Learning Biosignals using Deep Learning

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Deep Learning Sessions Lisbon

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Ph.D. in Biomedical Engineering - Learning Biosignals using Deep Learning

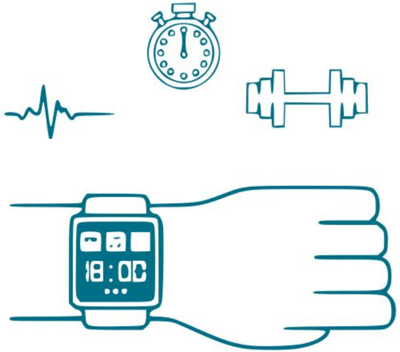
- **University:** Faculty of sciences and technology at Nova University of Lisbon - Portugal
- Currently working at **Loka, Inc.:** Applying ML to healthcare data
- Author and co-author of several **articles** about **Machine Learning applied to healthcare:**
    - D. Belo, J. Rodrigues, J.R. Vaz, P. Pezarat-Correia, H. Gamboa. **Biosignals learning and synthesis using deep neural networks.** BioMedical Engineering OnLine 16 (1), 115 7. 2017.
    - D. Belo, N. Bento, H. Silva, A. Fred, H. Gamboa. **ECG Biometrics Using Deep Learning and Relative Score Threshold Classification.** Sensors 20 (15), 4078, 2020.
    - J. Pestana, D. Belo, H. Gamboa. **Detection of abnormalities in Electrocardiogram (ECG) using Deep Learning.** 13th International Conference on Bio-inspired Systems and Signal Processing 2019. 2019.

Motivation

Healthcare as a driving force

- **Healthcare as a driving force:** one of the most powerful factors in empowering **wellbeing**;
- **Technology:** Developed countries has seen a rise in **life expectancy**, access to state-of-the-art **diagnostics**, **therapeutics**, and **innovative technology**;
- **Medical Health Records:** increasing the **medical practitioners' accessibility** to patient data;
- **Investment Increase:** The European Union the investment has **increased 9.6%** (**2013 to 2016)**, resulting in the value a total of **1.35 billion euros** (PORDATA, 2019)

Motivation



The accessibility to wearables

- **Accessibility:** The acquisition of human physiological activity **was confined in the healthcare facilities**;
- **Digital Revolution:** Since the digital revolution the world has faced a great change in the **sensing industry**;
- **Wearable devices:** New developments in **sensing devices** have been **growing smaller and less-invasive** over time;
- **Data Acquisition:** Nowadays biosignal information may be gathered by **wearables and mobile devices**;
- **Big Data:** These devices produce a **large quantity of information**.

Motivation

- **Artificial Intelligence (AI) breakthrough**: boosted by **Deep Neural Network (DNN),** commonly known as **Deep Learning (DL)**, technologies;
- **Artificial Intelligence (AI):** branch of computer science developed to **mimic and help human intelligence**;
- **Economic Benefits:** gained by the early AI adopters;
- **Transformation Potential:** Lewandowski (2019) reports that 74% believed that AI has the potential to transform the industry;
- **Healthcare Application**: Most of the applications are in the areas of image, localization, security and health industry (Statista, 2017).

The recent rise of Artificial Intelligence

Motivation

Healthcare as a driving force

The accessibility to wearables

The recent rise of Artificial Intelligence

Objectives

- This presentation provides several signal processing techniues and **Deep Learning** architectures for a wide-range of biosignals and objectives;
- Some of the architectures were benchmarked in three different contexts:
    - **Synthesis**: synthesis of biosignals;
    - **Authentication:** electrocardiogram (ECG) biometric systems;
    - **Detection:** abnormal ECG detection.
- The study of these algorithms **helps unveiling new knowledge** about the intrinsic nature of the biosignals.

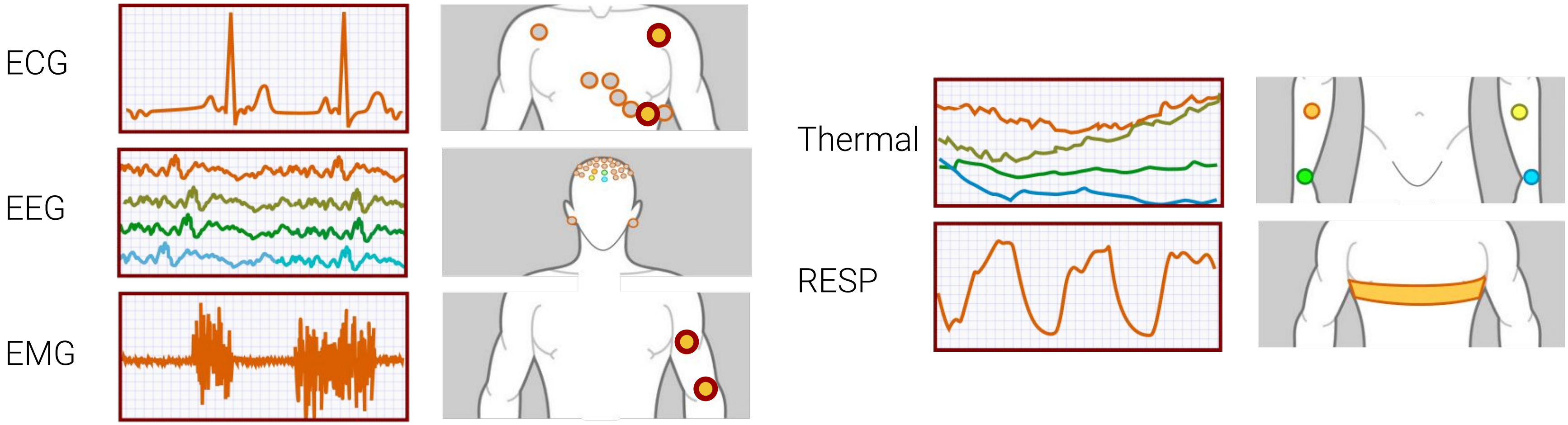
Overview

1. Context
2. Biosignal Processing
3. Architectures
4. Applications
5. Conclusion
6. Future Remarks
7. Contributions
8. References
9. NASA FDL Challenge: Generation of Biosignal Data

Context

Biosignals

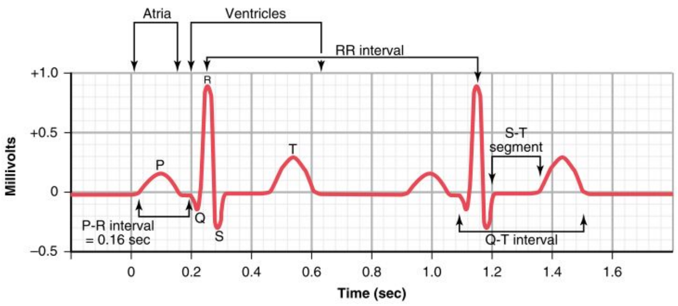
A biosignal is **originated by the physiological process** of living beings and can be **measured** and **monitored** continuously by an appropriate **sensor**.

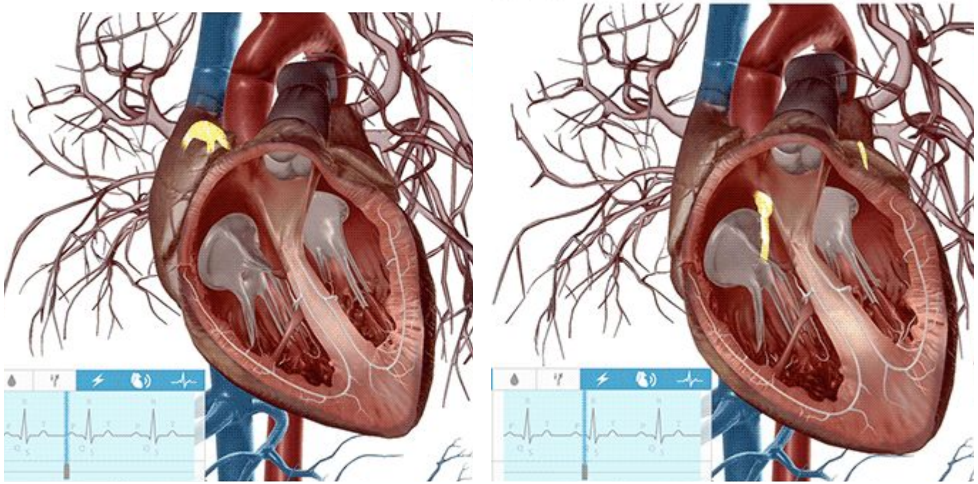


Context

Electrocardiogram

- Electrical Signal that controls the heartbeat
- Characteristic shape and waves
- May reveal diseases, e.g. arrhythmia

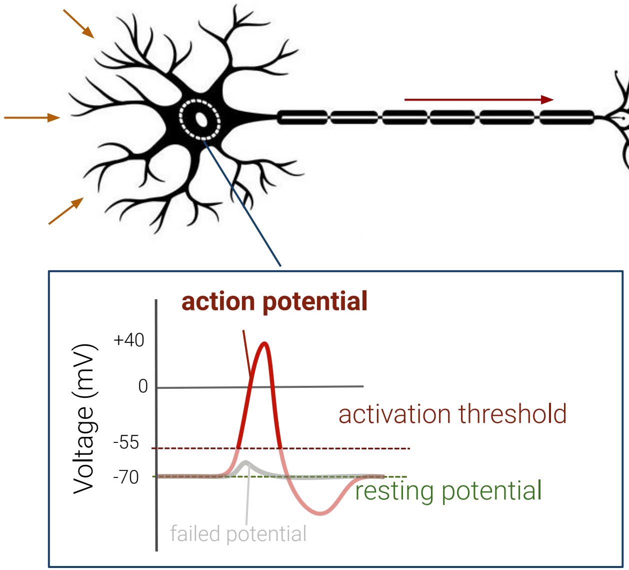




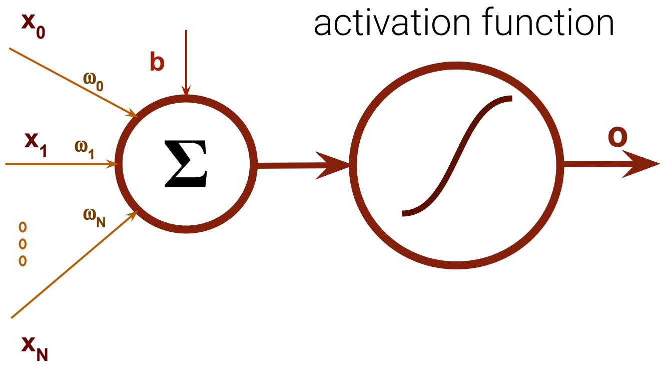
In the left: Atria contraction. **In the right:** QRS complex.
From https://www.visiblebody.com/anatomy-and-physiology-apps/physiology-and-pathology

Context

Neuron



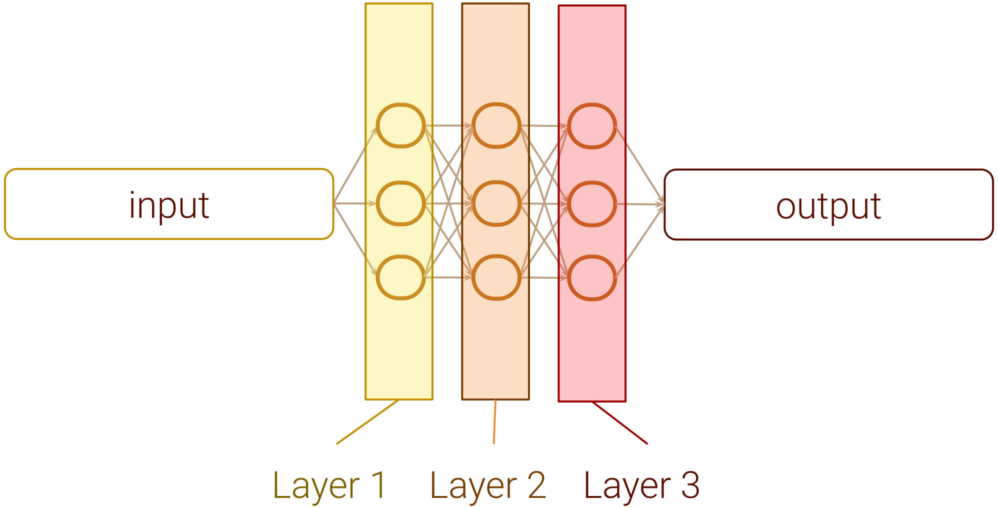
Artificial Neuron



$$\mathbf{o} = \sigma\left(x \cdot w^{T} + b\right)$$

Context

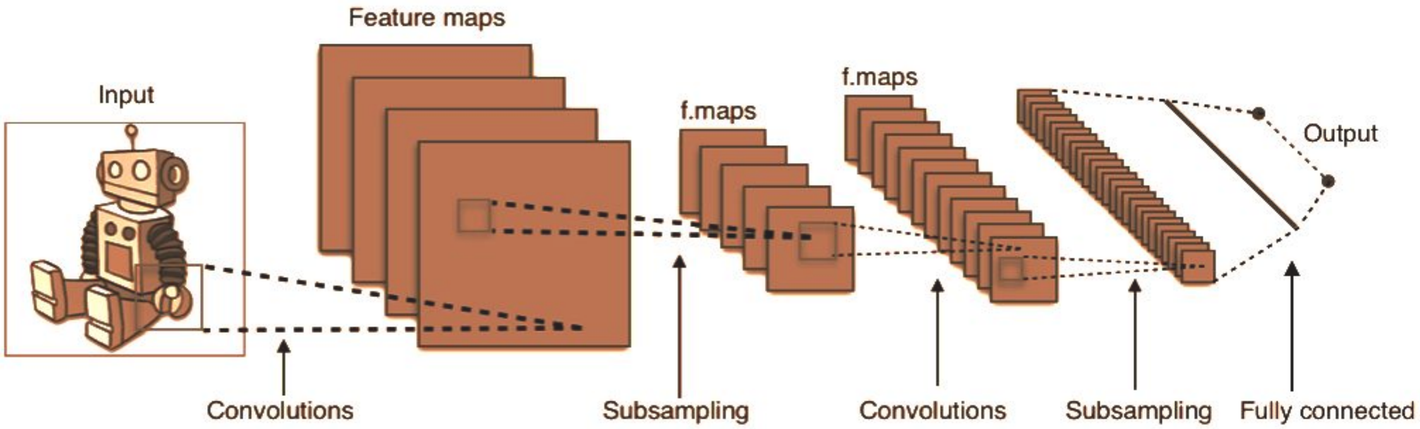
Artificial Neural Networks



As we increase the number of hidden layers, our networks become deeper.

Context

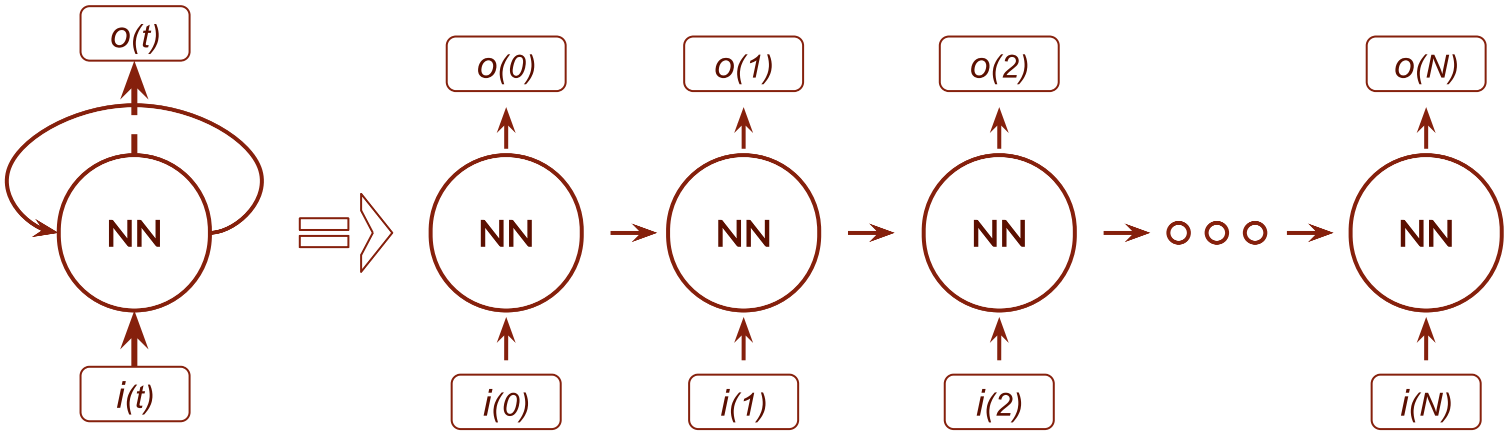
Convolutional Neural Networks (CNN)



[AlexNet - Adapted from (Aphex, 2015)]

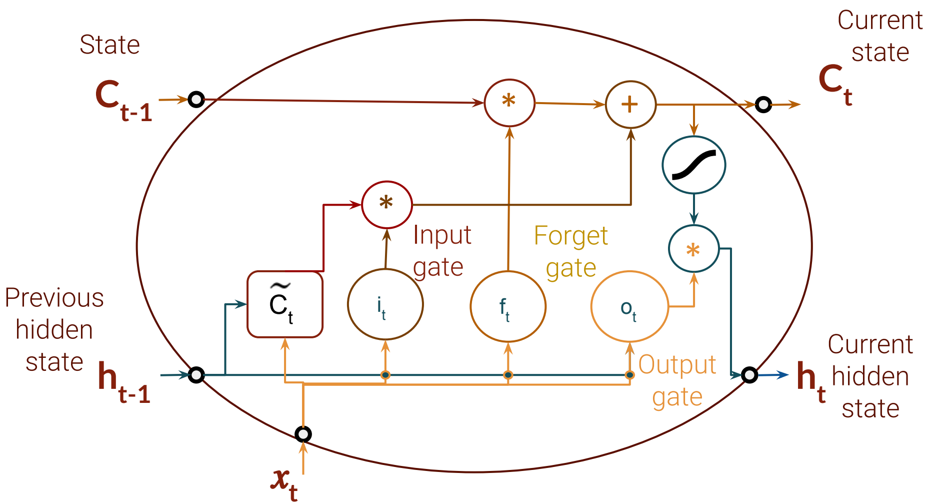
Context

Recurrent Neural Networks (RNN)



Context

Long-Short Term Memory (LSTM)



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \;+\; b_f\right)$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \;+\; b_i\right)$$

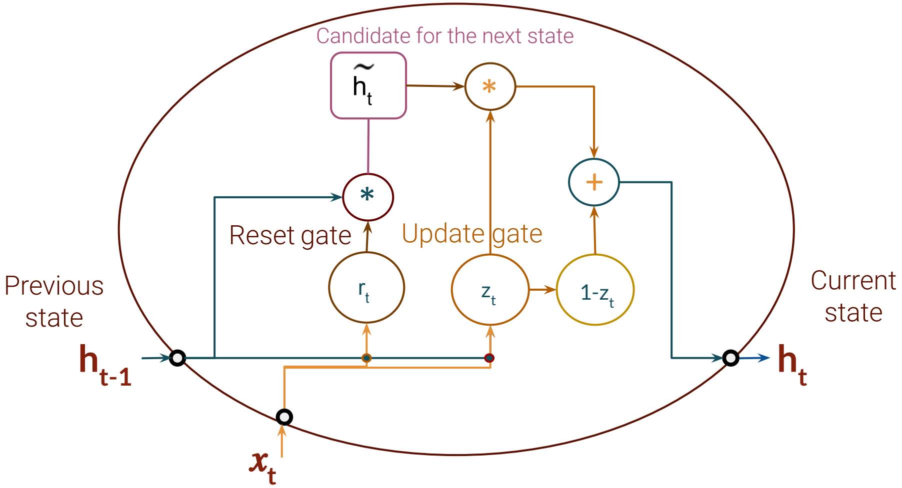
$$o_t = \sigma\left(W_o \; [h_{t-1}, x_t] \;+\; b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \;+\; b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Gated Recurrent Units (GRU)



