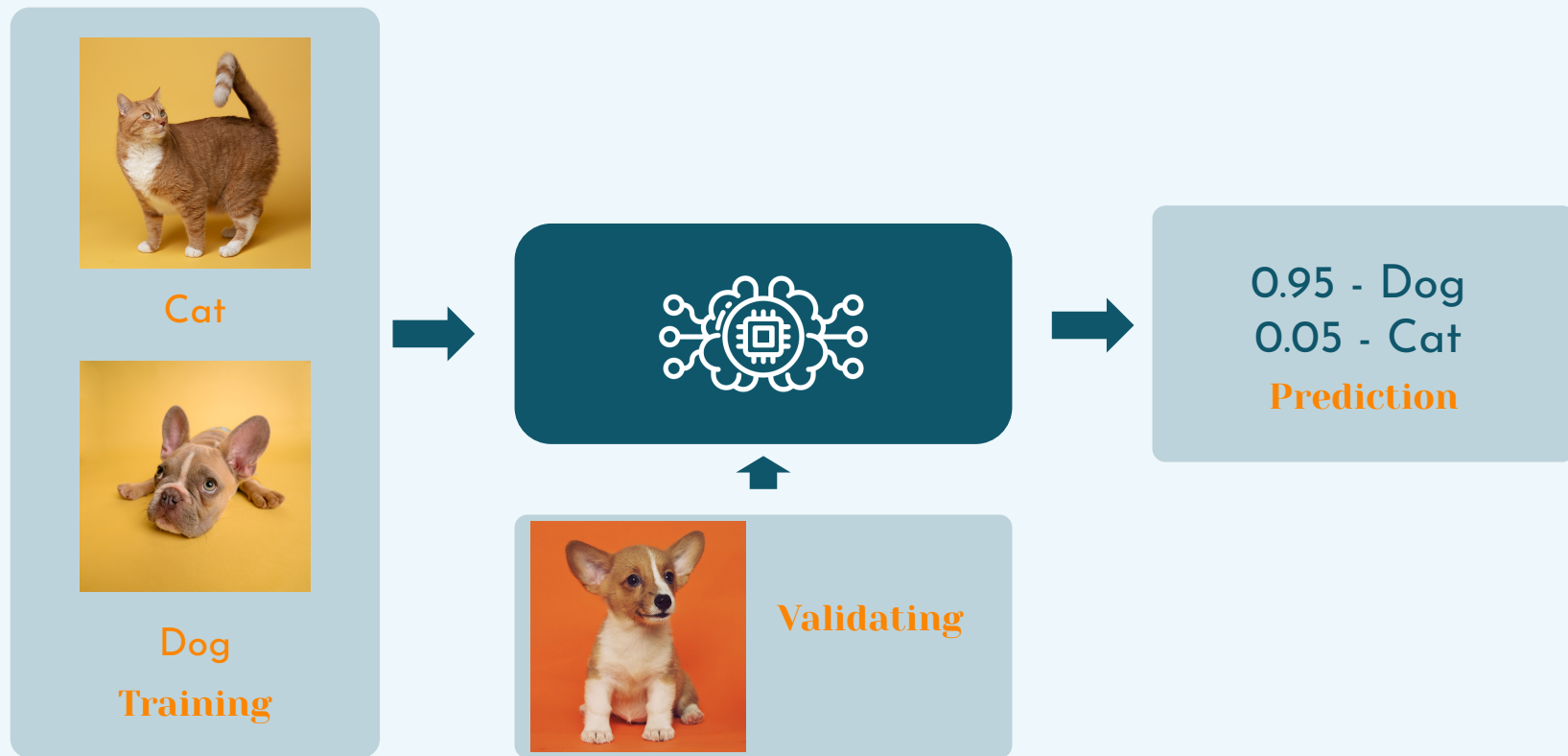
CNNs for Classification: Training



CNNs for Classification: **Training**



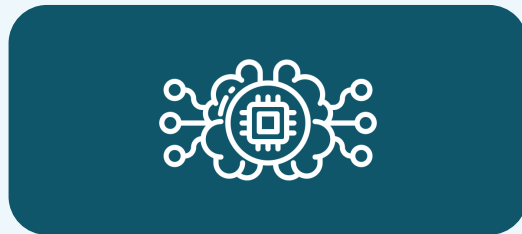
CNNs for Classification: **Training**



CNNs for Classification: Testing



Cat? Dog?

