AUSTRIAN INSTITUTE OF TECHNOLOGY
TOMORROW TODAY

Deep Learning for Electrical Biosignals and Applications in Medical Products

28th Deep Learning Meetup in Vienna, 24th June 2019
Talent Garden Austria

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www.encevis.com | www.ait.ac.at

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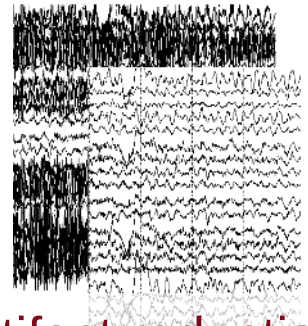
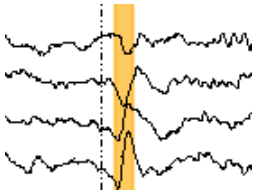
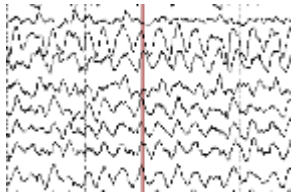
U.S. FOOD & DRUG ADMINISTRATION



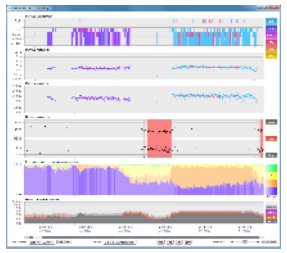
Artifact reduction