$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

Context

Optimization

Loss functions

Mean Squared Error

$$L = \frac{1}{N}\sum_{n}^{N}(y_n - \hat{y}_n)^2$$

Categorical Class Entropy

$$L = -\frac{1}{N}\sum_{n}^{N}[y\log(\hat{y}) + (1-y)\log(1-\hat{y})]$$

Optimizers

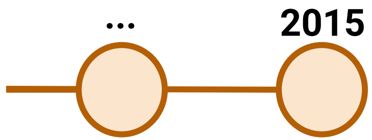
Adam

$$\theta_e = \theta_{e-1} - \eta\frac{\hat{m}_e}{\sqrt{\hat{v}_t} + \epsilon}$$

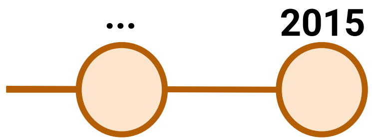
RMSProp

$$\theta_e = \theta_{e-1} - \frac{\eta}{\sqrt{E\left[(\nabla L(\theta))^2\right]_t + \epsilon}}(\nabla L(\theta)]_t$$

State-of-the-art



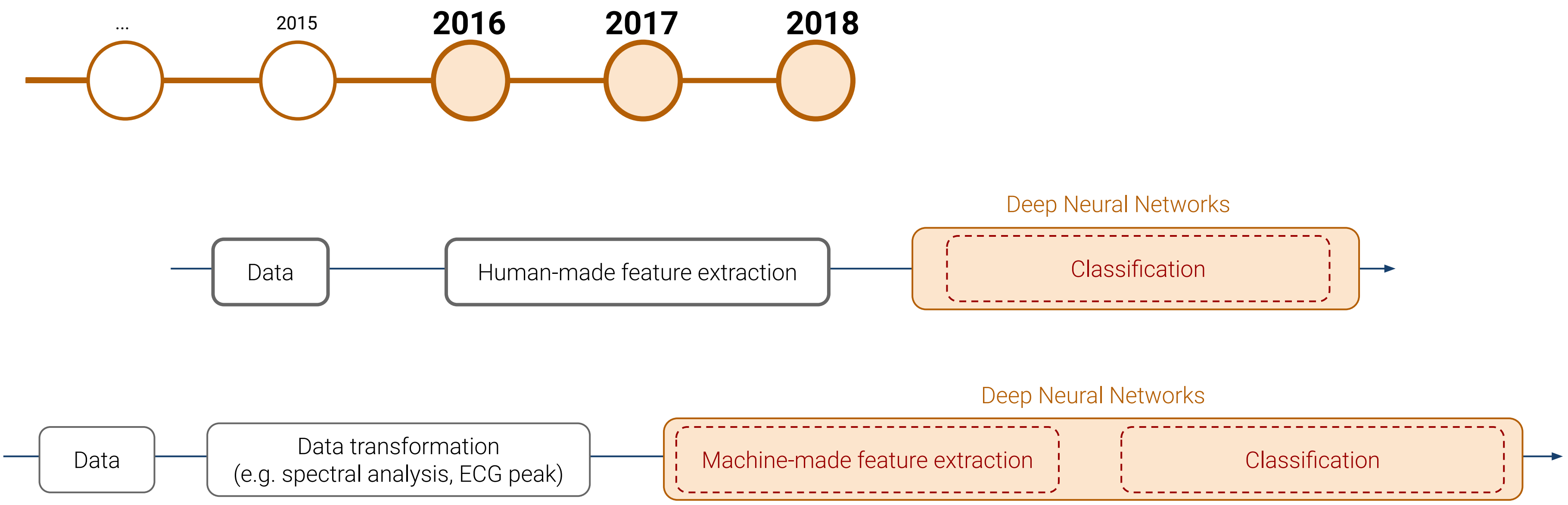
State-of-the-art



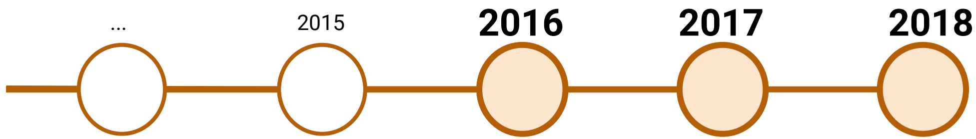
- **Most** of the papers in Deep Learning applied to biosignals **were published after 2015**;

- One remarkable **exception** is Matinez et al. (2013):
    - **CNN** architecture was used to **extract features** and **classify** from **Blood Volume Pressure (BVP)** and **ElectroDermal Activity** (**EDA)**;
    - It was used to **classify** that features into **relaxation**, **anxiety**, **excitement** and **fun states**;
    - This algorithm **outperformed human-extracted features algorithm**.

State-of-the-art

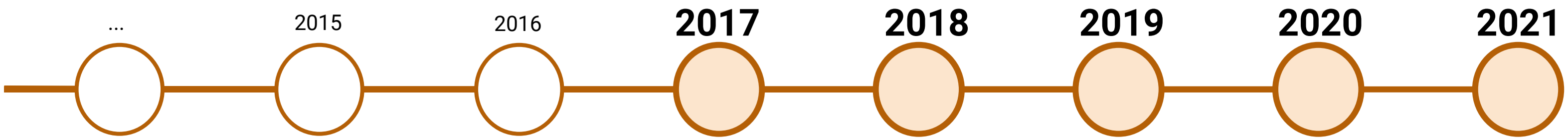


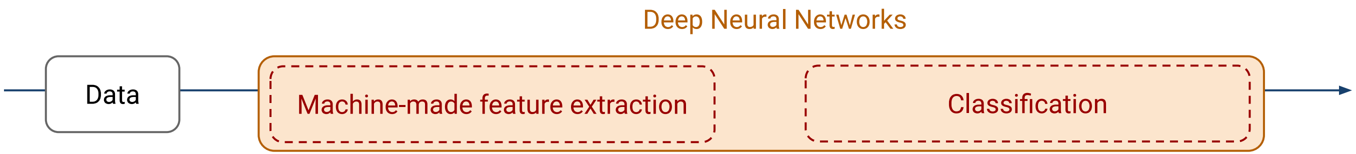
State-of-the-art



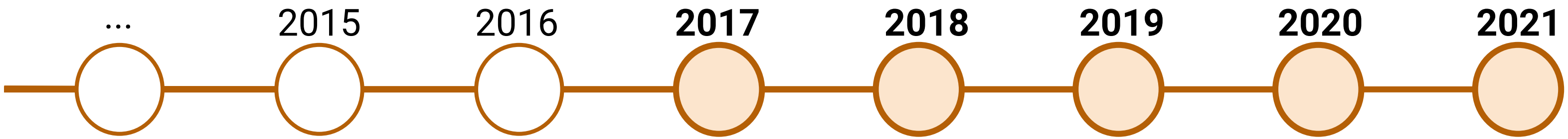
- Articles published during this period was the **direct application of CNN to human-made features**:
  - Usually applied to **EMG**, **EEG**, **ECG**, and **Phonocardiogram (PCG)**;
  - **Conversion of these signals to image** (e.g. spectral analysis) and using **CNN architectures** (e.g.AlexNet);
  - Examples of applications are:
    - the recognition of physical **actions** through **EMG** (Geng et al. (2016));
    - detection of **changes of sleep** from **EEG** (Tsinalis et al. (2016));
    - detection of **atrial fibrillation** (Xia et al. (2018))

State-of-the-art





State-of-the-art



- In the application of **Deep Learning to raw data** is more active since 2017:
  - **Learning of features is made by the Deep Learning** architecture;
  - Examples using **CNN**:
    - Detection of **arrhythmias** from **ECG** by Hannun et al. (2019). This work uses **34 layered CNN** to detect 12 different classes, **outperforming specialist recognition**.
  - Examples using **RNN**:
    - **Arrhythmia** detection with stacked **LSTM** (Thill et al. (2019));
    - **Combination of CNN and LSTM** to detecting **sleep** stages from **EEG** (Dong et al. (2018)).

State-of-the-art

Best Results for each application scenario:

Synthesis (2017)

McSharry et al. (2003) - Sum of **diphasic waves** for EMG and ECG;

Gamboa et al. (2012) - EMG synthesis using **autoregressive models** and **noise input**;

After 2017, Deep Learning started to be used for synthesis using CNN and GAN architectures)

Authentication (2020)

Gargulio et al. (2015) achieved **99%** accuracy for identification using **Support Vector Machine** for **Fantasia** dataset;

Rahbi (2013) reached **99%**, using a to a Hidden Markov Model (**HMM**) for **MIT-BIH** dataset;

Luz et al. (2018) used two CNN for authentication reaching 1,33% EER (**CYBHi** dataset).

Detection (2019)

No articles were found for detection of deviation from the normal time-series;

Detection of noise: John et al. (2018) - 98.93% of accuracy with a 16 layer CNN;

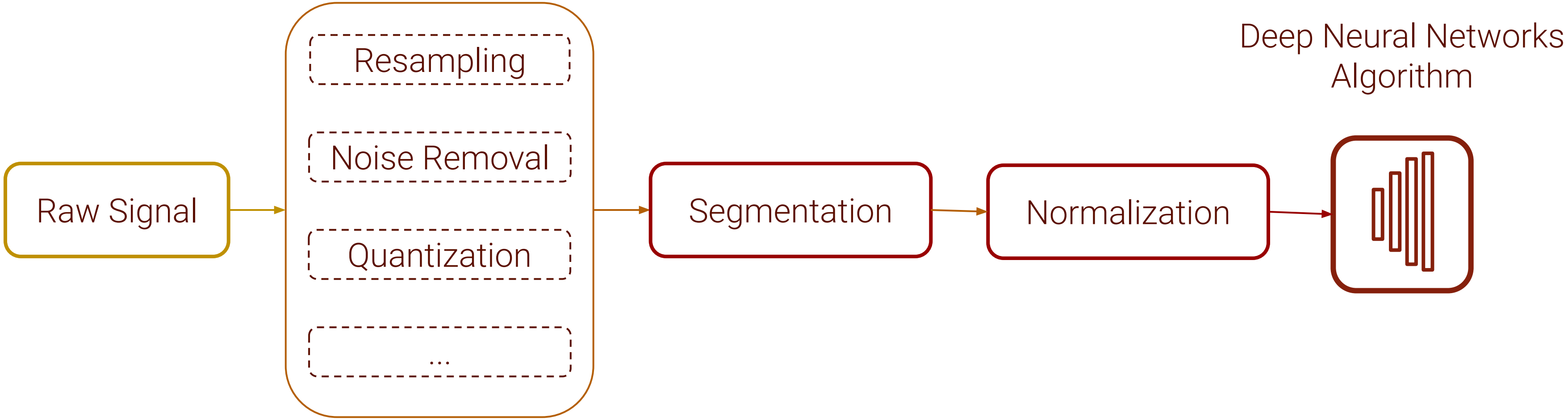
Detection of arrhythmias: Acharya et al. (2017) - 92.5% used a 11 layered CNN for the detection of atrial fibrillation, atrial flutter, and ventricular fibrillation.

Biosignal Processing

Deep Learning algorithms are able to learn **non-linear** and **complex** relationships between **inputs** and **outputs** $\longrightarrow$ Highly dependent on quality of inputs.

Signal processing serves the purpose of **cleaning non-relevant information** and "**simplification**" of signals $\longrightarrow$ Increase Deep Learning performance.

Biosignal Processing

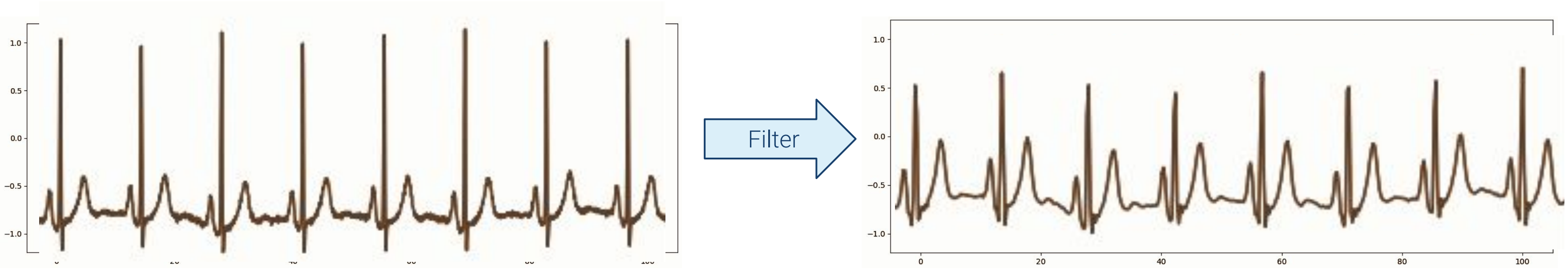


Biosignal Processing

Noise removal

Noise corresponds to non-relevant information that is included in the signals - e.g. 50 Hz noise introduced by electrical current.

The application of smoothing filters helps to reduce it.

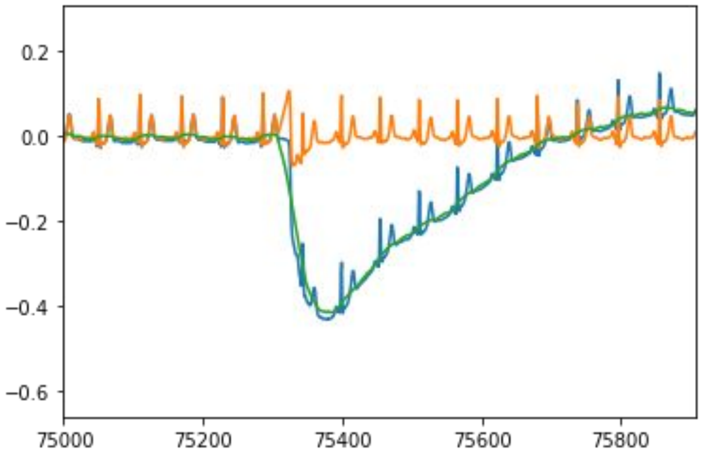


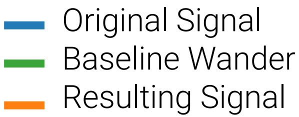
Biosignal Processing

Baseline Wander Removal

Corresponds to low-frequency noise - e.g. in ECG signals, it might be the contaminated with respiration contraction/relaxation of the rib muscles.

The application of smoothing filters helps to reduce it.

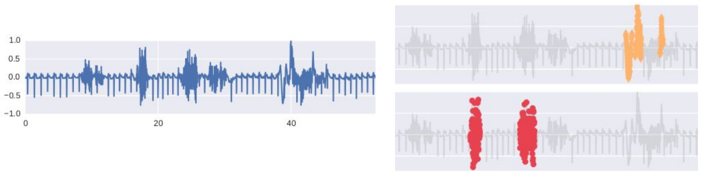




Biosignal Processing

Noise removal

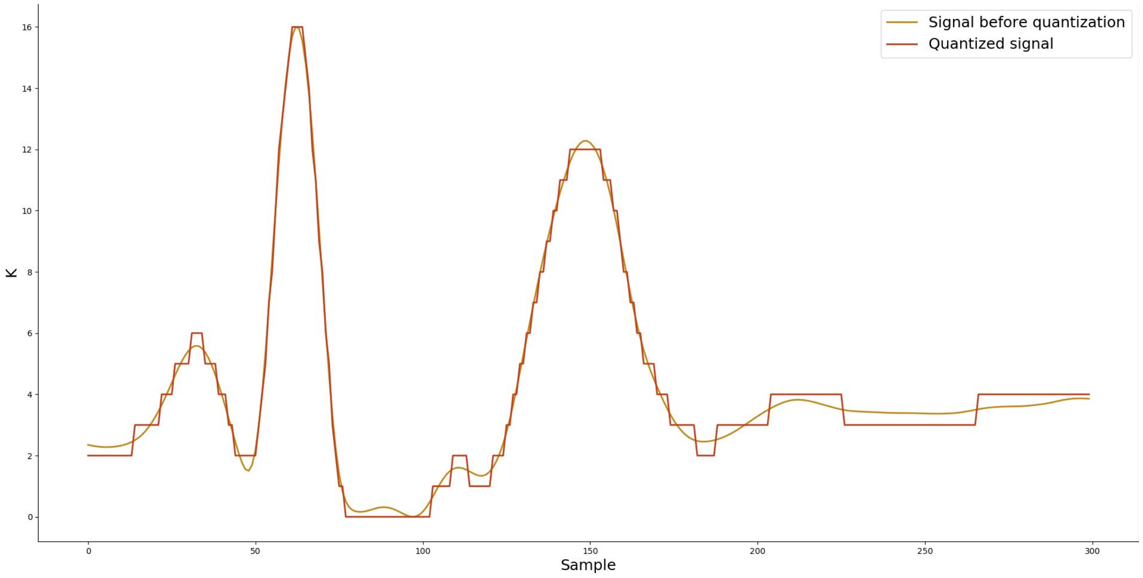
- Mean and std threshold
- Agglomerative clustering



[From Rodrigues, Belo et al. (2017)]

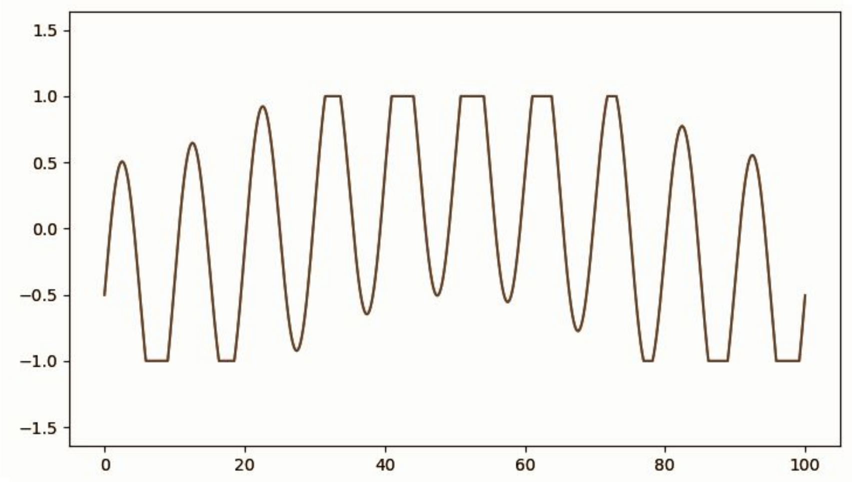
Biosignal Processing

Quantization



Clipping Histogram Edges

Process of limiting the range of values that the inputs will have. Protect the algorithm from disrupting artifact data



Biosignal Processing

Normalization types

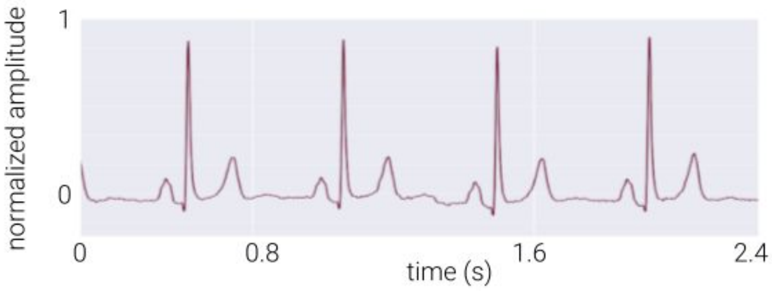
Absolute maximum	$$\overline{x} = \frac{x}{\max(\lvert x \rvert)}$$
Amplitude	$$\overline{x} = \frac{x}{\max(x) - \min(x)}$$
Standard Deviation	$$\overline{x} = \frac{x}{\mathrm{std}(x)}$$
Absolute maximum and minimum removal	$$\overline{x} = \frac{x - \min(x)}{\max(\lvert x - \min(x) \rvert)}$$