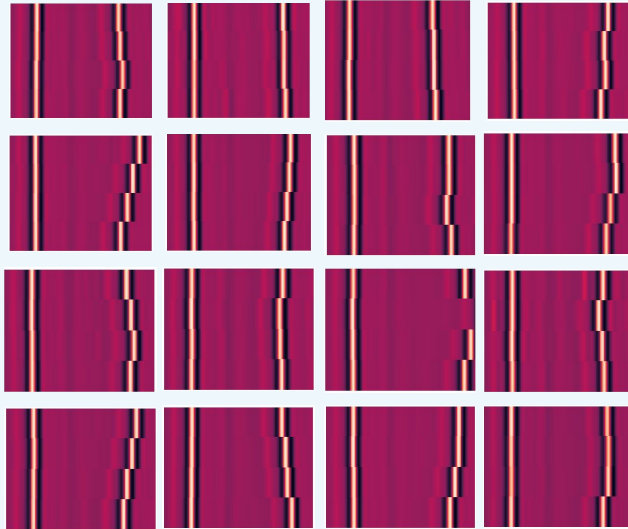


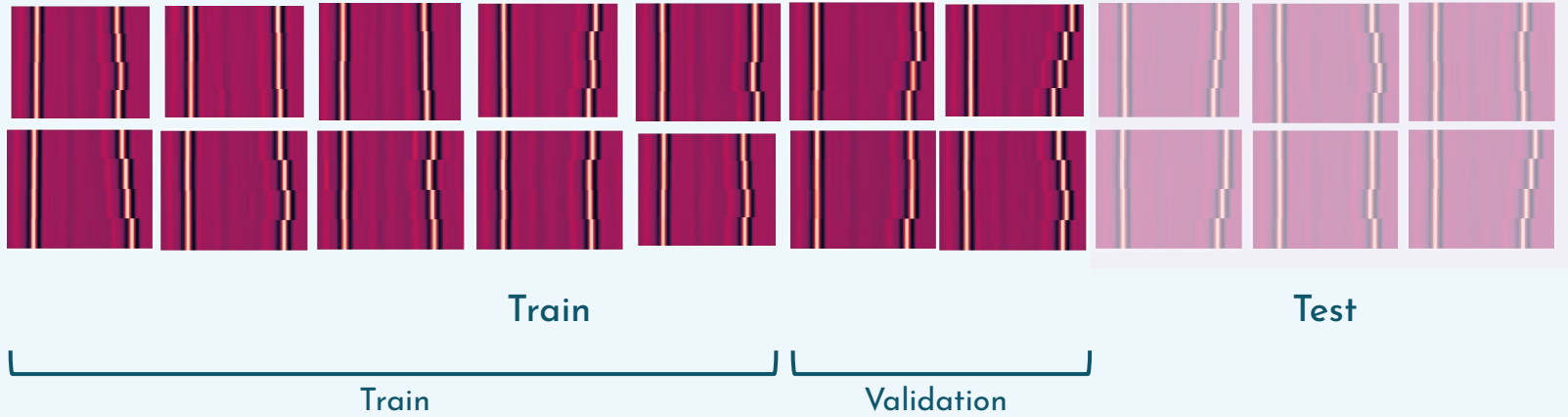
0.03 - Dog
0.97 - Cat

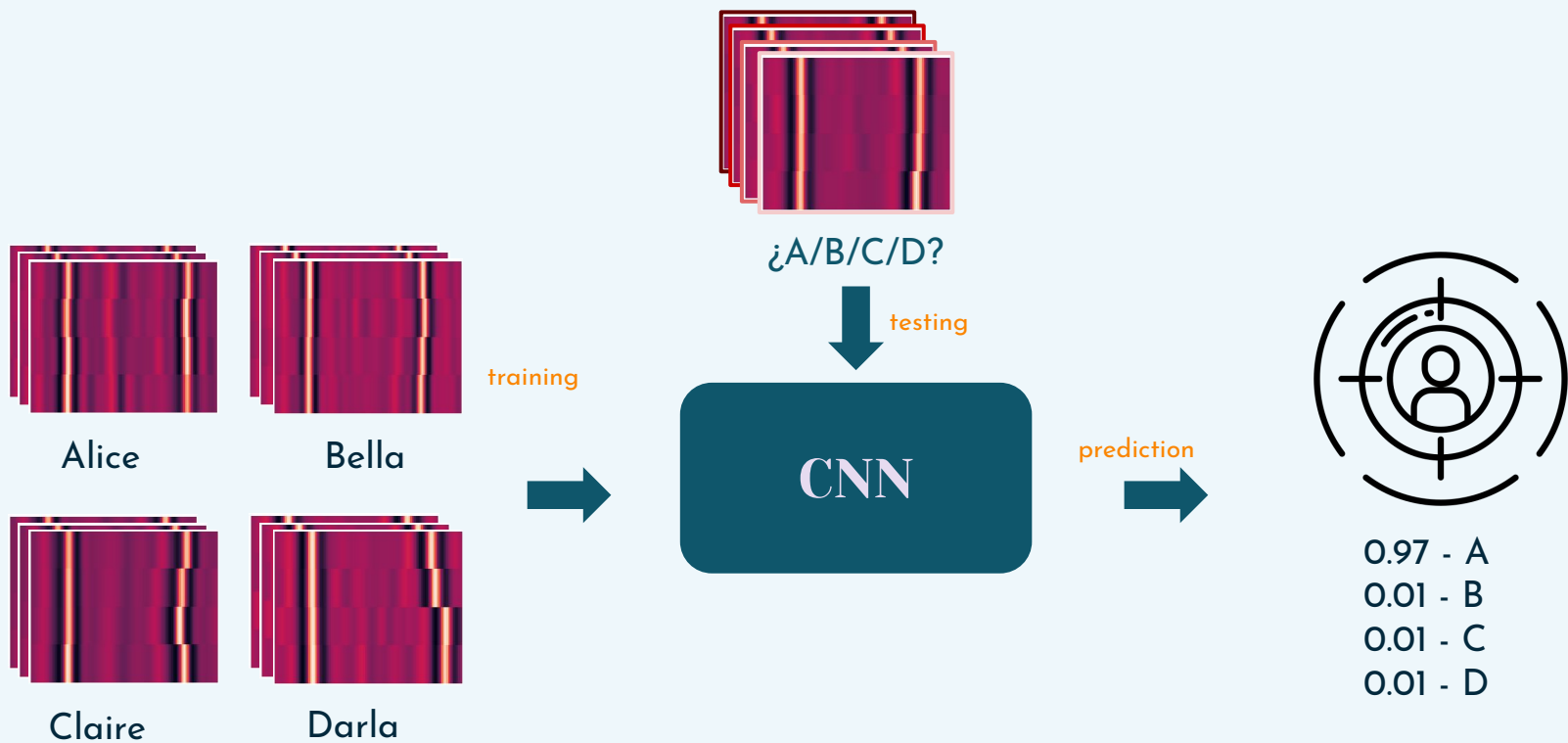
Prediction

ECM database

Obtained from different ECGs from different users

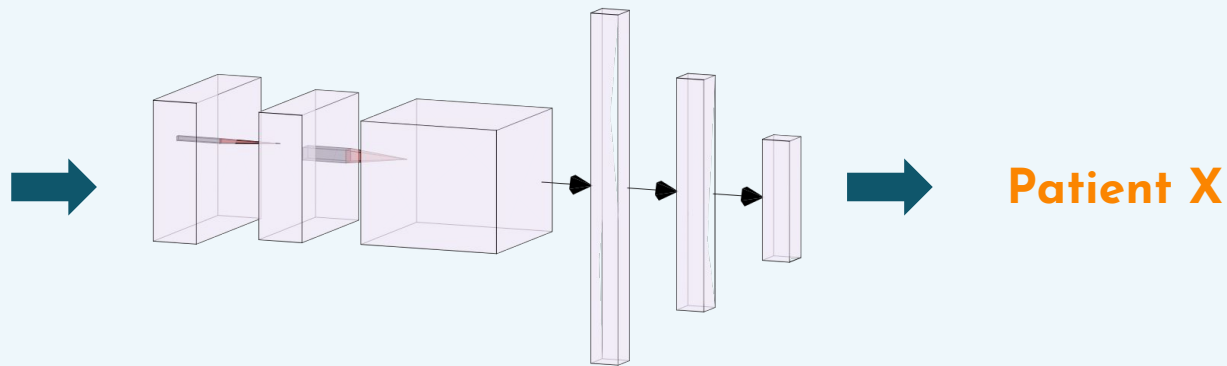












Who is this?







A 2-layer CNN

ECM Datasets

	Train (%) Validation	Test (%)	#ECMs		
			(3bpf)	(5bpf)	(7bpf)
 Normal Sinus Rhythm Database (NSRDB)	80 30	20	54,000	54,000	54,000
 MIT-BIH Arrhythmia Database (MIT-BIHDB)	90 10	10	35,949	21,149	15,119
 Physikalisch-Technische Bundesanstalt Database (PTBDB)	90 10	10	9,854	5,891	4,180
 Glasgow University Database (GUDB)	90 10	10	8,099	4,816	-

ECM Datasets

	Subjects	Records	Sampling Rate (Hz)
 Normal Sinus Rhythm Database (NSRDB)	18	18	128
 MIT-BIH Arrhythmia Database (MIT-BIHDB)	47	48	360
 Physikalisch-Technische Bundesanstalt Database (PTBDB)	290	549	1000
 Glasgow University Database (GUDB)	25	125	250

Control Users

Control users are the ones considered to be healthy. Users from the **NSRDB** are used as the **baseline** for the studies as a biometric system.

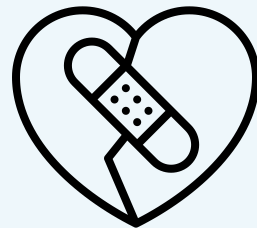


Influence of bpf and time costs of convergence

bpf	Epochs	Accuracy (%)	FAR (%)	FRR (%)
3	100	99.50	0.03	0.50
	150	99.04	0.06	0.96
	200	99.69	0.02	0.31
5	100	99.78	0.01	0.22
	150	99.82	0.01	0.18
	200	99.69	0.02	0.31
7	100	99.67	0.02	0.33
	150	99.84	0.01	0.15
	200	99.84	0.01	0.16

Users with CVD

In a **real-world scenario** there are healthy users and users with different **CVD**. A study over the **MIT-BIHDB** and the **PTBDB** will show the adaptability to this real-world scenario.



Study of ELEKTRA over the MIT-BIHDB

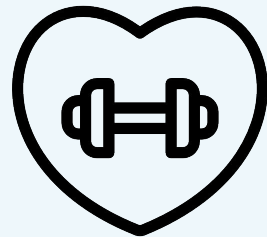
Exp	#EKM	Epochs	Accuracy (%)	FAR (%)	FRR (%)
3	35,949	100	96.88	0.07	3.12
		150	96.80	0.07	3.20
		200	96.38	0.71	3.17
5	21,149	100	96.12	0.08	3.88
		150	97.63	0.05	2.37
		200	97.89	0.07	3.27
7	15,119	100	95.92	0.09	4.08
		150	96.12	0.08	3.88
		200	97.89	0.04	2.11

Study of ELEKTRA over **CVD** from users of the PTBDB

bpf	#EKM	Epochs	Accuracy (%)	FAR (%)	FRR (%)
3	7,266	150	89.61	0.05	11.45
		200	93.91	0.05	10.20
		250	94.40	0.03	6.04
		300	97.09	0.03	6.04
5	4,350	150	84.13	0.10	15.87
		200	88.91	0.01	11.09
		250	93.04	0.05	6.96
		300	95.00	0.03	5.00
7	3,066	150	65.10	0.25	34.90
		200	81.21	0.13	18.79
		250	88.26	0.09	11.74
		300	86.58	0.10	13.42

Users with different heartbeat rates

The **GUDB** is the database chosen to evaluate users performing **activities**. Those activities are: *sitting*, *walking on a treadmill*, doing a *maths exam*, using a *hand-bike* and *jogging* on a treadmill.



Study of ELEKTRA over the **GUDB**

bpf	#EKM	Epochs	Accuracy (%)	FAR (%)	FRR (%)
3	8,099	150	89.06	0.45	11.62
		200	88.81	0.47	11.49
		250	91.32	0.36	9.06
5	4,816	150	79.19	0.87	20.81
		200	81.89	0.75	18.11
		250	82.47	0.73	17.53

Study of ELEKTRA over the GUDB by activity with 3bpf

Activity	#EKM	Epochs	Accuracy (%)	FAR (%)	FRR (%)
Sitting	1,335	200	99.19	0.03	0.81
Walking	1,556	250	98.59	0.06	1.41
Maths	1,474	200	94.00	0.25	6.00
Biking	1,529	200	95.51	0.19	4.49
Jogging	2,205	150	82.63	0.72	17.37

Requirements for a biometric system

Efficiency



Inclusivity



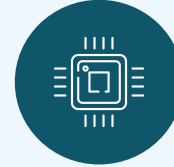
Non-fiducial
analysis



Performance



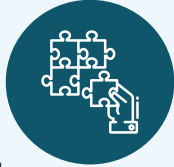
Low-cost sensor
support



Affordable
architectures



Reproducibility

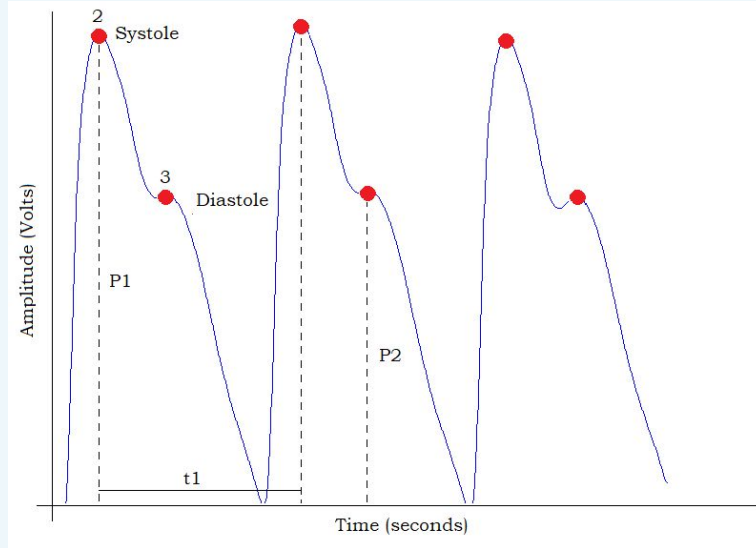


Impostor
awareness



Extending the Methodology to PPG Signals

What is PPG?

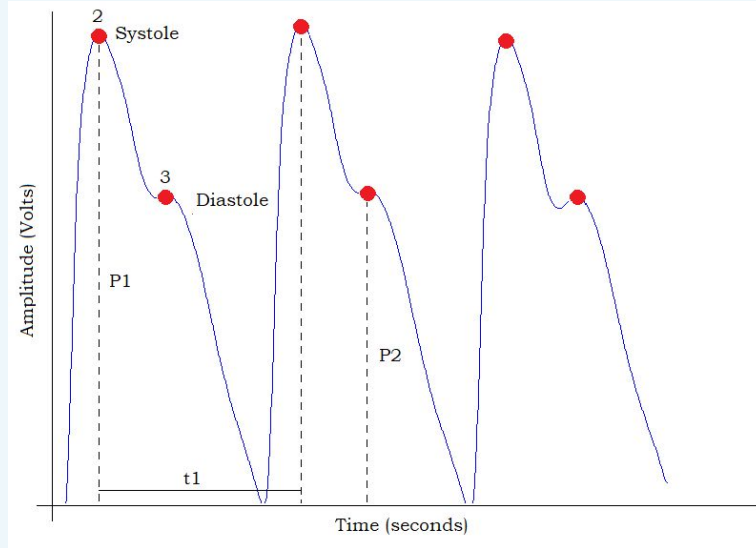


Photoplethysmography
(PPG)