All can use a time window
(absolute maximum example)

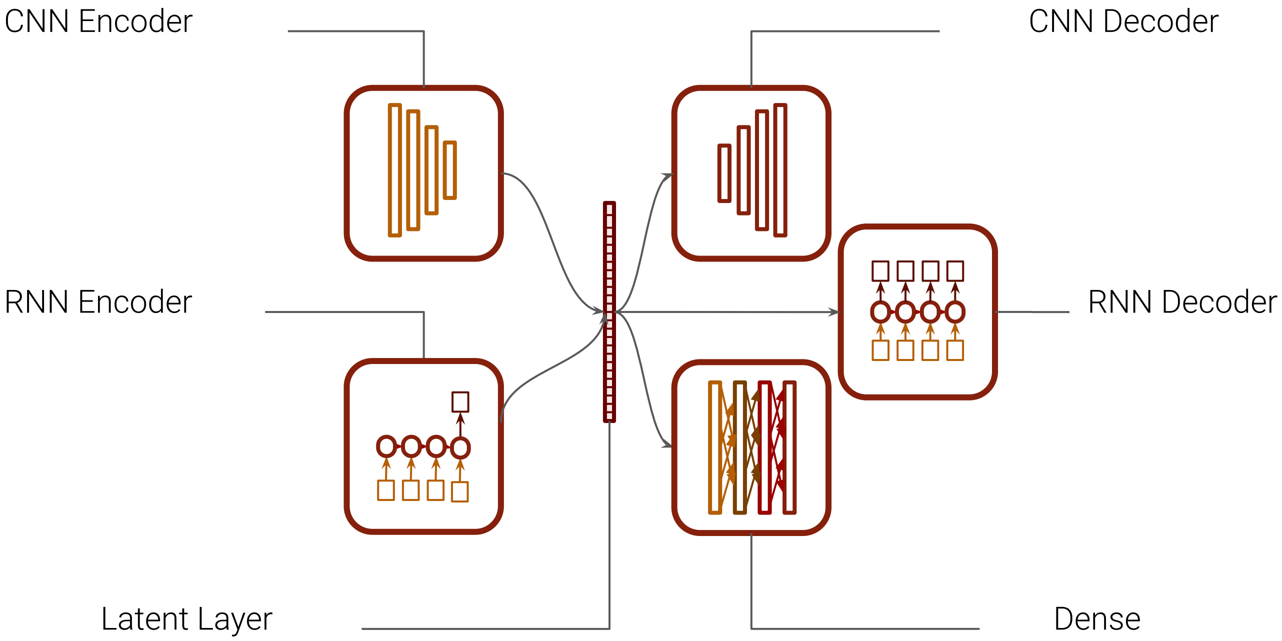
$$\overline{x}_n = \frac{x_n}{\max\left(\left|x_{[n-W/2:n+W/2]}\right|\right)}$$

Biosignal Processing

Signals Segmentation

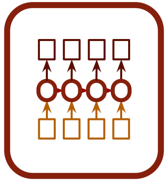


Architecture Modules



Architectures

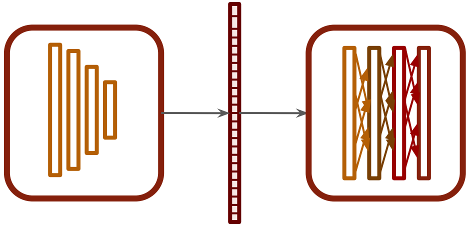
RNN Encoder-Decoder



- In this configuration a model may learn to **predict the following sample** based on the previous ones;
- This configuration may be used in order to make a **model learn about the signal's morphological mechanisms**;
- This configuration only "classifies" the next sample, as the model does not absorb the complexity of a biosignal with "continuous" values;
- Therefore, after the signal is **segmented in overlapping time windows**, one should **quantize** the signal and consider each integer as a "class";
- The network is fed with the time windows and the **output will be the same time-window dephased by one sample**.

Architectures

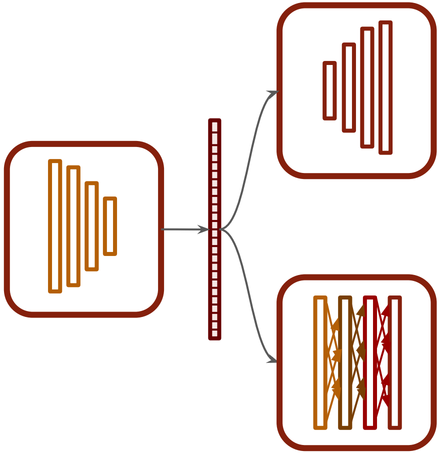
CNN Encoder with a Dense Module



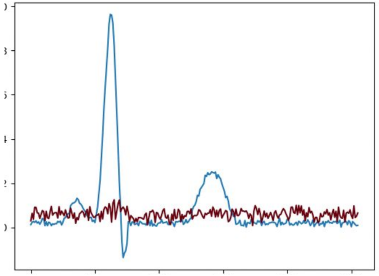
- **The Convolutional Encoder can be used with a dense module** to allow the weights to make a map between the input and the output;
- **Filters will be learned** in this configurations when using a 1D CNN;
- When fed with a time-window the **filters will activate if morphological shapes are detected**;
- The **dense layers will relate the latent vector** with the activated neurons for the desired **output**.

Architectures

CNN Autoencoder with Dense Layer



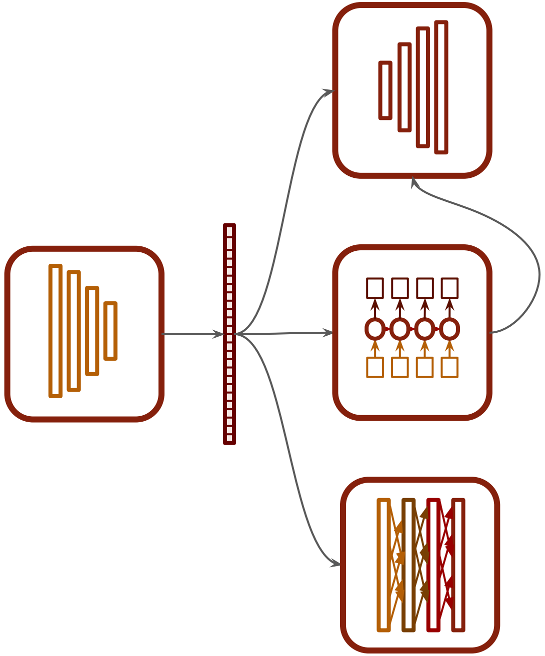
- The autoencoder learns the input and
- This configuration is used for **feature learning** used in transfer learning or active learning;
- The **latent layer will contain the features**, and the Dense Network will classify for a specific **task**;



Autoencoder output while training

Architectures

CNN Autoencoder, RNN Encoder and Dense Layer

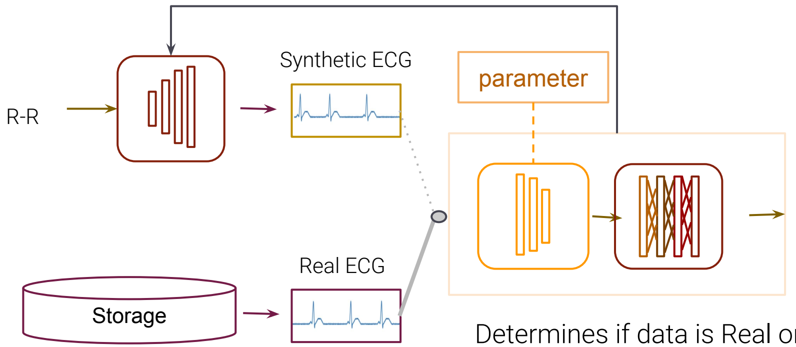


- This configuration uses the **prediction of the next latent layers** based on the previous ones;
- After learning the codification of several windows from an autoencoder, this will give the **feature state of several windows**;
- The **dense layer is a classification layer**, that gives results according to the application;
- Can be used as **active learning** mechanism, **noise detector** or even **prediction of pathological events**;

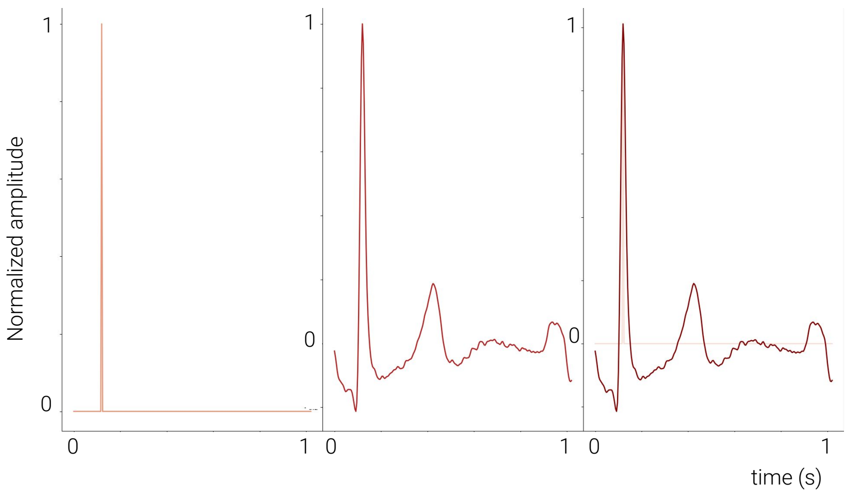
Architectures

Other architectures are explored

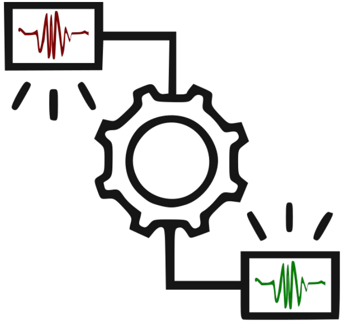
Generational adversary network for domain transfer



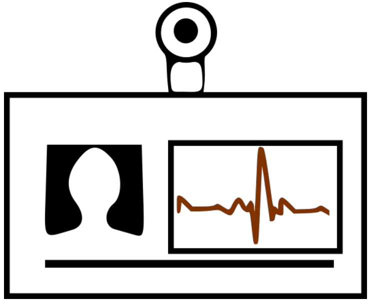
Determines if data is Real or Synthetic



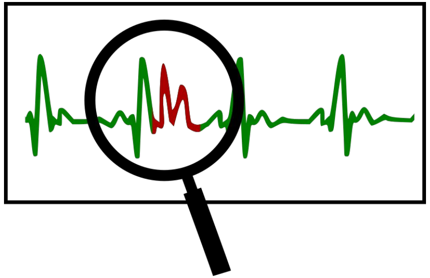
Application Scenarios



Synthesis



Authentication

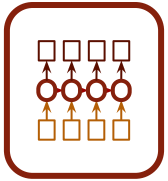


Detection

Synthesis

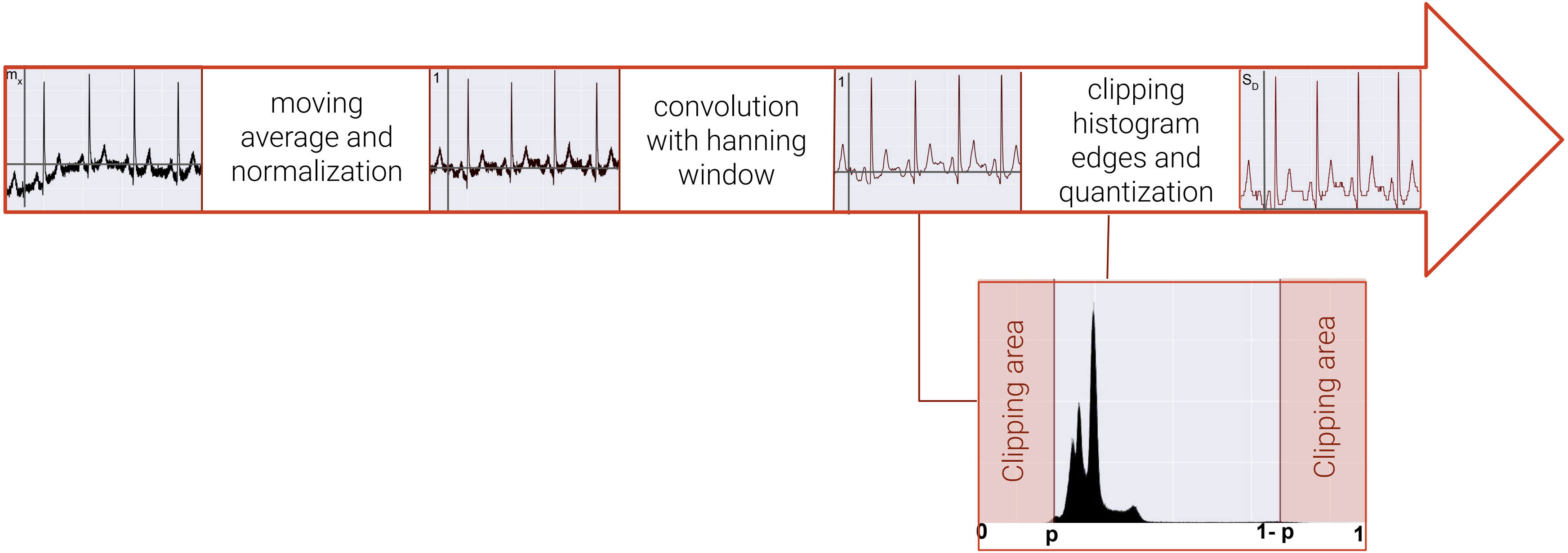
Biosignal Synthesis

- The **encoder-decoder RNN** was used for this project;
- The **objective** is to create more data and to **make** the network **learn and replicate the mechanics behind biosignal generation**;
- This algorithm was **tested** in **synthesizing three** types of **biosignals**:
  - **Thoracic mecanogram (RESP)** during respiratory movements;
  - **Electromyogram (EMG)** from a leg while riding a bicycle;
  - **Electrocardiogram (ECG)** in normal conditions.



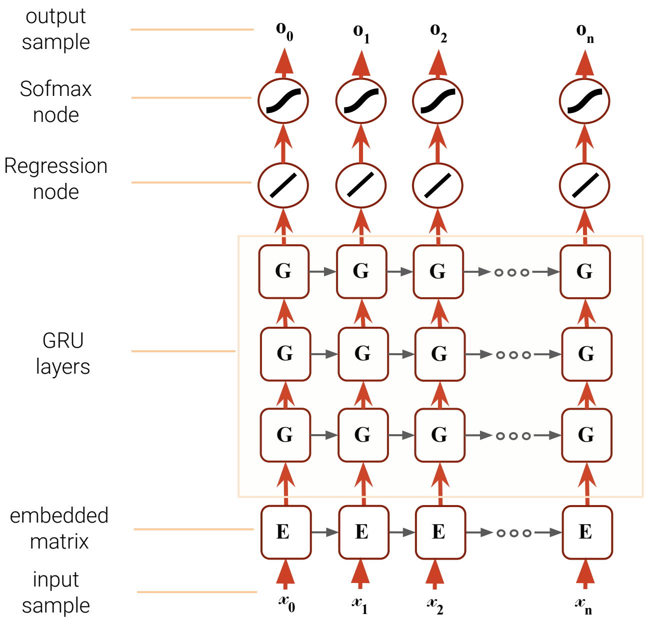
Synthesis

ECG Synthesis - Preprocessing



Synthesis

Architecture



- The signal is **segmented** in time-windows with overlap;
- x is the **quantized** sample;
- The **E is the embedded matrix**, which codes the input to the sequence of **3** Gated Recurrent Units (**GRU**, G in the diagram);
- Each column of the matrix **E** corresponds to each possible input;
- **The last GRU** sends the output to a **feedforward node** with linear activation;
- **The logits** (output of the feedforward node) pass through a **softmax** function **giving the next most probable sample**;

Synthesis

Training

Data: PhysioNet **Fantasia** Dataset (**ECG** and **RESP**) and FMH ergometer data (**EMG**)

Loss Function: Categorical class entropy

Optimizer: RMSProp

Cross-Validation:

Measurement: **Mean squared error** between the predicted and the input

Each model was fed with windows of:

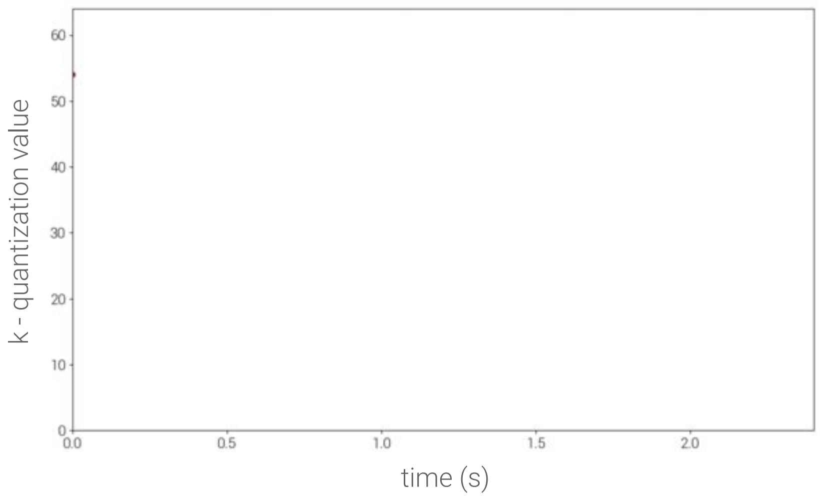
1. the **same source** signal **which trained the model**;
2. **other records** of signals of the **same type** (did **NOT train** the model);
3. of **other types** of signals.