PowerPuff Girls
(PPG)

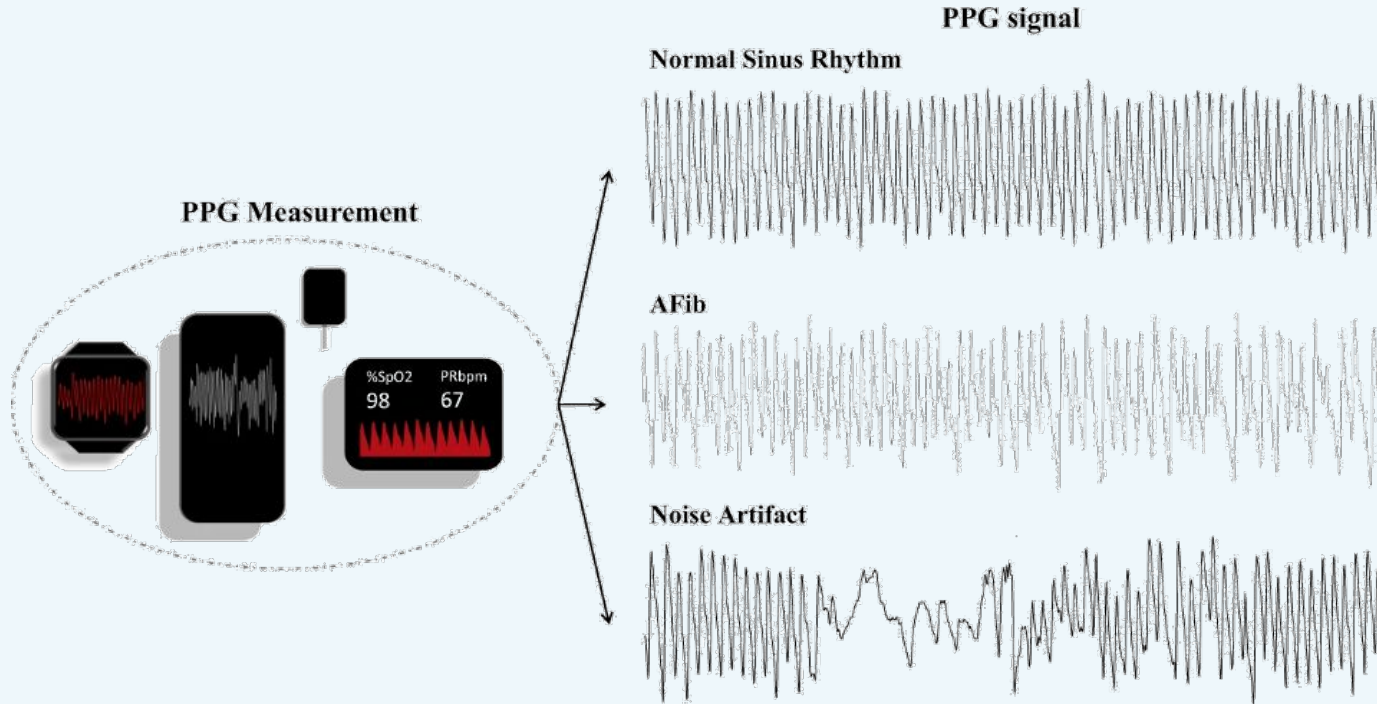
What is PPG?



PhotoPlethysmoGraphy (PPG)

- It measures **blood volume** changes in peripheral circulation.
- A LED emits light on the skin and a **photodetector** measures **variations** in light absorption forming **fluctuations** in a PPG signal.

What is PPG?



Photoplethysmography based atrial fibrillation detection: a review, Nature 2020

PPGs and AFib Detection



Non-invasive and Easily accessible



Captures Irregular Heart Rhythms in AFib



High Sensitivity to High Rate Variability (HRV)



Works Well in Daily Scenarios

PPGs On Matrix Setup

1

AFib causes high **irregularity** in heartbeat intervals that are easily **captured** through PPGs

2

PPG also reflects **individual cardiovascular traits** as in Patient Identification

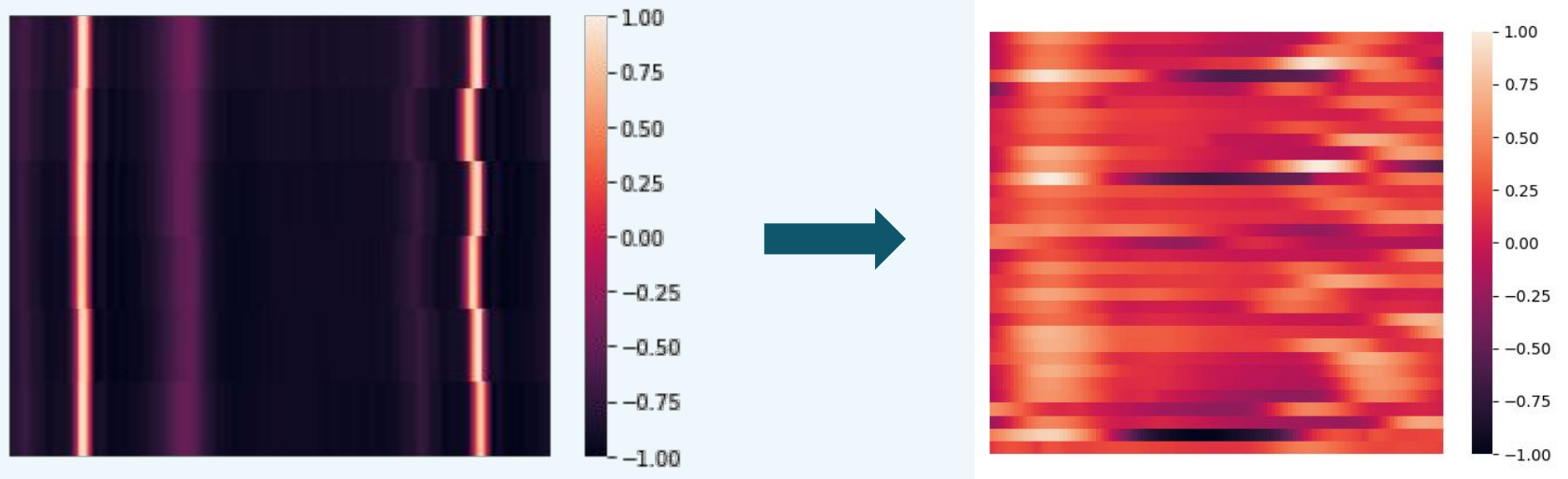
3

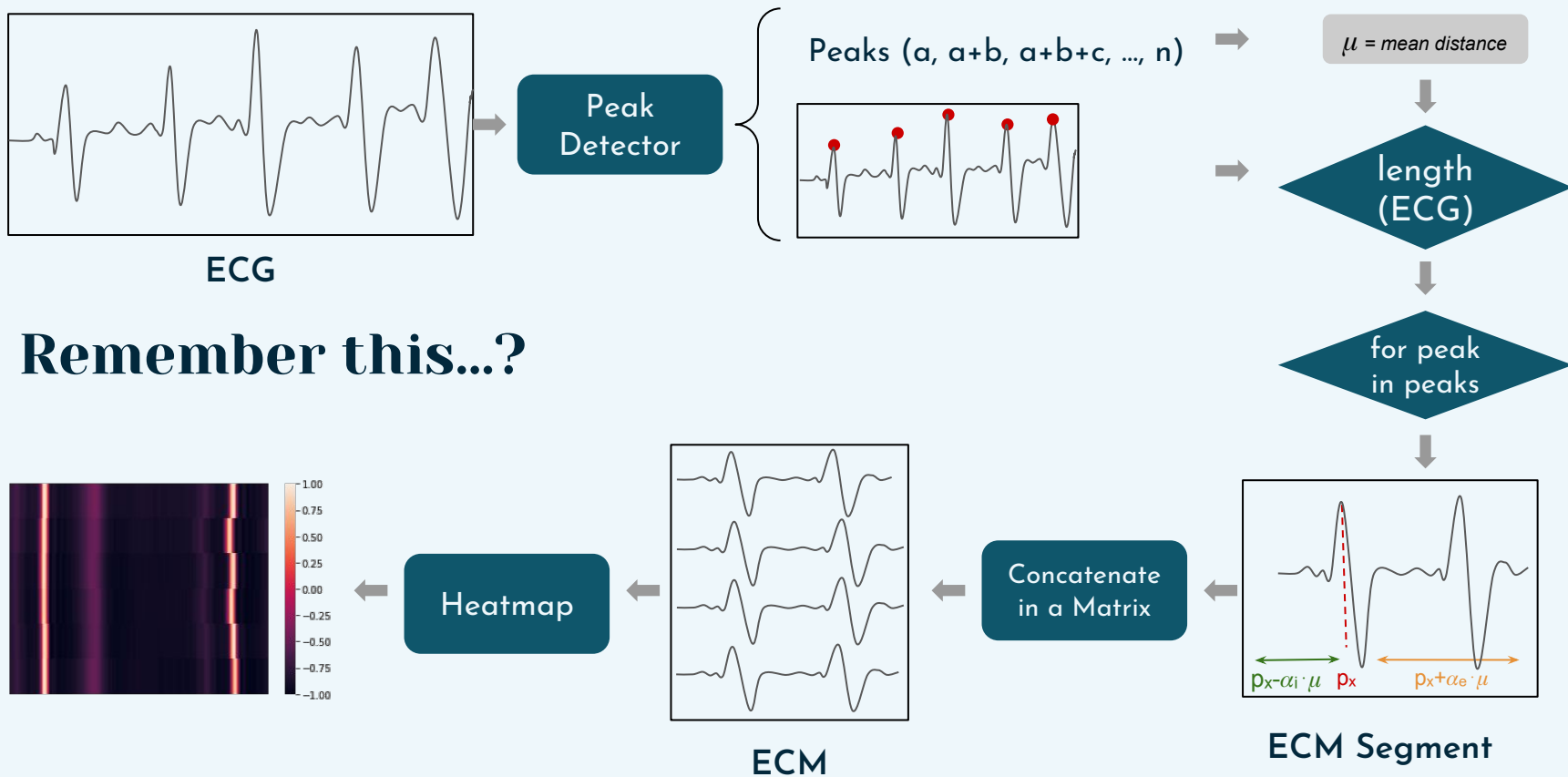
Time-series PPG data may miss subtle AF indicators for **feature extraction** in AI models