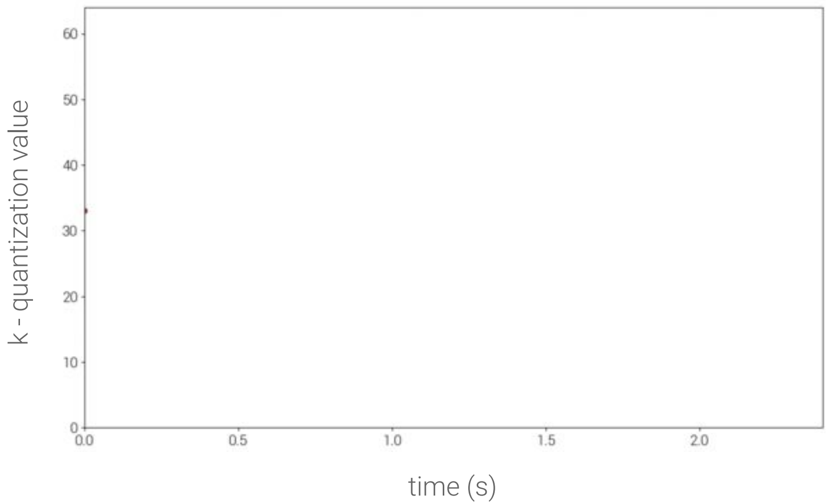
Synthesis

Synthesis

Made by choosing the **most probable next value** in the sequence, **starting with a random** value

Do to the **recursive** nature of the RNN, one can make **very large sequences** of signal



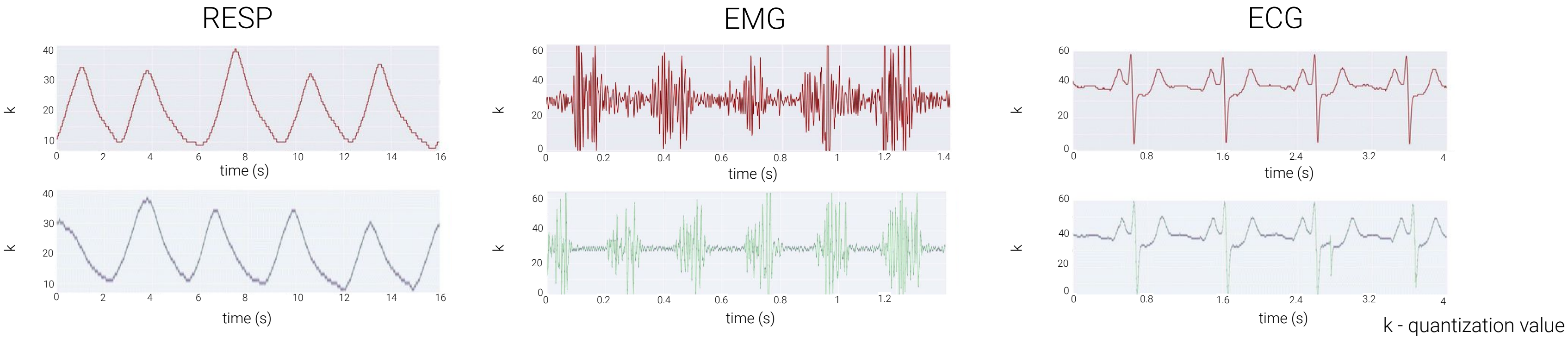


Synthesis

Results

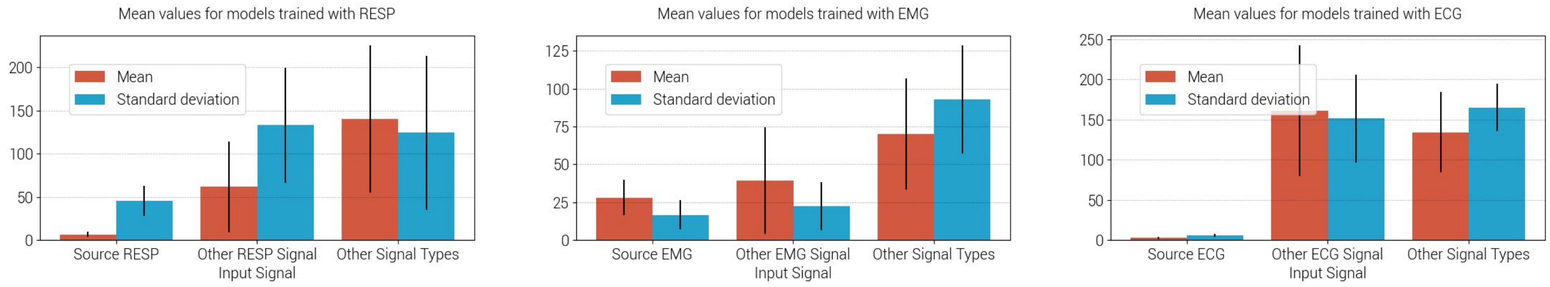
Input

Output



Prediction error of the test set

(MSE)

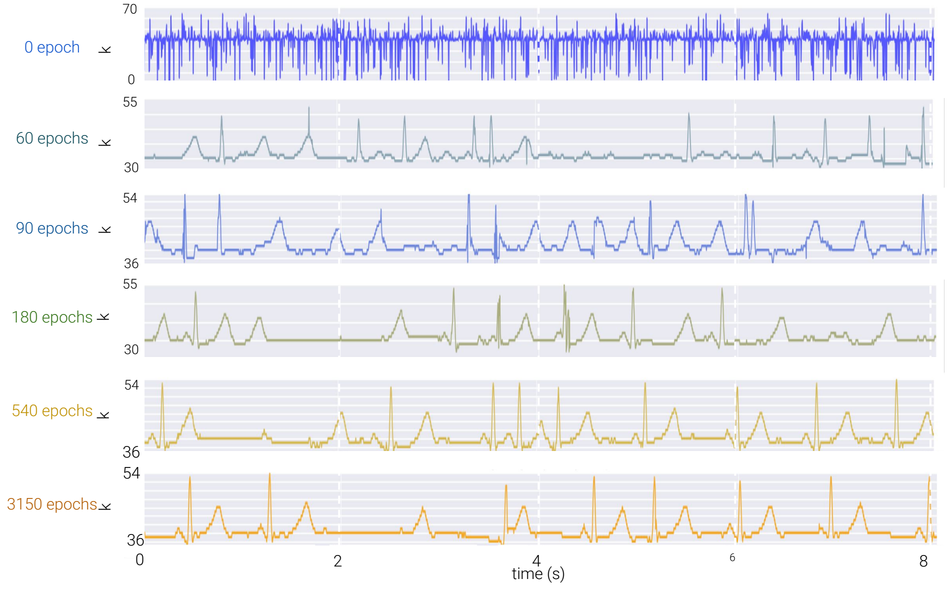


[Belo, et al. (2017) Biosignals learning and synthesis using deep neural networks. *Biomedical engineering online*, 16.1: 115.]

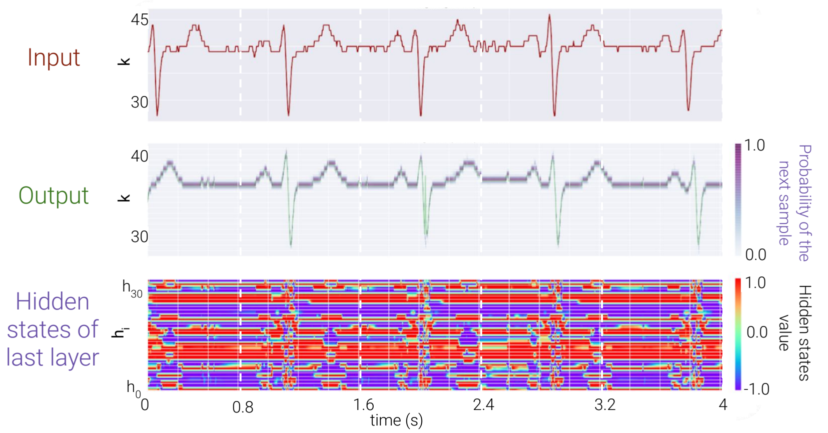
Synthesis

Exploring the Synthesis Network

Learning stages of the ECG



Inner states of the network



k - quantization value

h_i - i-th hidden state of the logits layer

Synthesis

From synthesis to authentication

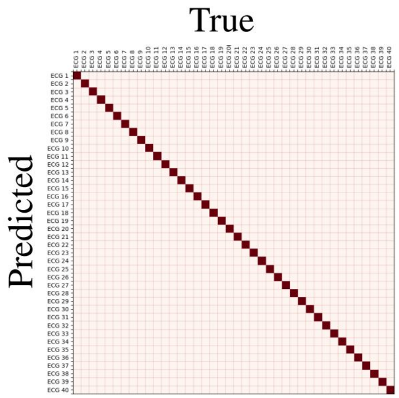
After developing this algorithm we made an hypothesis:

a. If **model A** is trained with ECG of **person A;**

b. when **model A is fed** with ECG **with person B** the prediction **error is higher**;

c. when fed with ECG of **person A**, the error is lower.

After checking the lowest errors we got this confusion matrix



Authentication

ECG Biometry

Two algorithms were tested while performing the **identification** and **authentication** based on the **ECG signal**:

- **RNN:** The previous synthesis network;
- **TCNN:** A Time-Convolutional Neural Network;

Identification - checking the source of that ECG signature - **validation made by accuracy**;

Authentication - prove the ECG's claimed owner - **validation made by equal error rate (EER)**;

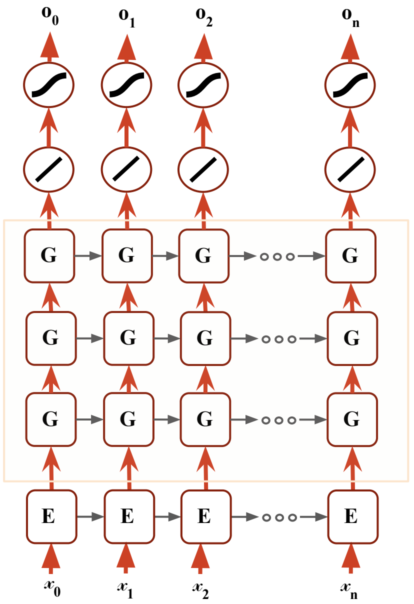
Several aspects make the ECG a suitable input for biometric systems:

- All ECGs are different for each individual, it is a signal that all living humans possess, and is **hard to counterfeit**;
- Using **off-person ECG** acquisition could be used in **high-security settings**.

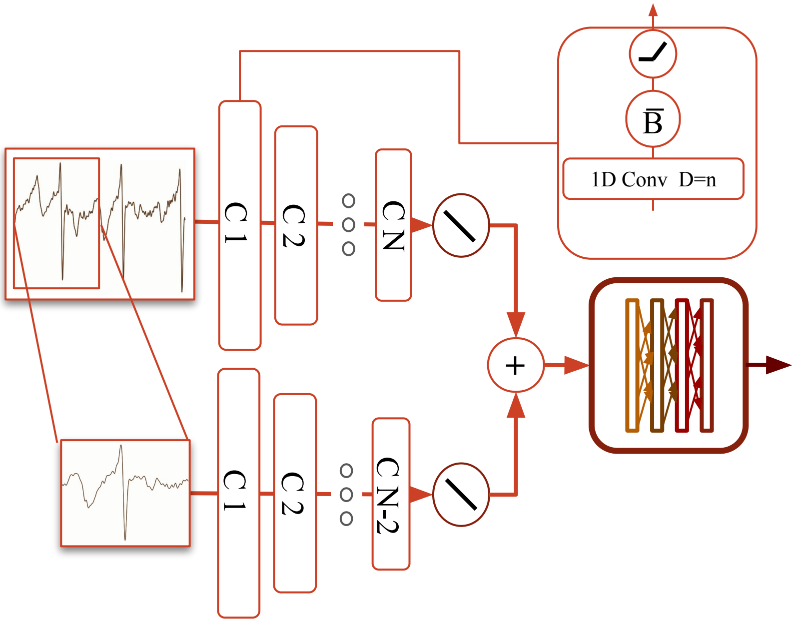
Authentication

Algorithms

Recurrent Neural Network (RNN)

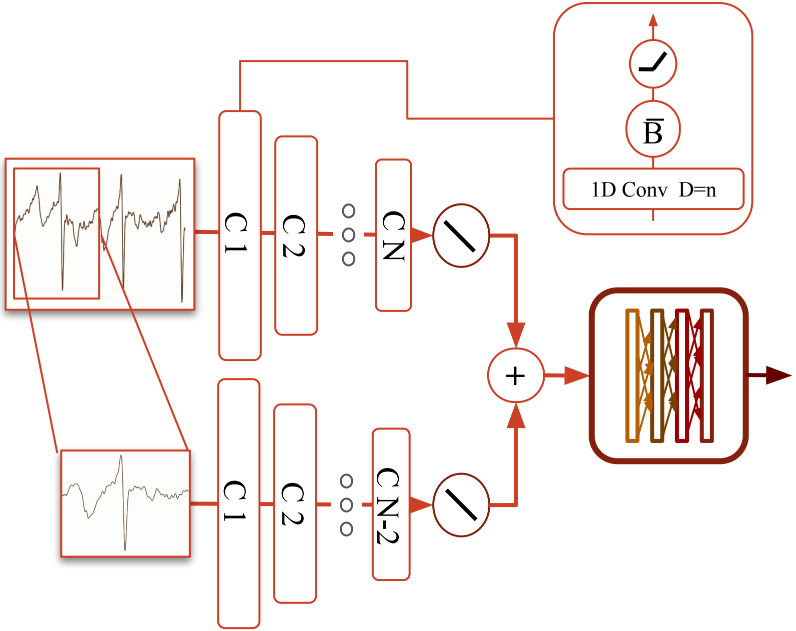


Time-Convolutional Neural Network (TCNN)



Authentication

TCNN Algorithm



- The signal is **segmented** in time-windows with overlap;
- The **QRS complex is extracted** from the time-window;
- Each window **is fed to its own network** with **dilated convolutions**;
- These **dilated convolutions reduce the dimensionality** after **each layer**;
- The output vectors are **summed in the fusion layer** represented by the + symbol.
- The **dense layer classifies** which person it belongs to
- **Optimization:** Adam Optimizer
- **Loss:** Categorical Class Entropy

Authentication

Classification

Score:

RNN: $$S(p,i,w) = \frac{o_p}{max(o(i,w))}$$

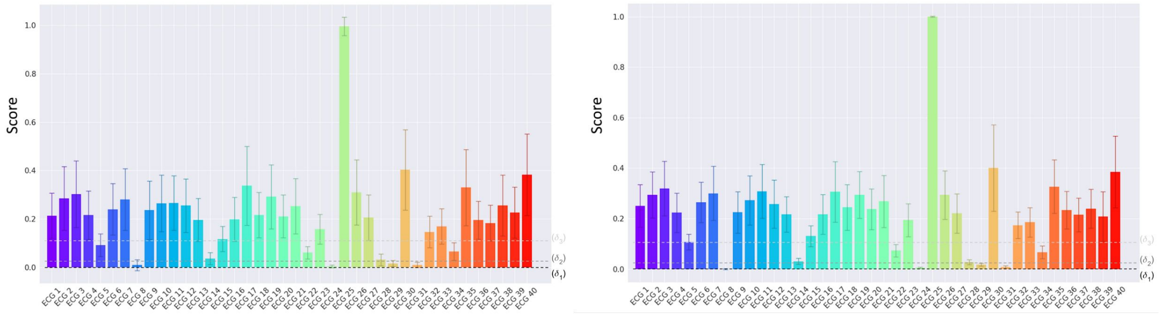
TCNN: $$S(p,i,w) = 1 - \frac{o_p}{max(o(i,w))}$$

output of the **p**redictor

maximum of all the **o**utputs for all the **p**redictors for that **i**ndividual and time-**w**indow

Classification:

The selection is made by choosing the **minimum scores**



(a) Batch Size of 1 (b) Batch Size of 20

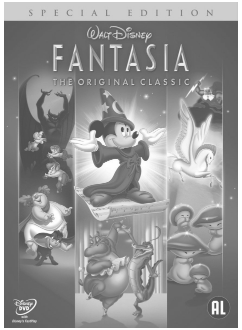
Score distribution for predictor ECG8 of the RNN model for two different batch sizes

Authentication

Data

Fantasia

Resting supine position ECG while watching the movie



MIT-BIH

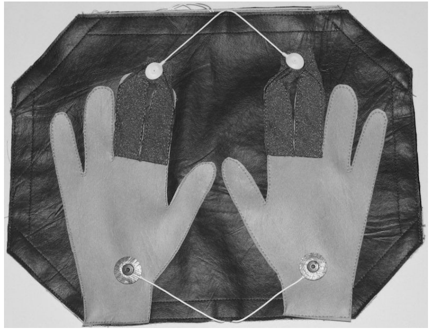
Ambulatory arrhythmia for evaluation of arrhythmia detectors

[From Moody et al. (2001)]

CYBHi

Check **Y**our **B**iosignals **H**ere

off-person ECG - 2 moments (**M1** and **M2**)



[From Silva et al. (2014)]

Authentication

Validation

Identification:

Measured by the **higher** the **accuracy**, **sensitivity**, and **specificity:**

T - **T**rue
F - **F**alse
N - **N**egative
P - **P**ositive
R - **R**ate

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

Authentication:

Lower the **EER**, **better** the authentication algorithm

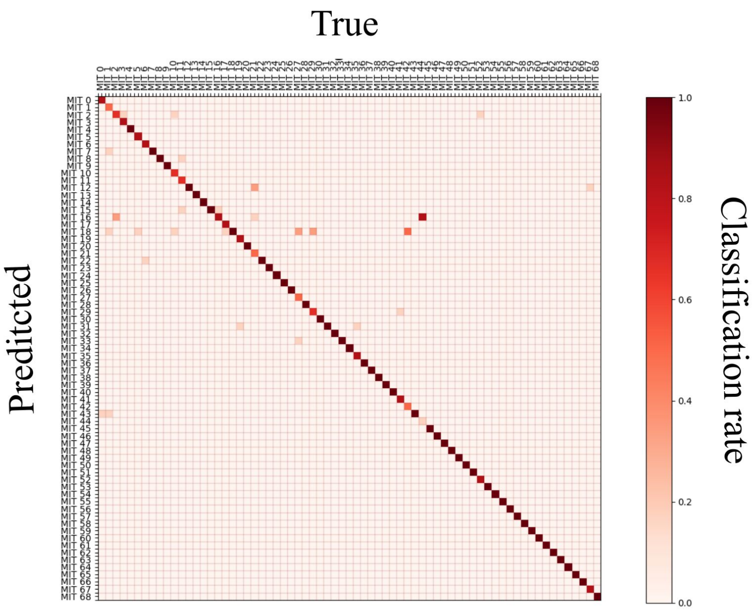
$$FNR = \frac{FN}{TP + FN}$$

$$FPR = \frac{TN}{TN + FP}$$

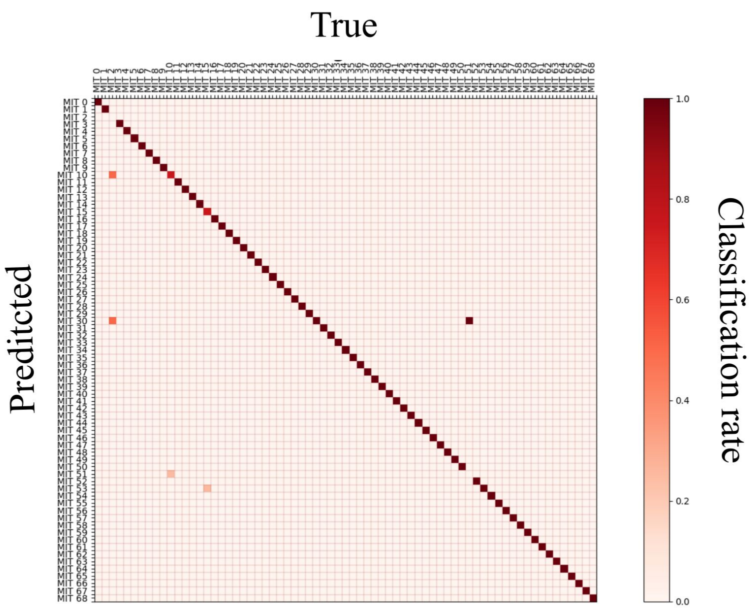
$$\mathrm{EER} = \mathrm{FNR} = \mathrm{FPR}$$

Authentication

Identification confusion matrices - MIT-BIH



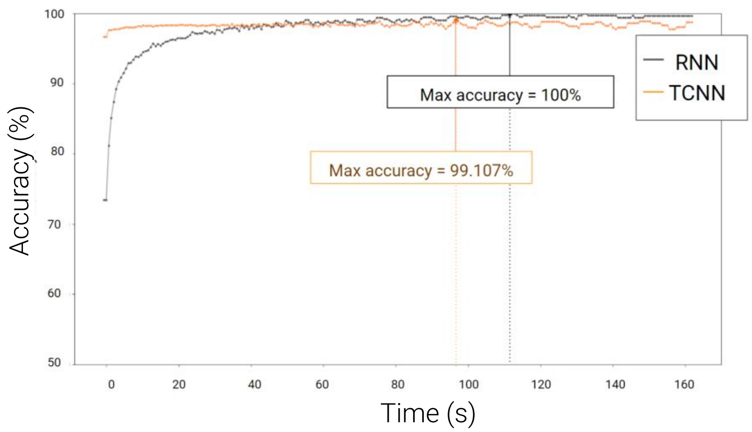
Confusion matrix example for the **RNN** approach (±1.8 MIN).
Accuracy: 92.7%; Specificity: 99.9% ; Sensitivity: 96.4%.