4

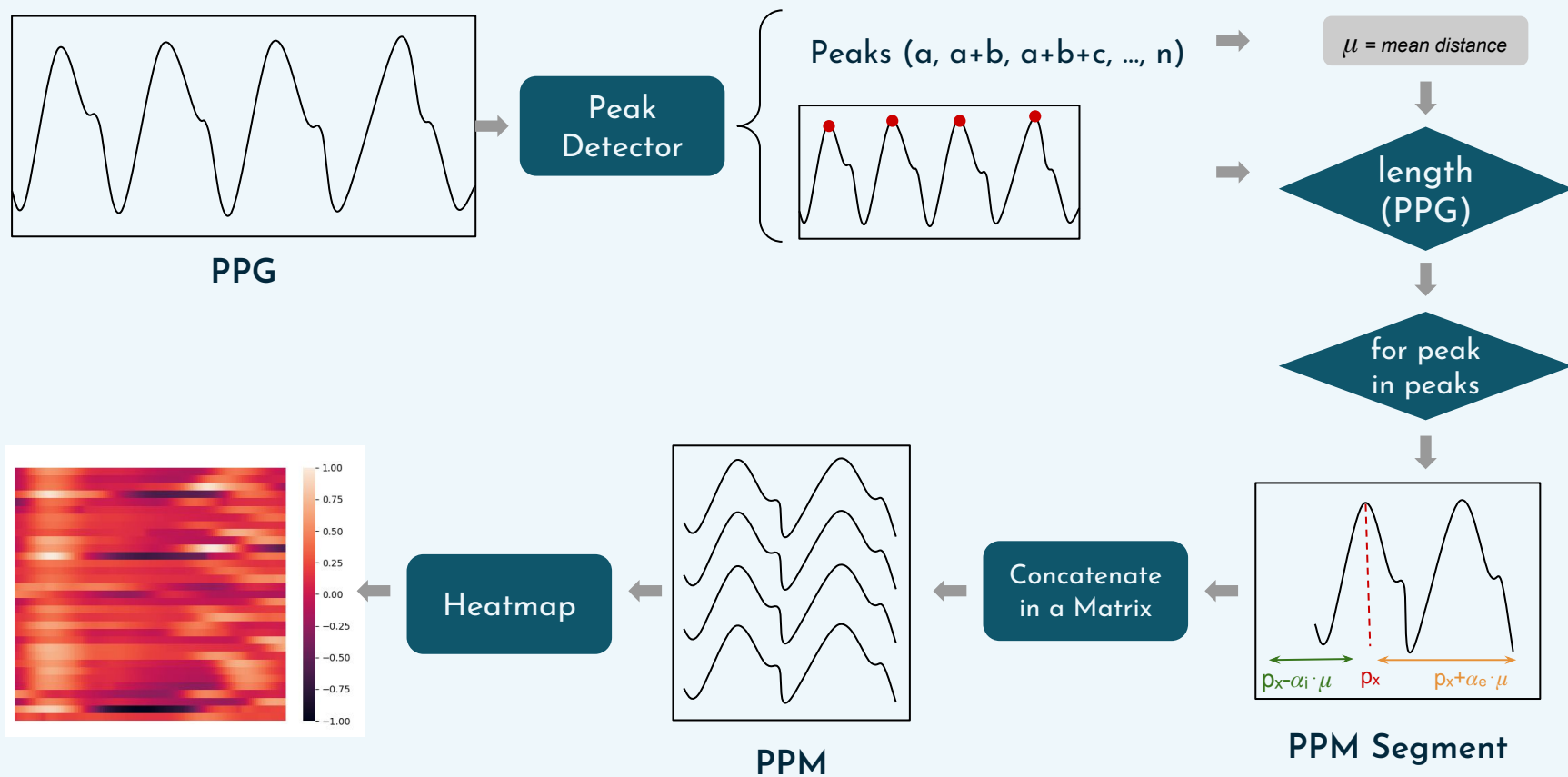
Works well in **wearable devices** and can be integrated into telemedicine for automated detection

Integrate ECM Setup to PPM





Remember this...?