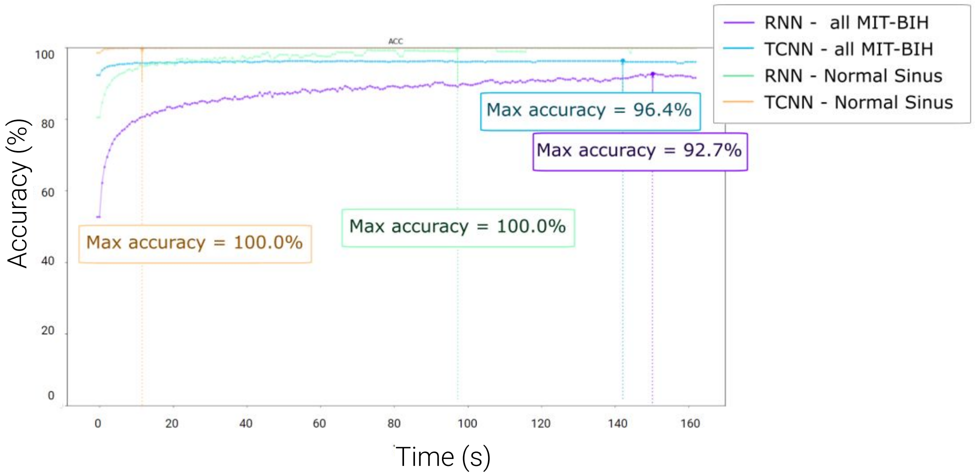
Confusion matrix example for the **TCNN** approach (±1.6 min).
Accuracy: 96.4%; Specificity: 99.9%; Sensitivity: 91.3%.

Authentication

Identification Results



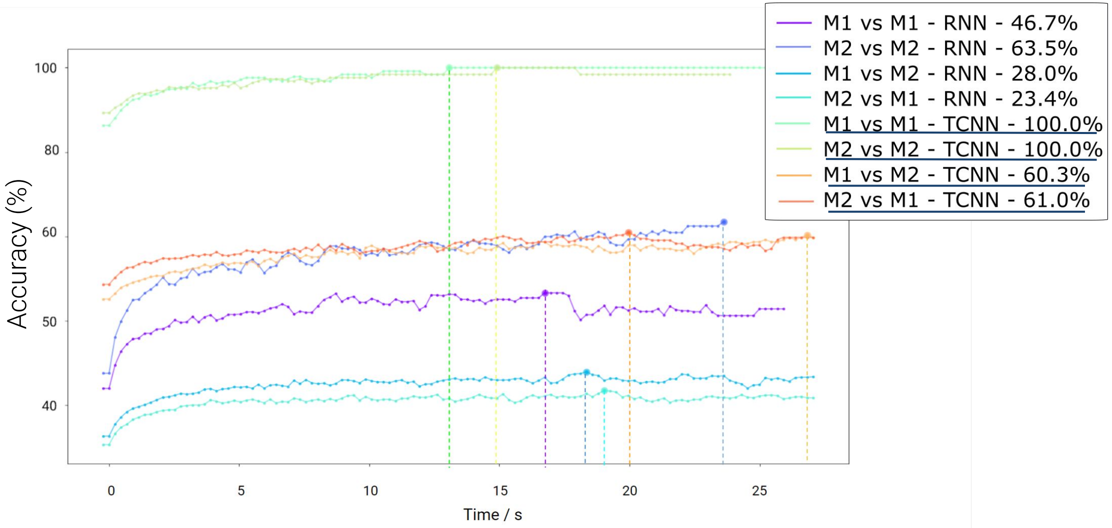
Accuracy for Fantasia evolution with the **batch size**
(i.e. time per identification unit)



Accuracy for MIT-BIH evolution with the **batch size**
(i.e. time per identification unit)

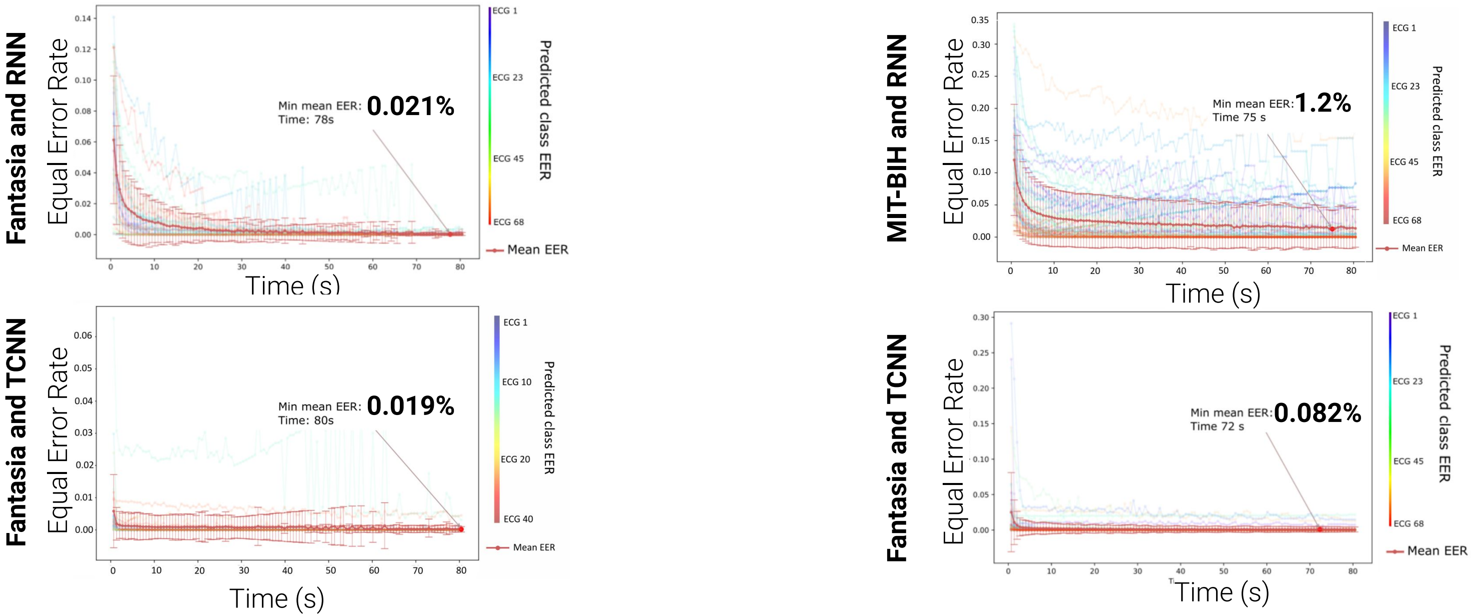
Authentication

Identification Results



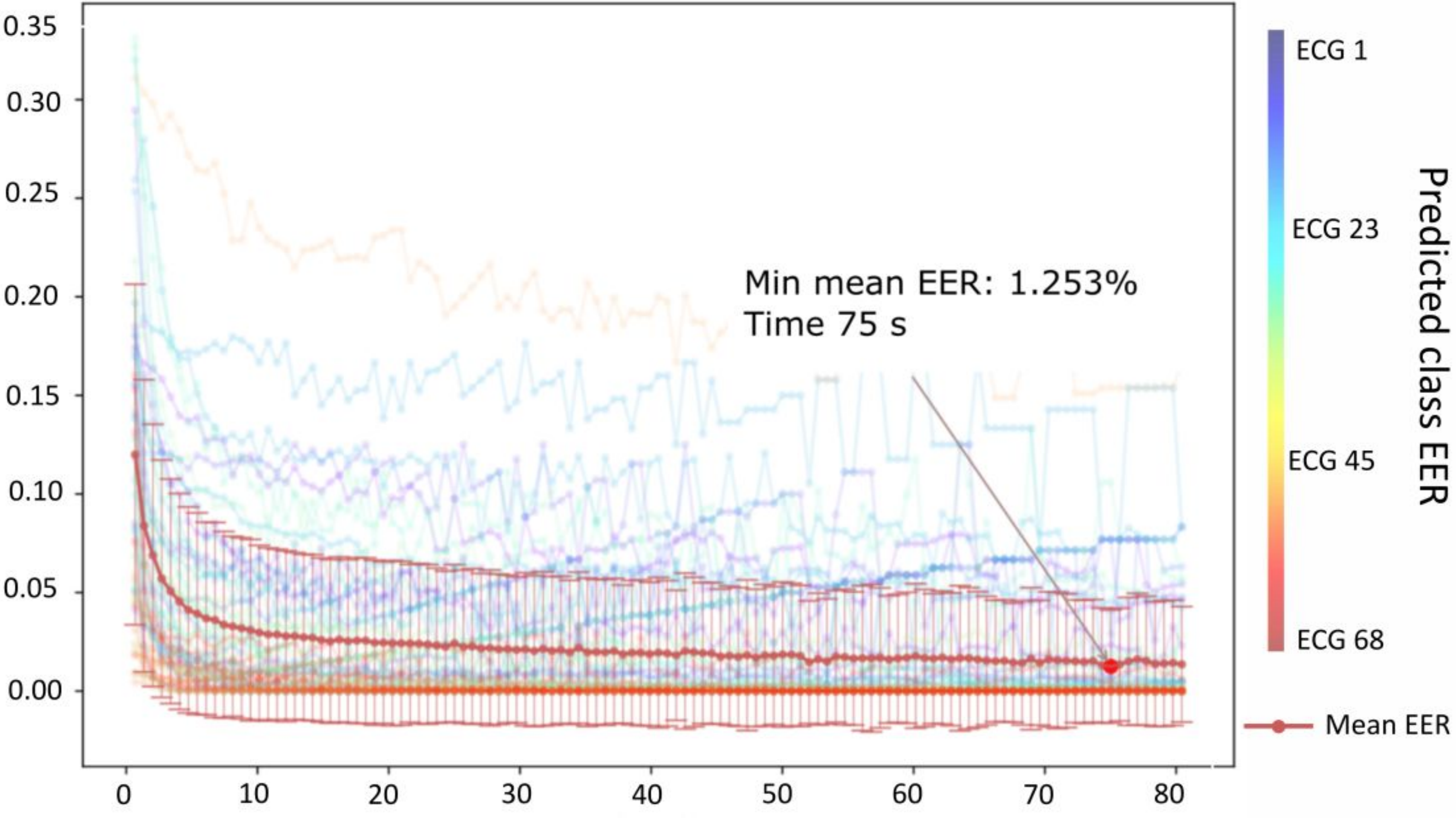
Accuracy for CYBHi evolution with the **batch size**
(i.e. time per identification unit)

Authentication Results



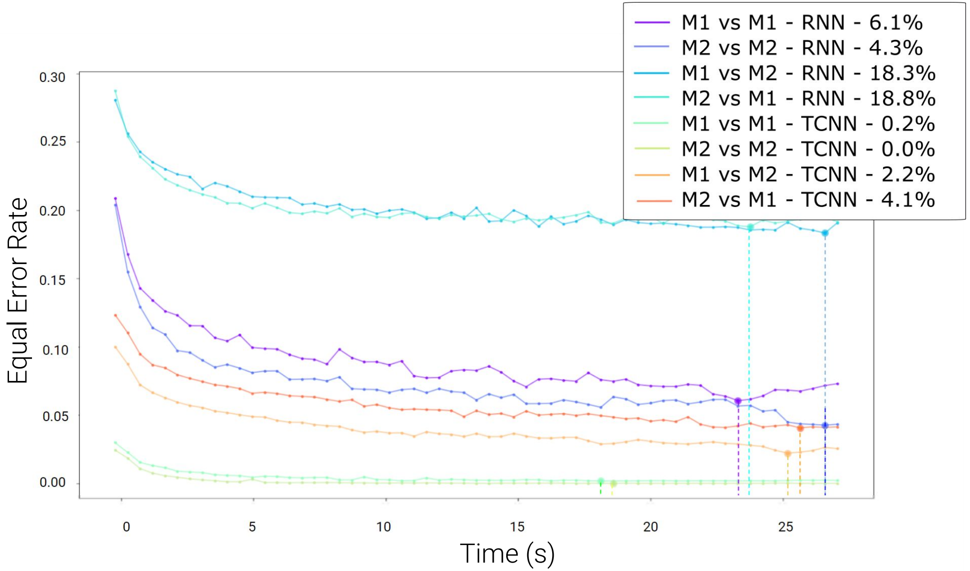
EER evolution with the **batch size** (i.e. time per authentication unit) for **Fantasia** and **MIT-BIH**

on


0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
50
60
70
80
Min mean EER: 1.253%
Time 75 s
ECG 1
ECG 23
ECG 45
ECG 68
Predicted class EER
Mean EER

Authentication

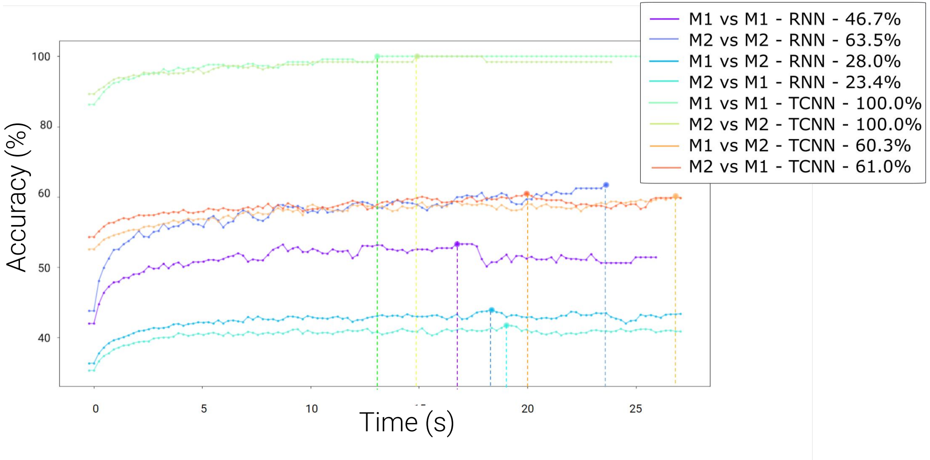
Authentication Results



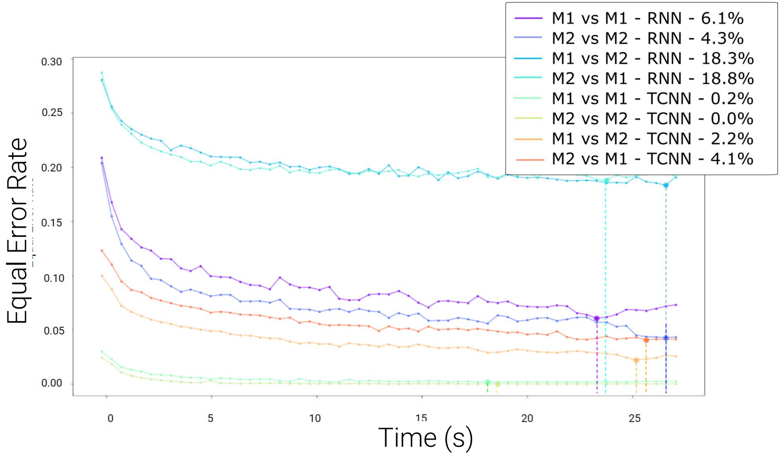
EER evolution with the **batch size** (i.e. time per authentication unit)

Authentication

Results for CYBHi



Accuracy evolution with the **batch size**
(i.e. time per identification unit)



EER evolution with the **batch size**
(i.e. time per authentication unit)

Authentication

Comparative Study

Study	Database	Acc	EER
Tantawi et al. (2013)		90.0%	----
Tantawi et al. (2013)		95.9%	----
Gargiulo et al. (2015)	Fantasia	99.0%	----
RNN		**100%**	**0.02%**
TCNN		99.1%	**0.02%**
Wang et al. (2008)		98.1%	----
Fatemian and Hatzinakos (2009)		99.6%	----
Wang et al. (2008)		94.5%	----
Rabhi and Lachiri (2013)	MIT-BIH Sinus	99.0%	----
Sidek et al. (2014)		99.1%	----
RNN		**100%**	0.6%
TCNN		**100%**	**0.0%**
Lynn et al. (2019)	MIT-BIH Arr	98.6%	----
RNN	MIT-BIH	92.7%	1.5%
TCNN	Arr, Sin, Long	**96.3%**	**0.1%**
da Silva et al. (2014)		94.4%	----
Lourenço et al. (2012)		95.2%	----
da Silva Luz et al. (2018)	CYBHi M1 vs. M1	-----	1.3%
RNN		46.7%	6.1%
TCNN		**100%**	**0.2%**
Lourenço et al. (2012)		**90.2%**	----
da Silva Luz et al. (2018)	CYBHi	-----	12.8%
RNN	M1 vs. M2	28.0%	18.3%
TCNN		60.3%	**2.2%**
da Silva Luz et al. (2018)		-----	14.0%
RNN	CYBHi M2 vs. M1	23.5%	18.8%
TCNN		**61.0%**	**4.1%**
RNN	CYBHi	63.5%	4.3%
TCNN	M2 vs. M2	**100%**	**0.0%**

Provides state-of-the-art results for both **identification** (high accuracy) and **authentication** (low EER)

Provides state-of-the-art results even for databases with low Signal-to-Noise Ratio

[Bento, Belo et al. (2020). ECG Biometrics Using Deep Learning and Relative Score Threshold Classification, Sensors 20 (15), 4078.]

Detection

Is it possible?

At this time I asked myself:

"Is it possible for a DNN to learn the **default morphology** of a normal sinus rhythm signal and with that, **identify the divergence** caused by an occurrence?"

Detection

ECG anomaly detection objective

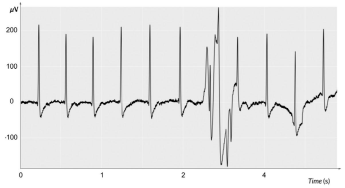
The **objective** is to **predict** when something **different from a normal** cycle of an **ECG** occurs;

It was tested in **two scenarios:**

Noise: Detection of **noise artifacts**;

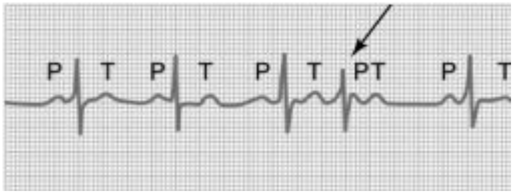
Arrhythmia: Detection of the presence of **symptomatic ECG cycles.**

Noise Artifacts



[From Rodrigues, Belo et al. (2017)]

Premature Contraction



[From Johna & Guyton (2011)]

Detection

ECG anomaly detection example

Data:

Autoencoder: Fantasia

Noise: Fantasia, and MIT-BIH Noise Stress (**Classes**: Normal Sinus (**NS**), Noise Affected Signal (**NAS**))

Arrhythmia: MIT-BIH Arrhythmia (**Classes**: Atrial Fibrillation (**AFIB**), Atrial Flutter (**AFL**), Ventricular Bigeminy (**B**), Paced Rhythm (**P)**, Pre-excitation (**PREX**), Sinus Bradycardia (**SBR**), and Normal Sinus Rhythm (**NSR**))

Optimizer:

All: RMSProp

Loss Function:

Autoencoder: Mean Squared Error

Noise and Arrhythmia Detection: Categorical Class Entropy

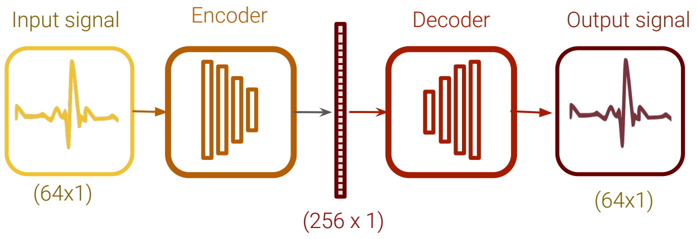
Detection

Autoencoder for feature learning

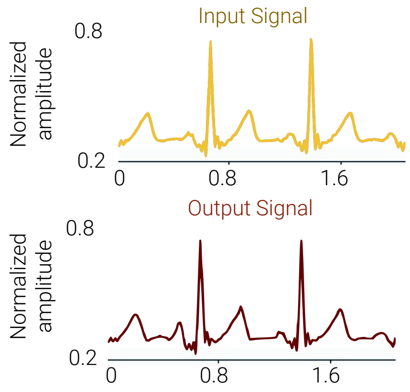
The **autoencoder** was only trained with **asymptomatic ECG**

After training, this autoencoder was fed with **both asymptomatic (NS) and noisy ECG (NAS)** to observe the differences in the feature vector

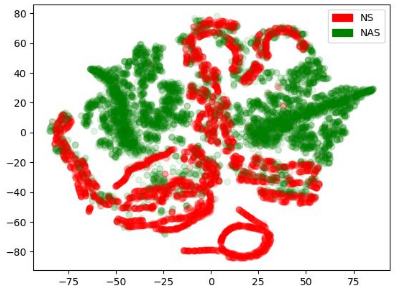
Architecture



Autoencoder example



Learned features TSNE

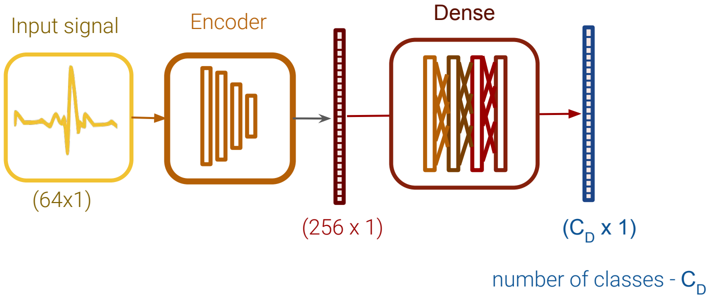


Detection

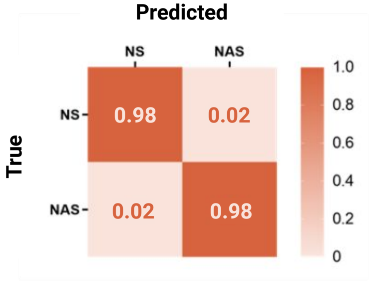
Noise Detection

After training the **encoder** with the autoencoder, the architecture was added with a **dense layer** (fully connected layer) for classification.

Architecture



Confusion matrix



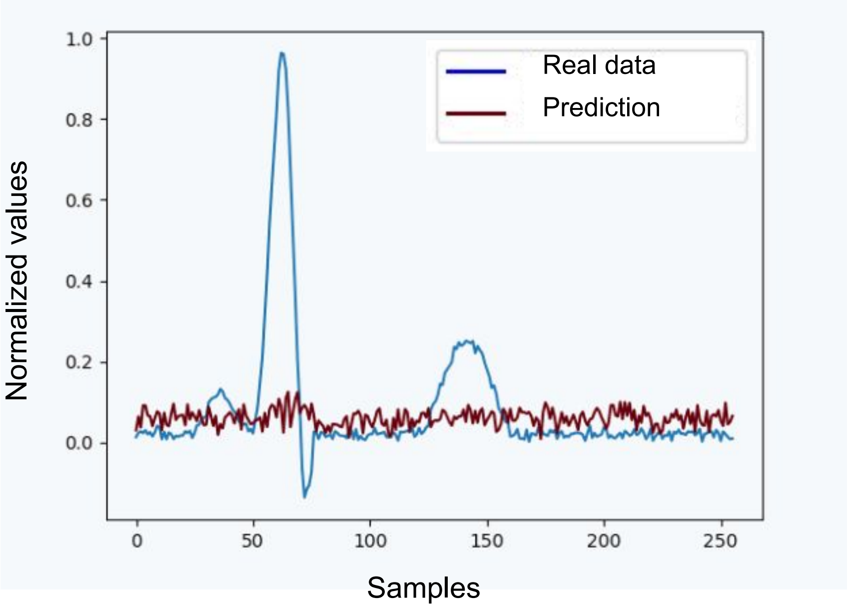
Results for noise detection

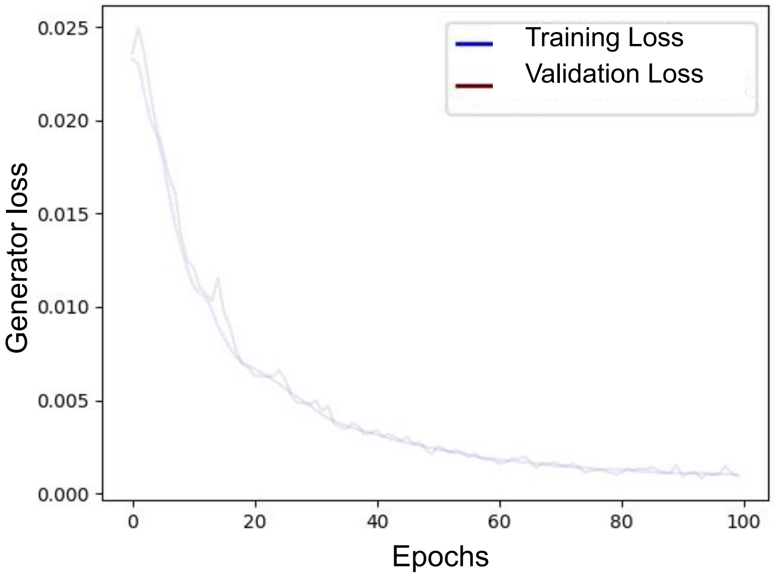
Accuracy (%)	Sensitivity (%)	Specificity (%)
98,18	98,21	98,15

Detection

Autoencoder training example

The generation of a signal after each epoch



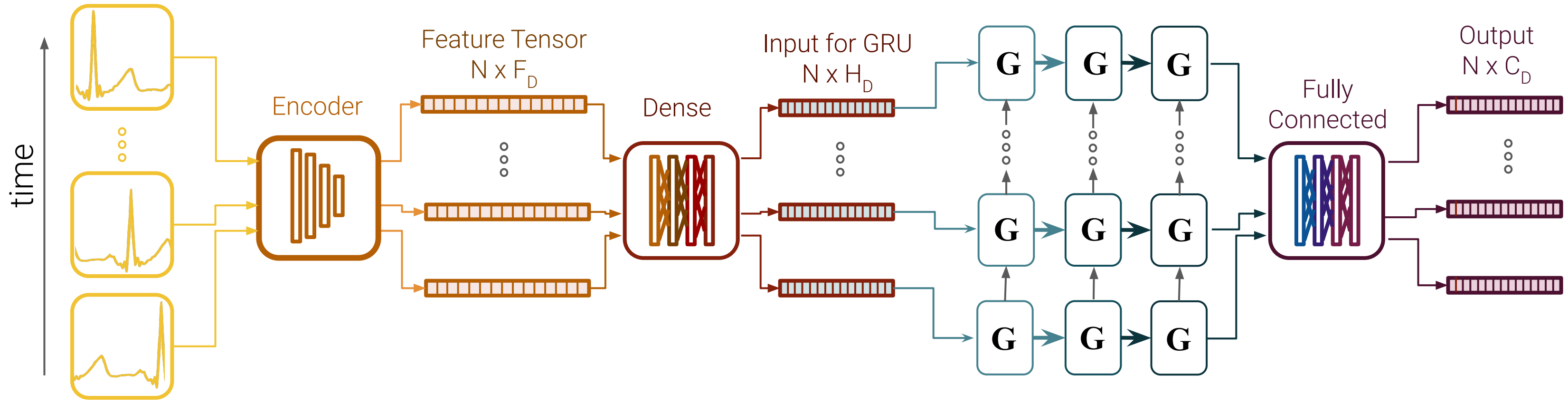


Detection

Arrhythmia detection architecture

Using the same **encoder,** the features are **fed** to a **dense layer** to be **fed** to a **RNN** architecture

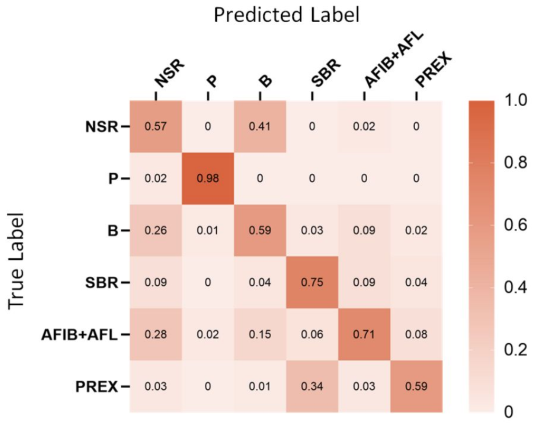
The last fully connected network makes a **decision based** on the time-windows **sequence**



Detection

Results for arrhythmia detection

Accuracy for ECG arrhythmia detection



Classification Matrix for Normal sinus rhythm (NSR), Ventricular paced rhythm (P), Bigeminy (B), Sinus bradycardia (SBR), Atrial Flutter (AFL), Atrial Fibrillation (AFIB) and Pre-excitation (PREX) arrhythmias

[Pestana, Belo, and Gamboa. "Detection of Abnormalities in Electrocardiogram (ECG) using Deep Learning." BIOSIGNALS. 2020.]

Conclusions

So **what** was **learned?**

What is the **usefulness** of **these architectures** in the **future**?

Conclusions

Synthesis: Innovation in the capacity to **learn and replicate several signals**. With the observation of the learned models can be directed to **the search of the internal neural structures** that generate the morphological aspects of the signal (Explainable AI);

Authentication: The achieved results **showed good performance**, but there is a **margin for improvement**, such as the introduction of **transfer learning** in the **training** process and the acquisition of **more data** per **person**;

Detection: The use of an **autoencoder** for learning the **normal morphology** of a signal helps in the **detection of divergence** in the expression of key characteristics of an **ECG cycle**;

Conclusions

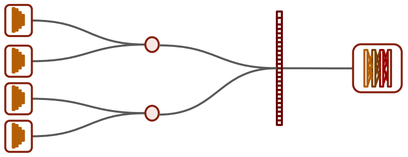
By analyzing and presenting several architectures and after proving their usefulness in the research of patterns within the biosignal field, **this thesis as shown that Deep Neural Networks (DNN) has a huge potential** in providing new solutions and to the field

Some mechanisms of these architectures may be exploited for **unveiling how biosignals work** and the reason behind the classification of some pathological events

Future Architectures

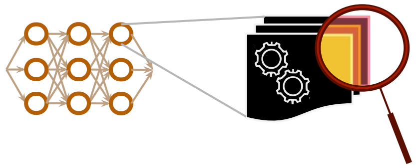
Fusion between networks:

Hierarchical Multimodal approach



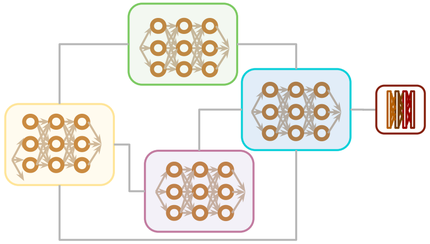
Explainable Artificial Intelligence:

Visualization of filters and through generation mechanisms



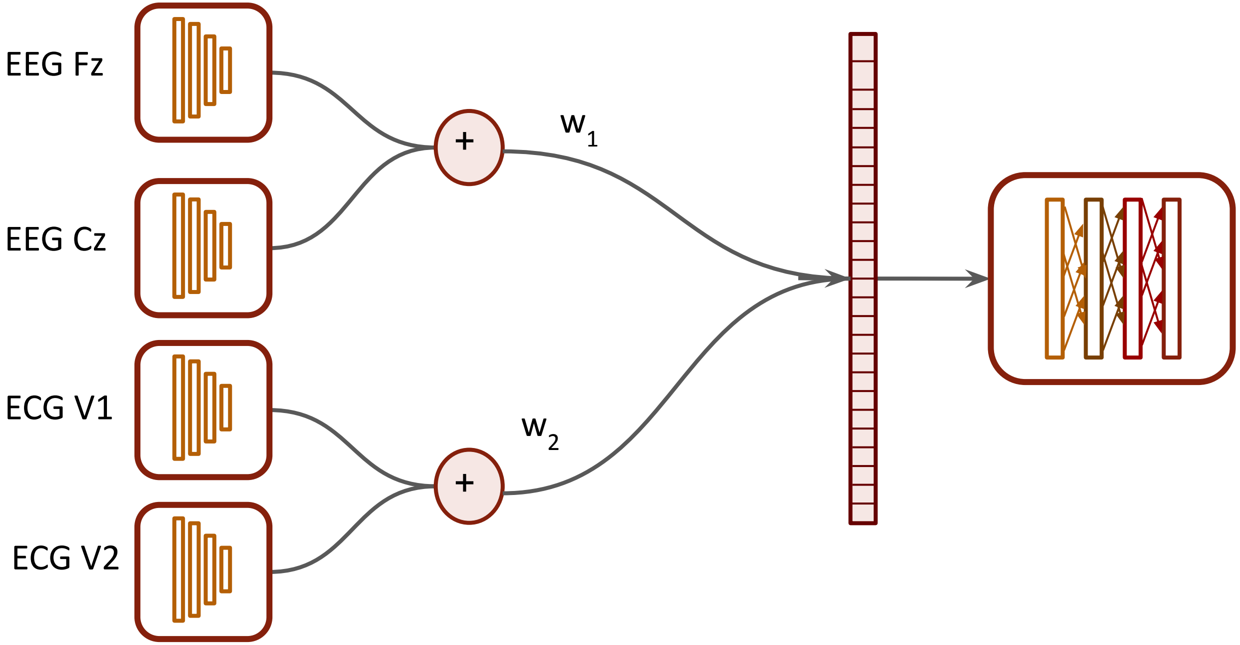
AI in healthcare:

Fusion between different networks to provide a more informative decision



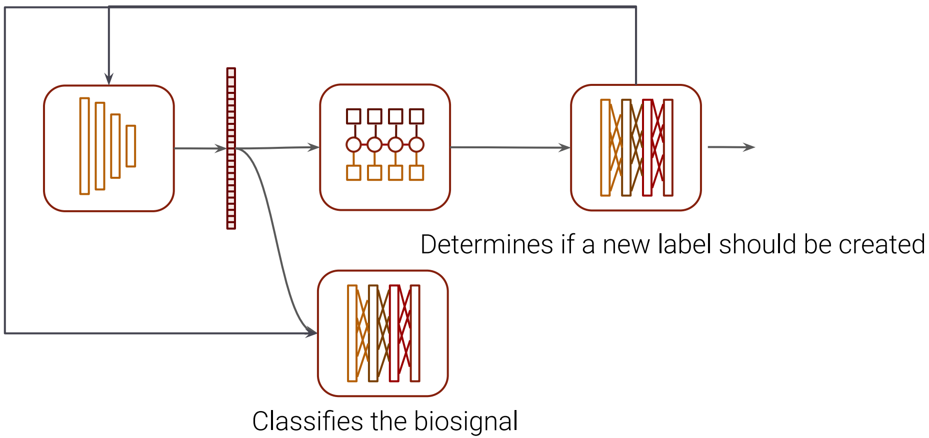
Future Architectures

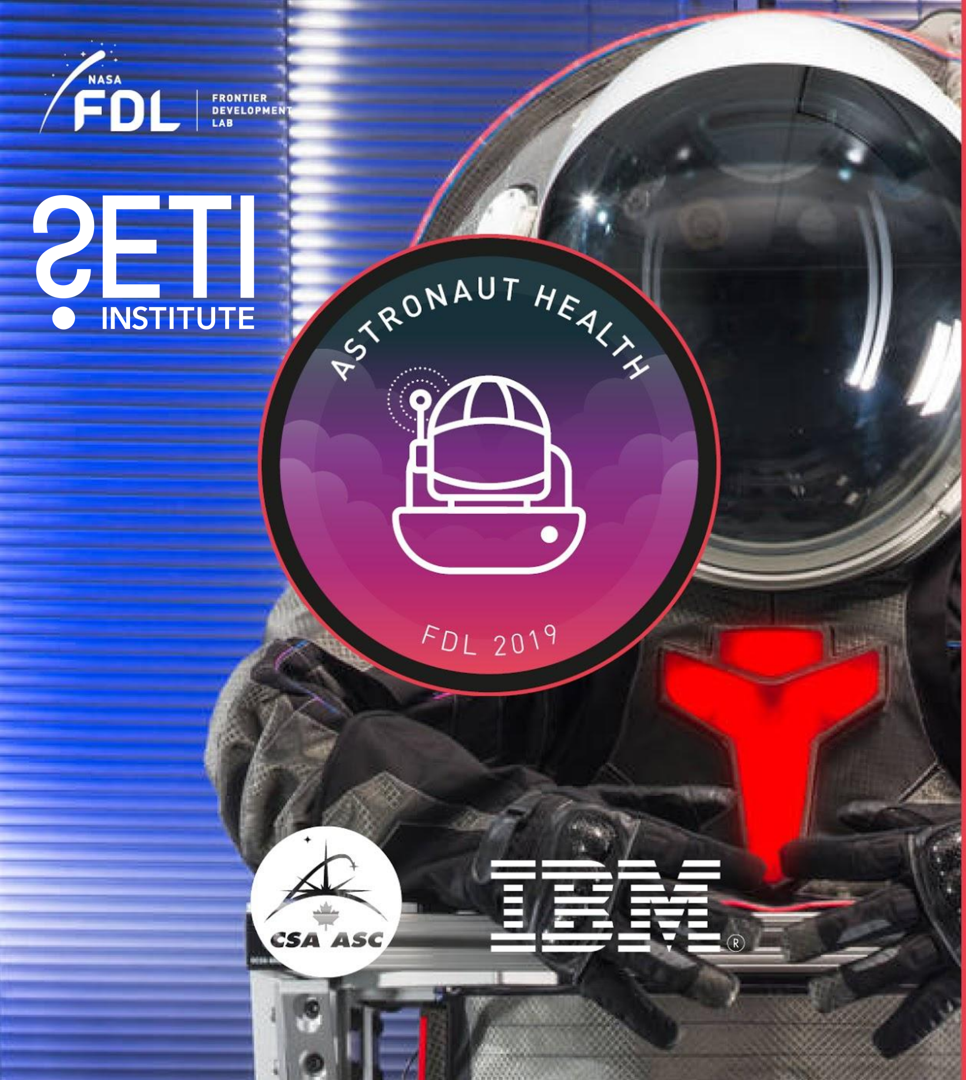
Hierarchical Multimodal approach



Future Architectures

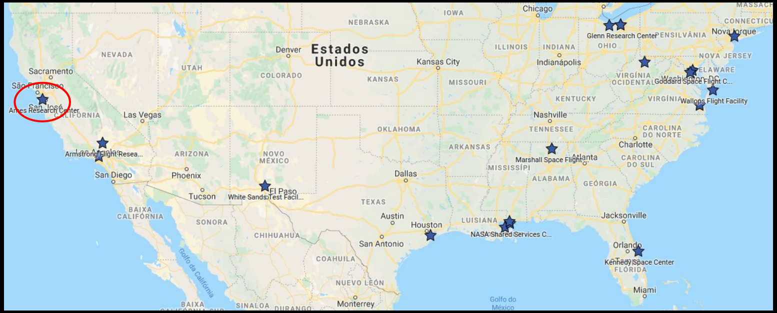
Reinforced Learning for Active Learning





GENERATION OF SIMULATED BIOSENSOR DATA

Frontier Development Lab Initiative


Chicago
IOWA
NEBRASKA
Glenn Research Center
PENSILVÂNIA
Nova Iorque
NEVADA
Denver
Estados Unidos
Kansas City
ILLINOIS
INDIANA
OHIO
NOVA JERSEY
Sacramento
UTAH
COLORADO
Indianápolis
São Francisco
San José
Ames Research Center
KANSAS
MISSOURI
VIRGÍNIA OCIDENTAL
Goddard Space Flight C...
KENTUCKY
VIRGÍNIA
Wallops Flight Facility
Las Vegas
Nashville
OKLAHOMA
TENNESSEE
CAROLINA DO NORTE
Armstrong Flight Resea...
ARIZONA
NOVO MÉXICO
ARKANSAS
Marshall Space Flight
Atlanta
Charlotte
San Diego
Phoenix
MISSISSIPI
CAROLINA DO SUL
Dallas
ALABAMA
GEÓRGIA
El Paso
Tucson
White Sands Test Facil...
TEXAS
BAIXA CALIFÓRNIA
Austin
Houston
LUISIANA
Jacksonville
SONORA
CHIHUAHUA
NASA Shared Services C...
San Antonio
Orlando
COAHUILA
Kennedy Space Center
FLORIDA
NUEVO LEÓN
Miami
Monterrey
Golfo do México