PPM Dataset: MIMIC-PERFORM



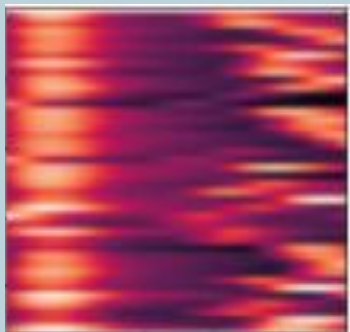
19 Patients with AFib



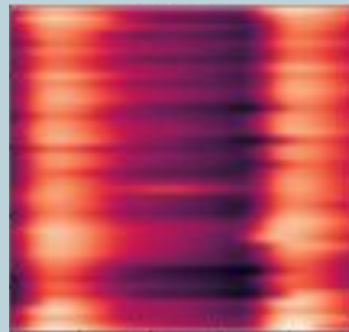
16 Control Users

Publicly available

From time-series to images



Example PPM
with AFib



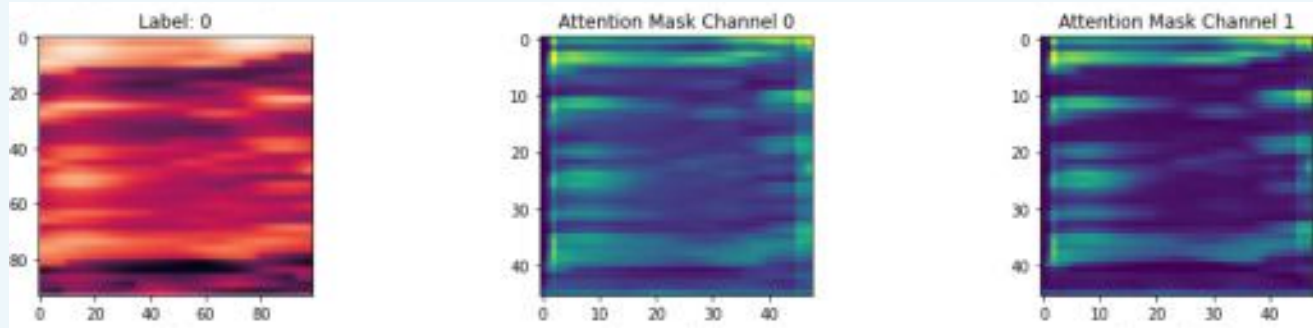
Example PPM
from control
user

100%

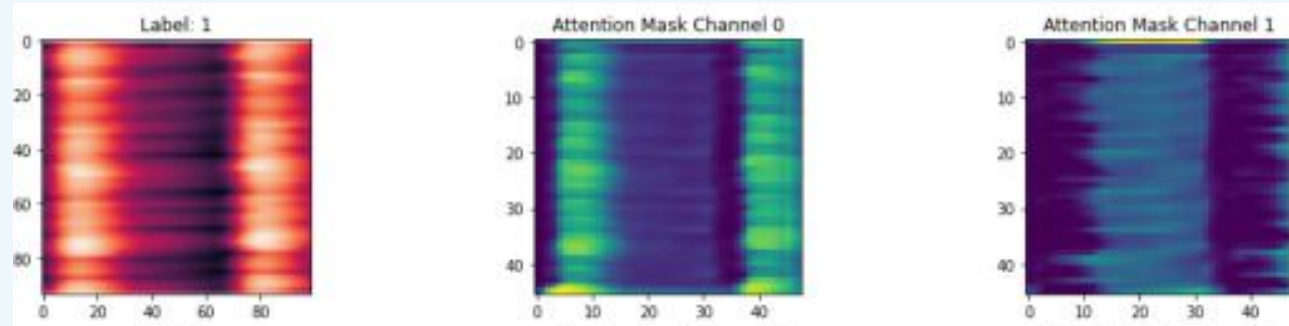
of accuracy detecting AFib when using PPM and a CNN.

Attention Mechanism: Explicability

Patient
with AFib



Control
User



Key Takeaways on PPMs for AFib detection

- ✓ PPMs are a game-changer for AFib detection in PPGs.
- ✓ PPMs provide a superior accuracy compared to traditional methods.
- ✓ Our method can be integrated into wearables for real-world AFib screening.

Summary and Conclusions

Takeaways – What did we learn?



Visualization is a powerful tool in cardiology. Heatmap representations enhance interpretability.



PPG-based matrices successfully represent PPG signals and help **detect AFib** with near-perfect accuracy.



Matrix representation improves both **accuracy** and **usability** as it can capture unique cardiac patterns and can be used in wearables and real-world monitoring.

Why this matters – Clinical & Biometric Impact



Clinical Relevance:

- **AFib detection:** non-invasive, scalable, and wearable-friendly solution.
- **Real-time Monitoring:** continuous heart health tracking.



Biometric Applications:

- **Patient Identification:** could be used in healthcare facilities.
- **Wearables and AI Integration:** Personalized health tracking and biometric security

**Your heartbeat is not just a
signal, it's your identity, your
health, and your future.**

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