NASA RESEARCH PARK
SHENANDOAH PLAZA - MOFFETT FIELD HISTORIC DISTRICT

SETI INSTITUTE

More info for the program:

https://frontierdevelopmentlab.org

FRONTIER DEVELOPMENT LAB 2019

FDL

APPLIED ARTIFICIAL INTELLIGENCE RESEARCH FOR ALL HUMANKIND

Challenges 2019

MISSION CONTROL FOR EARTH

LIVING WITH OUR STAR

ASTRONAUT HEALTH

THE MOON FOR GOOD

Researchers

Eleni Antoniadou

David Belo

Krittika D'Silva

Brian Wang

AI Mentors

Ronay Ak

Supriyo Chakraborty

Frank Soboczenski

Tony Lindsey

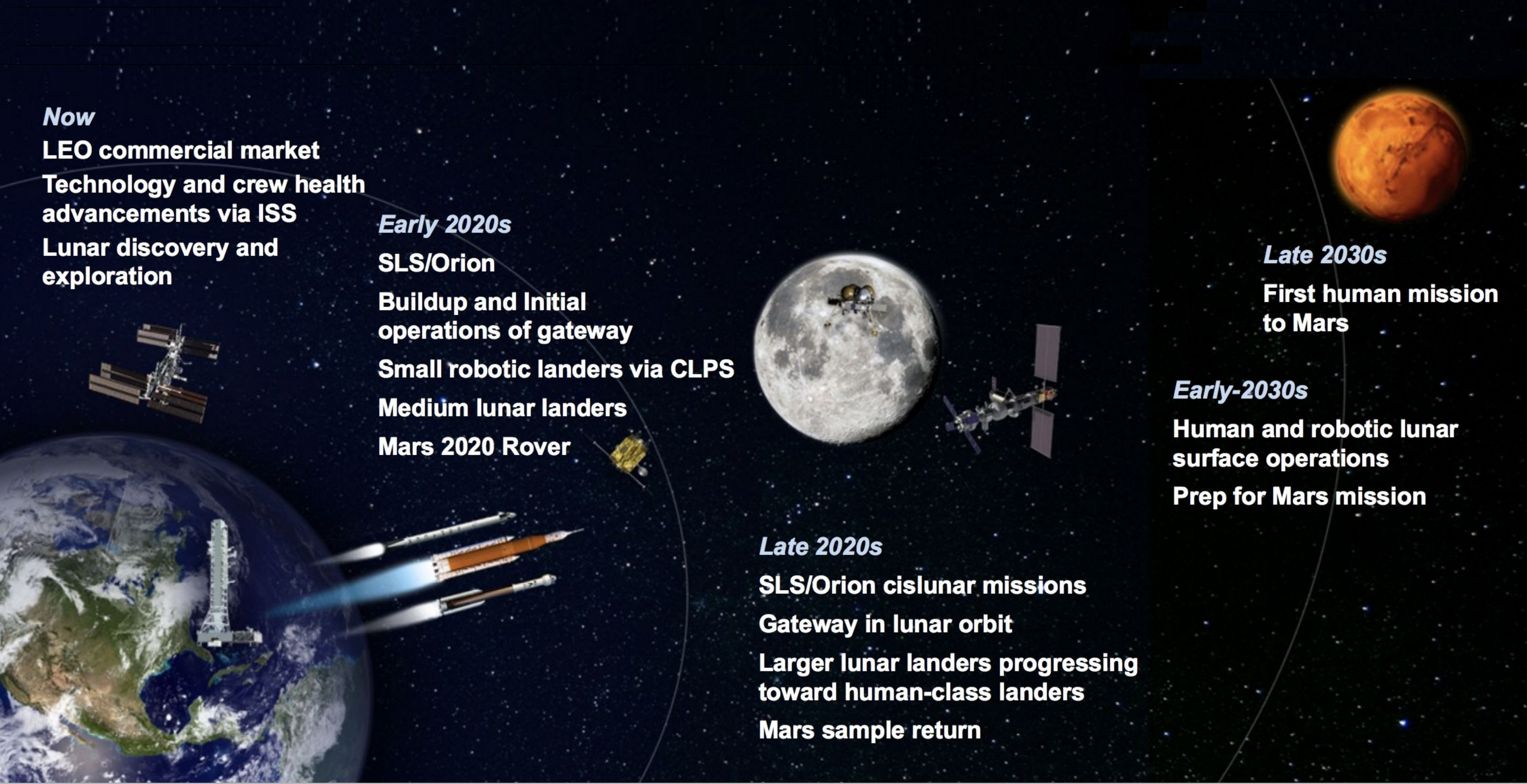
Mentors

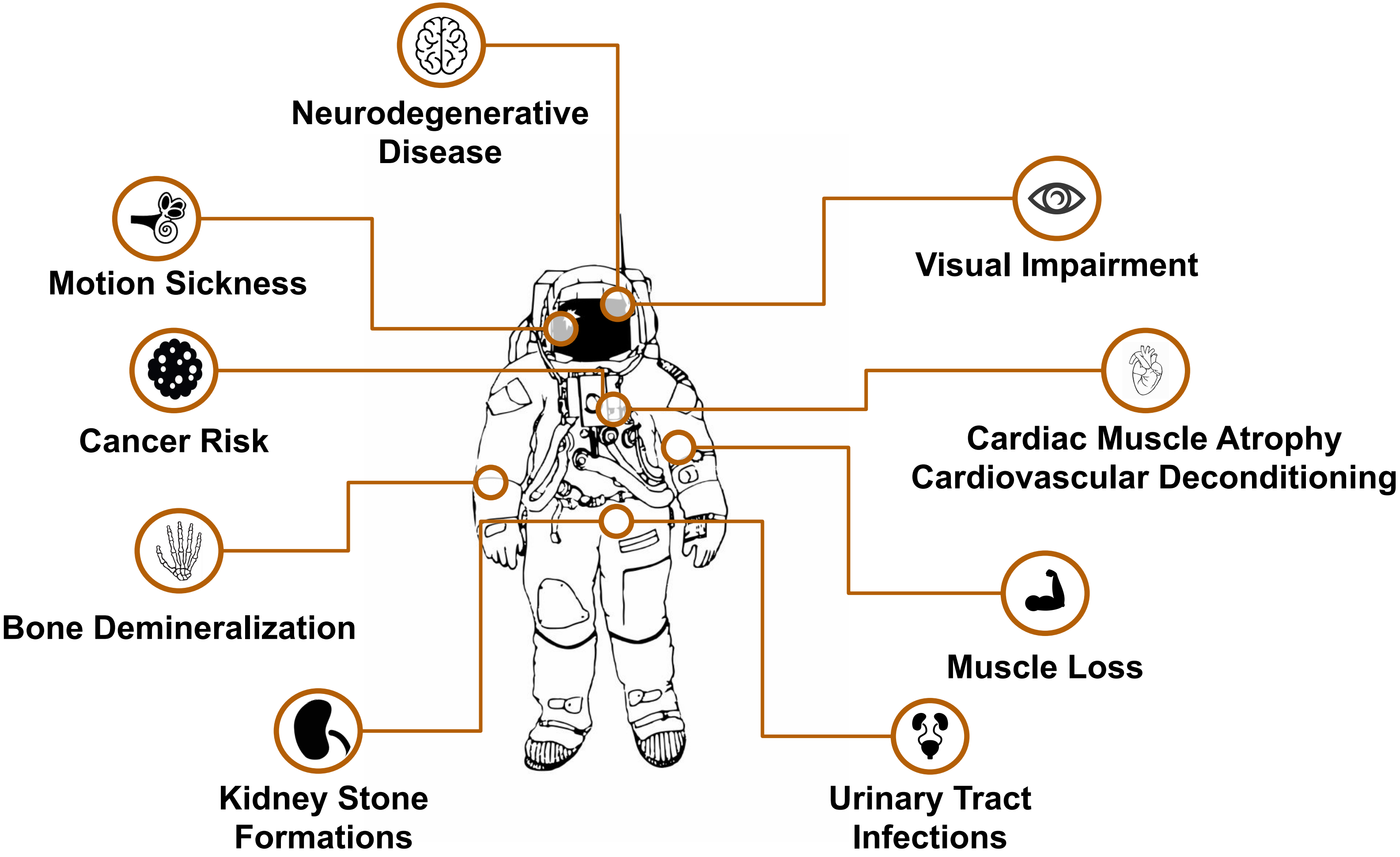
Tianna Shaw

Graham Mackintosh

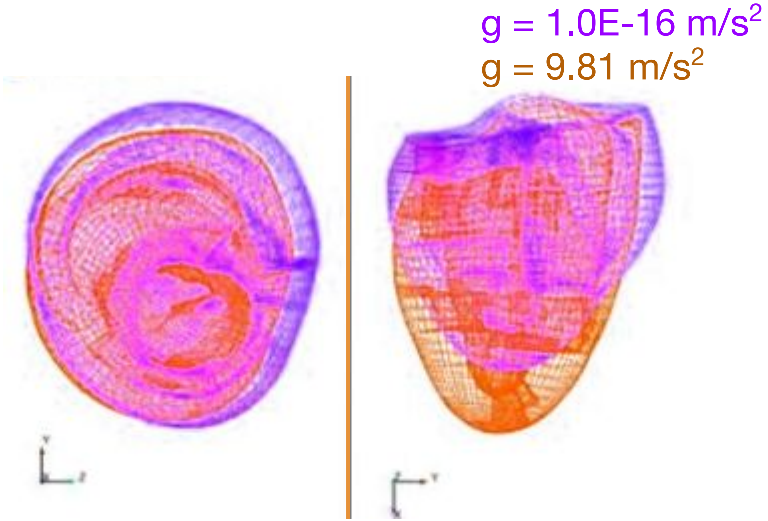
Annie Martin

Brian Russell


Now
LEO commercial market
Technology and crew health advancements via ISS
Lunar discovery and exploration
Early 2020s
SLS/Orion
Buildup and Initial operations of gateway
Small robotic landers via CLPS
Medium lunar landers
Mars 2020 Rover
Late 2020s
SLS/Orion cislunar missions
Gateway in lunar orbit
Larger lunar landers progressing toward human-class landers
Mars sample return
Early-2030s
Human and robotic lunar surface operations
Prep for Mars mission
Late 2030s
First human mission to Mars


Neurodegenerative
Disease
Motion Sickness
Visual Impairment
Cancer Risk
Cardiac Muscle Atrophy
Cardiovascular Deconditioning
Bone Demineralization
Muscle Loss
Kidney Stone
Formations
Urinary Tract
Infections

Cardiac Muscle Atrophy Cardiovascular Deconditioning



In red the Predicted change in a heart shape at end-diastole on Earth (orange) and in microgravity (purple). Credit: Dr. Chris May.

In: Suresh, Aswath, et al (2016) "Innovative Low Cost Mars Flyby Spacecraft for Safe Interplanetary Human Mission." *Mars Society Convention, Marspapers*..

Possible cardiovascular pathologies due to long exposure to low gravity

Atrial Fibrillation

Atrial Flutter

Premature Ventricular Contractions (PVC)

Long QT syndrome (LQTS)

Ventricular and Sinus Tachycardia

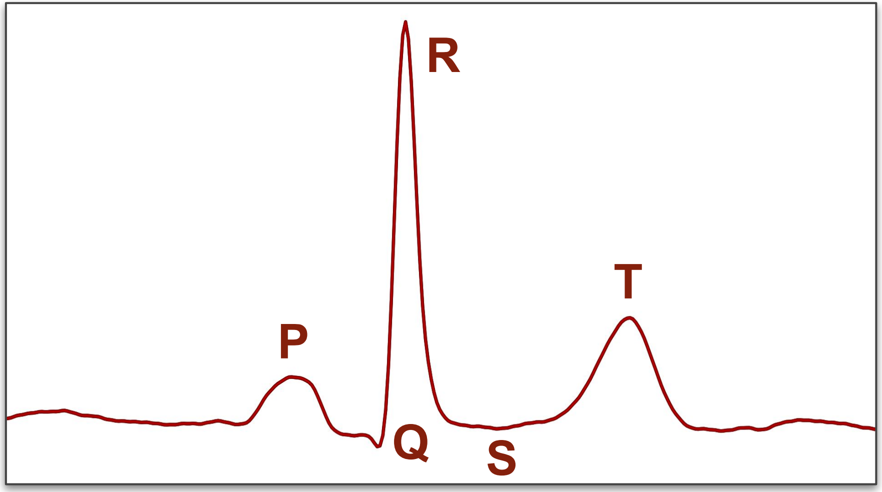
Bradycardia

Brugada's syndrome

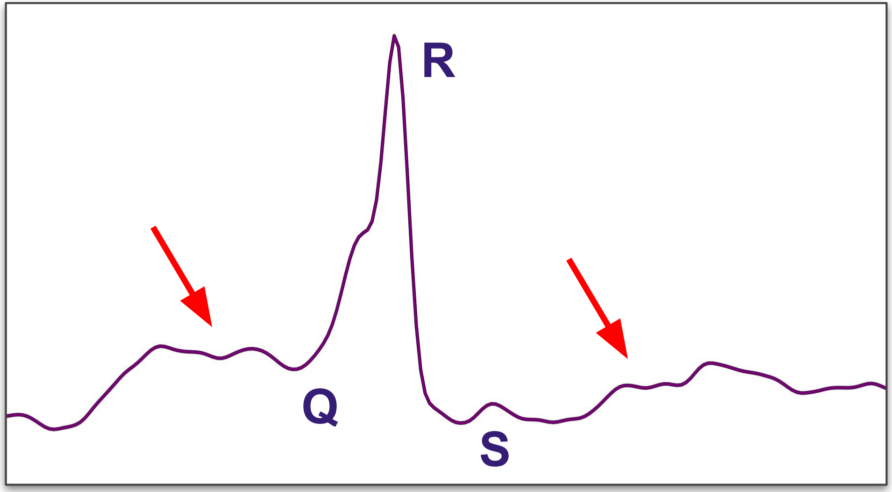
Wearable devices for health monitoring enable a quantitative understanding of changes, early diagnostics, and intervention.

We aim to synthesize symptomatic wearable cardiac data to enable and empower tools for diagnostics and prevention

Asymptomatic vs. Symptomatic ECG Signal

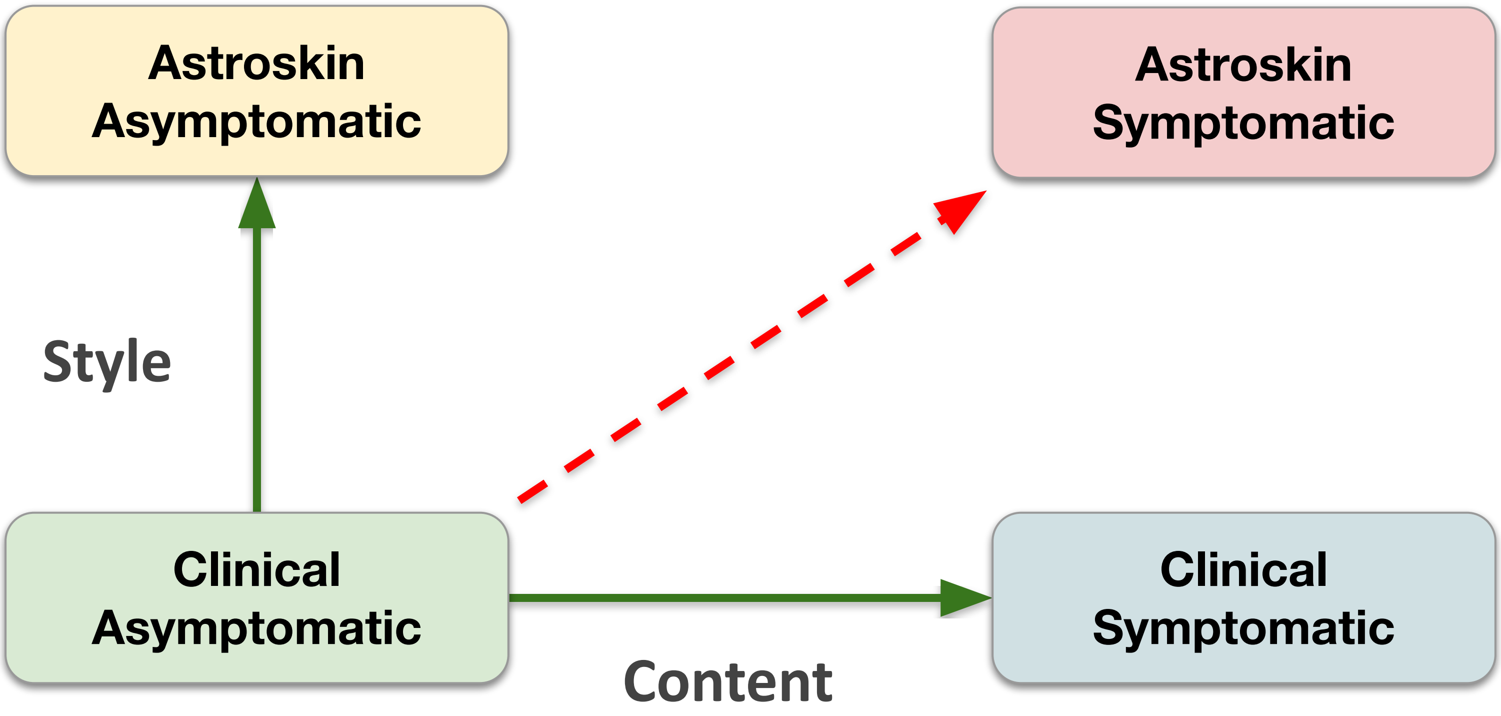


Healthy

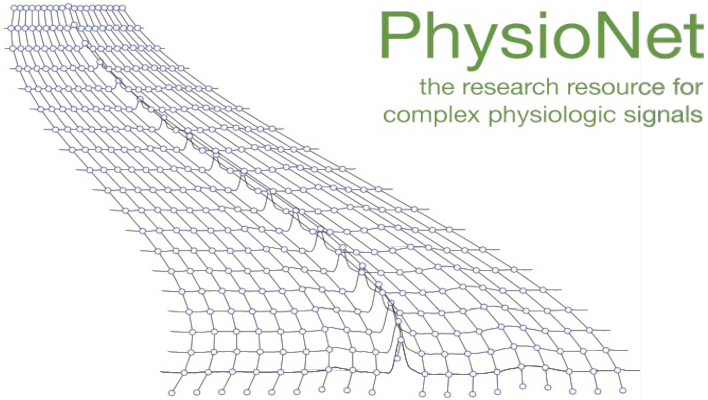


Atrial Fibrillation

Methodology



Clinical ECG vs. Wearable ECG



Public available datasets:

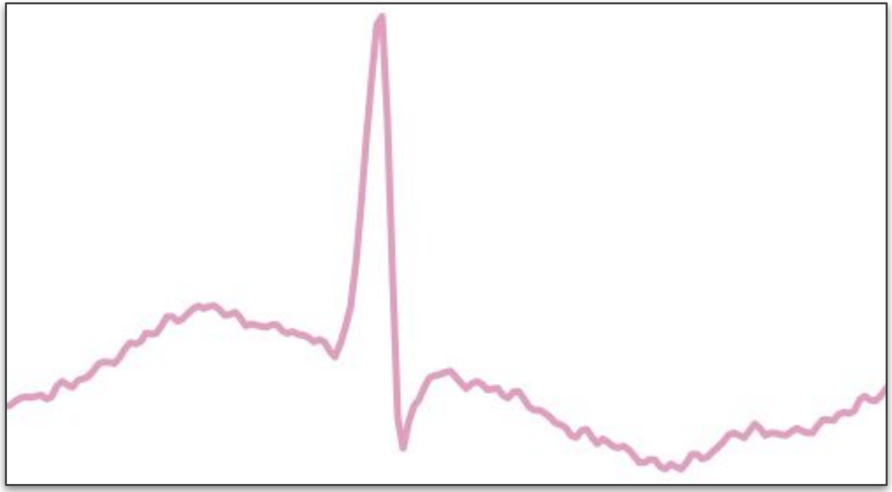
- Fantasia (490 hours of Asymptomatic ECG)
- MIT-BIH (95 hours of Atrial Fibrillation)

- HERA Mission (120 GB)
- NASA data
- CSA data

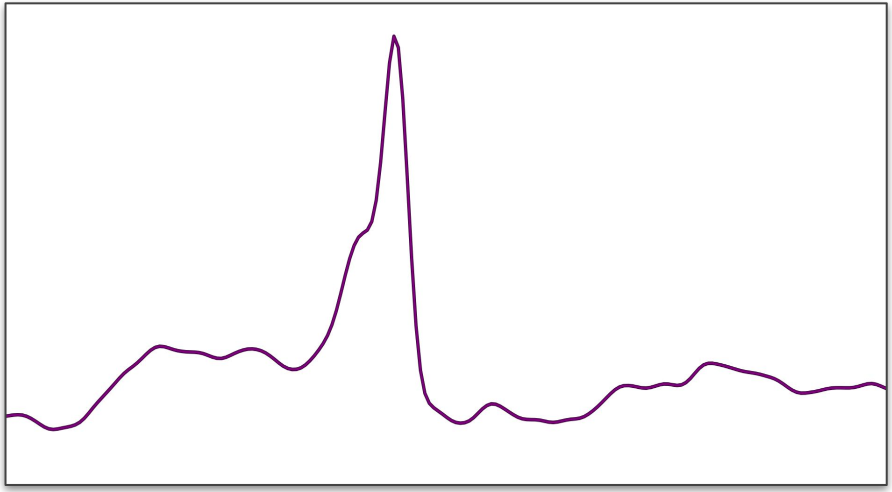
Style GAN

From: Karras, Tero, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2019.

Style vs. Content

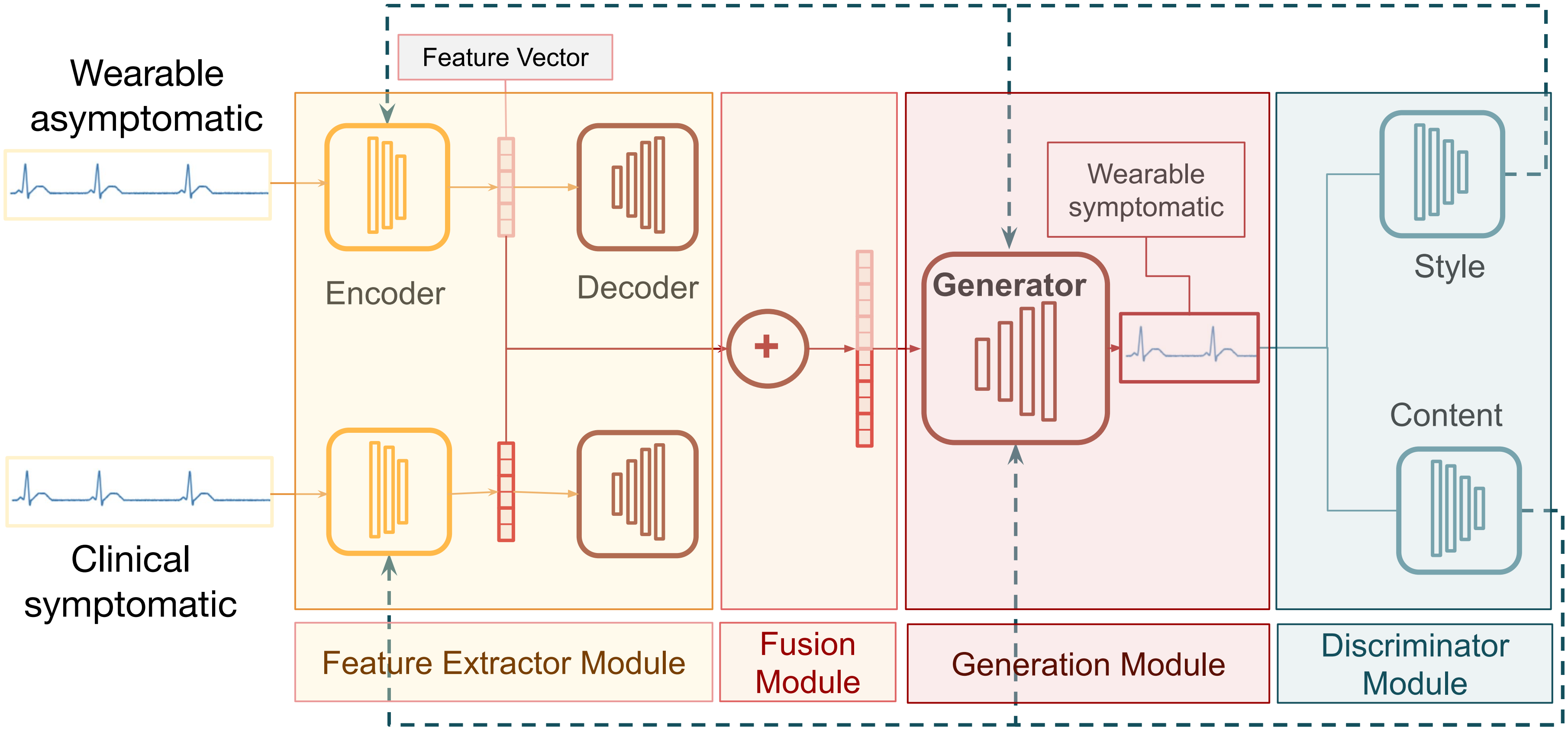


Wearable Style

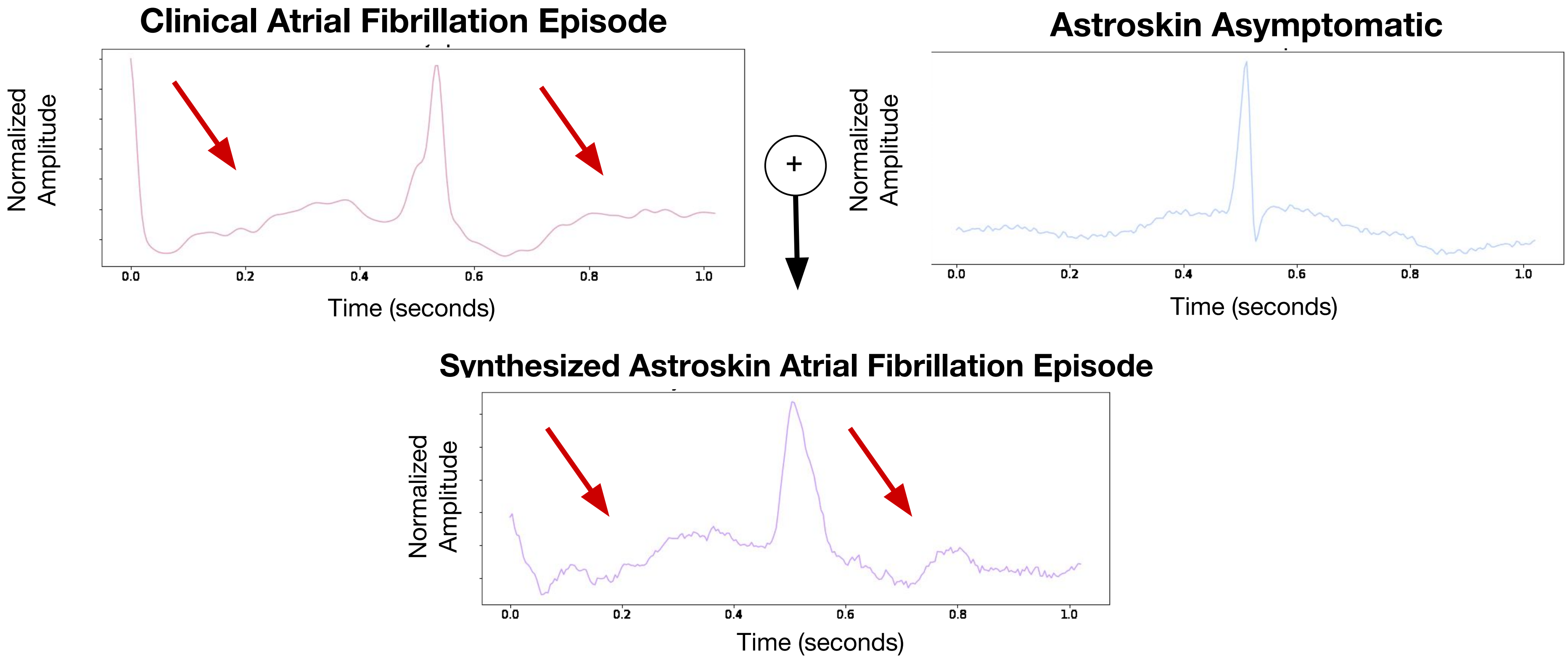


Symptomatic Content

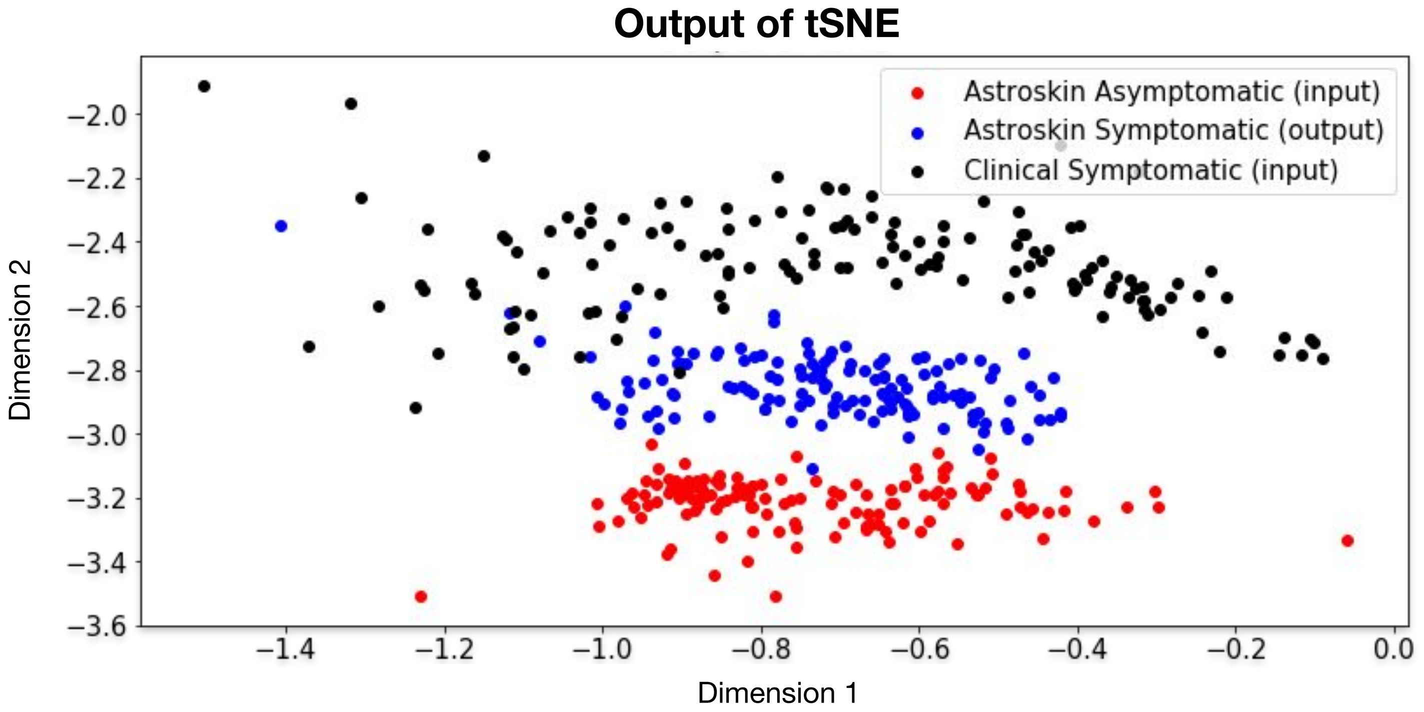
Architecture



Model Output



Visualization of Feature Space



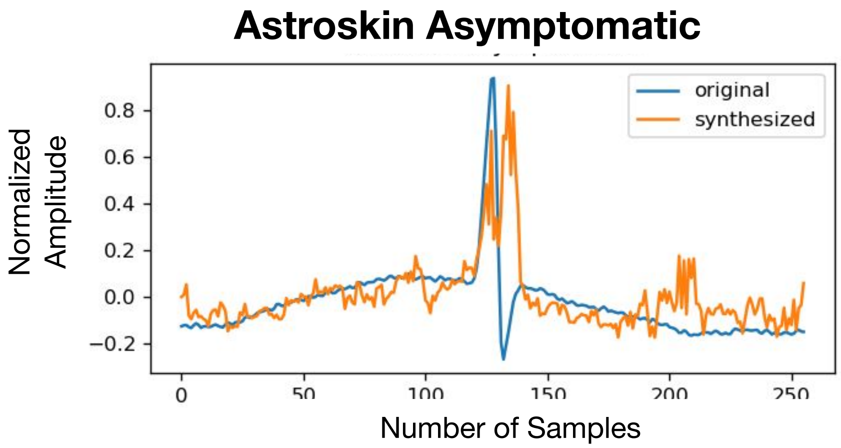
Results

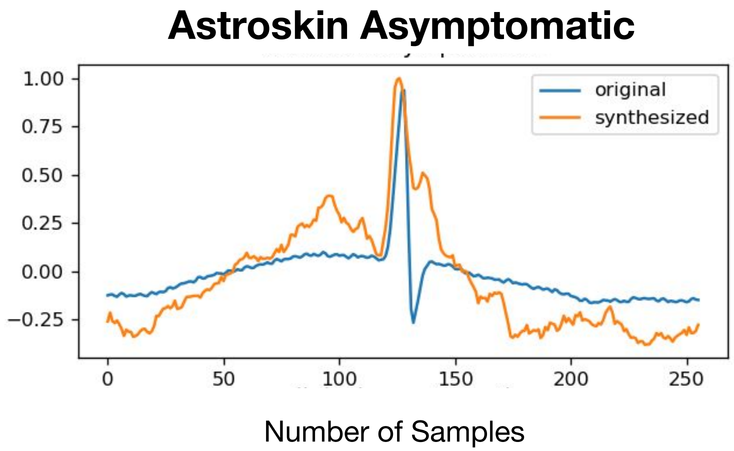
Baseline:

Model trained purely on Mean Squared Error

Our model:

Model trained with our discriminators and Mean Squared Error





Mean Squared Error: 7.79

Mean Squared Error: 3.04

Conclusions

- Our model can produce a new signal based on the morphological fusion of two signals;
- Results show that visually the Atrial Arrhythmia is present in the case studies;
- Need to be submitted to more robust validation systems;
- Only one second is available for now due to the R-peak alignment;
- No clinical validation was made.

Future Work

- Train the model with large dataset cohort
- Validate synthesized data with cardiologists
- Develop AI model for additional heart conditions (PVC, tachycardia, Brugada)
- Generate a continuous synthesized signal instead of time windows

Thank you for your attention

Questions?

List of Publications

- **Journals**:
  - D Belo, J Rodrigues, JR Vaz, P Pezarat-Correia, H Gamboa (2017) **Biosignals learning and synthesis using deep neural networks.** BioMedical Engineering OnLine 16 (1), 115 4
  - J Rodrigues, D Belo, H Gamboa (2017) **Noise detection on ECG based on agglomerative clustering of morphological features.** Computers in biology and medicine 87, 322-334 16.
  - VS Kublanov, AY Dolganov, D Belo, H Gamboa (2017) **Comparison of machine learning methods for the arterial hypertension diagnostics.** Applied bionics and biomechanics 2017 13
  - J Rodrigues, D Folgado, D Belo, H Gamboa (2019) **SSTS: A syntactic tool for pattern search on time series**. Information Processing & Management 56 (1), 61-76 3
  - N Bento, D Belo, H Gamboa (2019) **ECG Biometrics Using Spectrograms and Deep Neural Networks.** International Journal of Machine Learning and Computing (IJMLC)
  - Francisco S Melo et al. (2019) **Project INSIDE: towards autonomous semi-unstructured human–robot social interaction in autism therapy.** Artificial intelligence in medicine 96, 198-216 4
  - D. Belo, N. Bento, H. Silva, A. Fred, H. Gamboa (2020). **ECG Biometrics Using Deep Learning and Relative Score Threshold Classification.** Sensors 20 (15), 4078
- **Conferences**:
  - A Dolganov, V Kublanov, D Belo, H Gamboa (2018) **Development of the decision support system in treatment of arterial hypertension application of artificial neural networks for evaluation of heart rate variability signals**. 11th International Conference on Bio-Inspired Systems and Signal Processing 2018
  - J. Pestana, D. Belo, H. Gamboa (2019). **Detection of abnormalities in Electrocardiogram (ECG) using Deep Learning.** 13th International Conference on Bio-inspired Systems and Signal Processing 2019.

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- Y. Wang, J. Wan, J. Guo, Y. M. Cheung, and P. C. Yuen. Inference-based similarity search in randomized montgomery domains for privacy-preserving biometric identification. IEEE Transactions on Pattern Analysis and Machine Intelligence, PP(99):1–1, 2017 2017.
- Zhang, D. Zhou, and X. Zeng. Heartid: A multiresolution convolutional neural network for ecg-based biometric human identification in smart health applications. IEEE Access, 5:11805–11816, 2017.

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- E. J. da Silva Luz, G. J. P. Moreira, L. S. Oliveira, W. R. Schwartz, and D. Menotti. Learning deep off-the-person heart biometrics representations. IEEE Transactions on Information Forensics and Security, 13(5):1258–1270, May 2018.
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