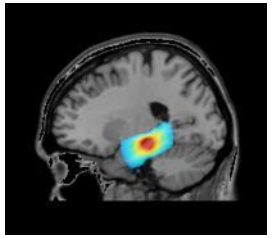
Spike detection



Seizure detection



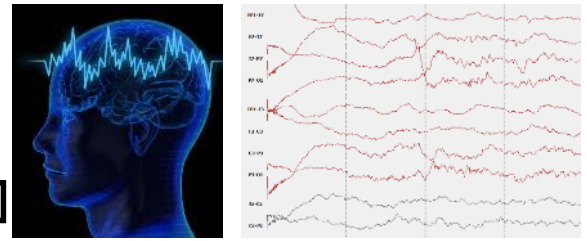
EEG trending



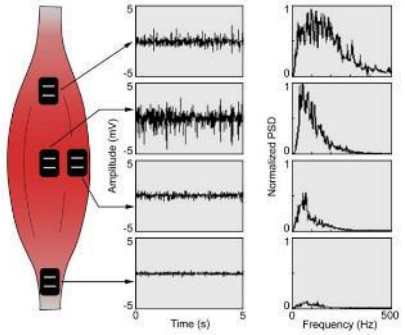
Source Localization

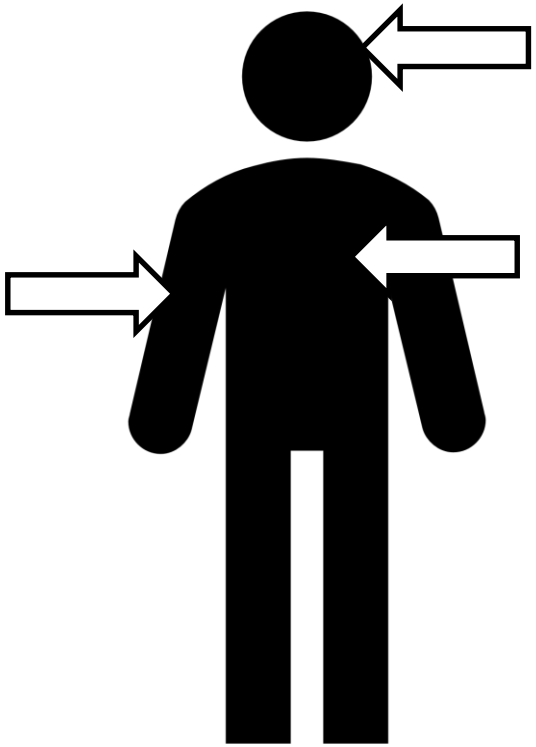
Sources of Electrical Biosignals

EEG - Brain

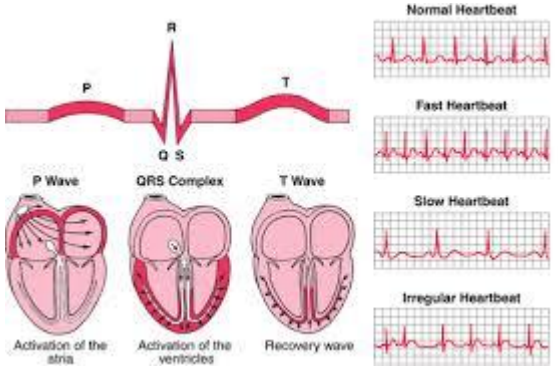


EMG - Muscles

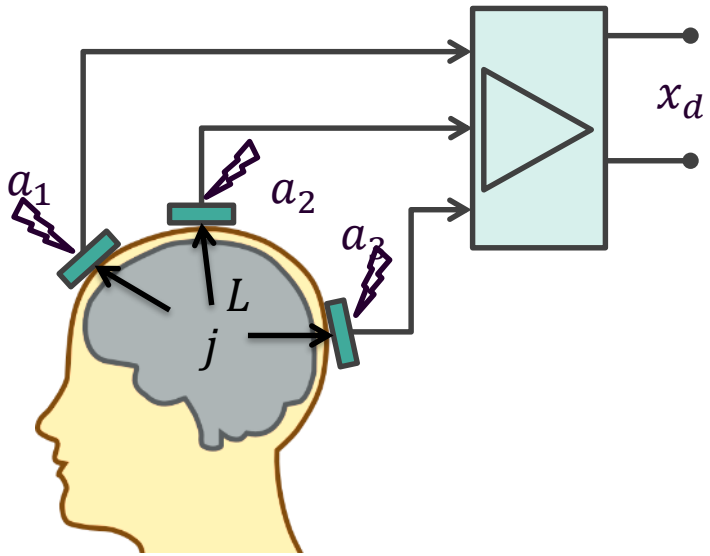


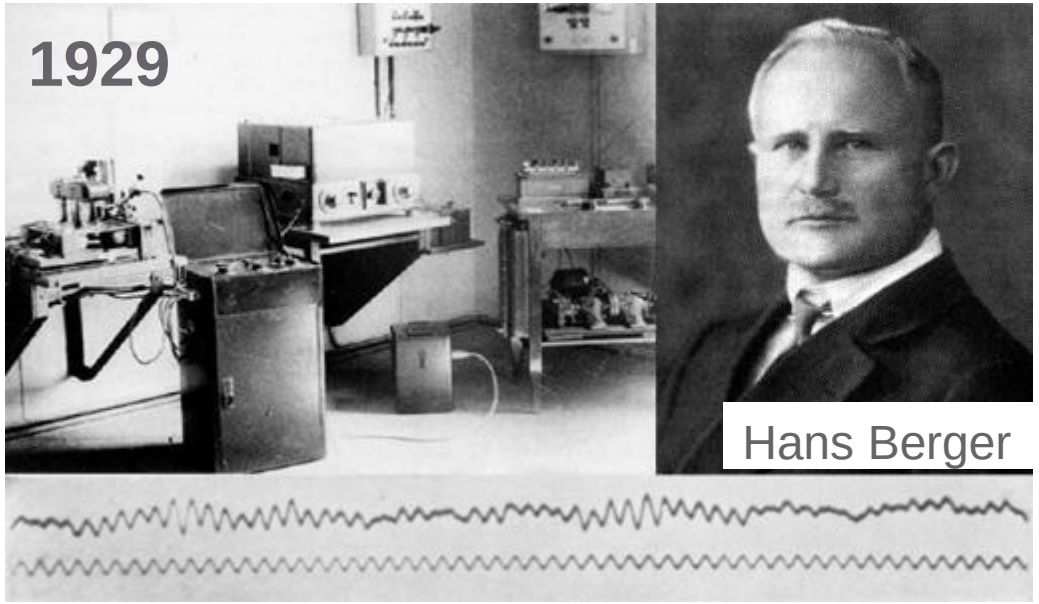


ECG - Heart

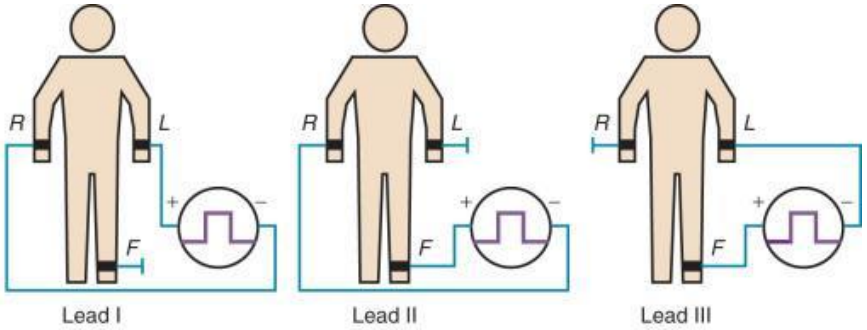


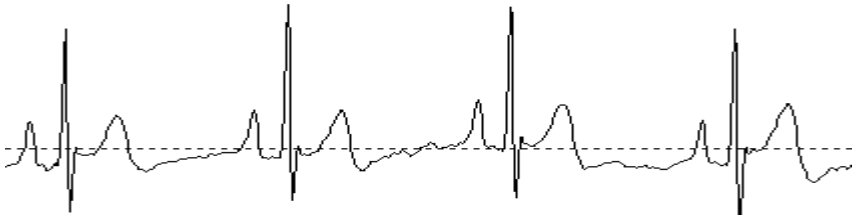
Capture Electric Biosignals





EEG

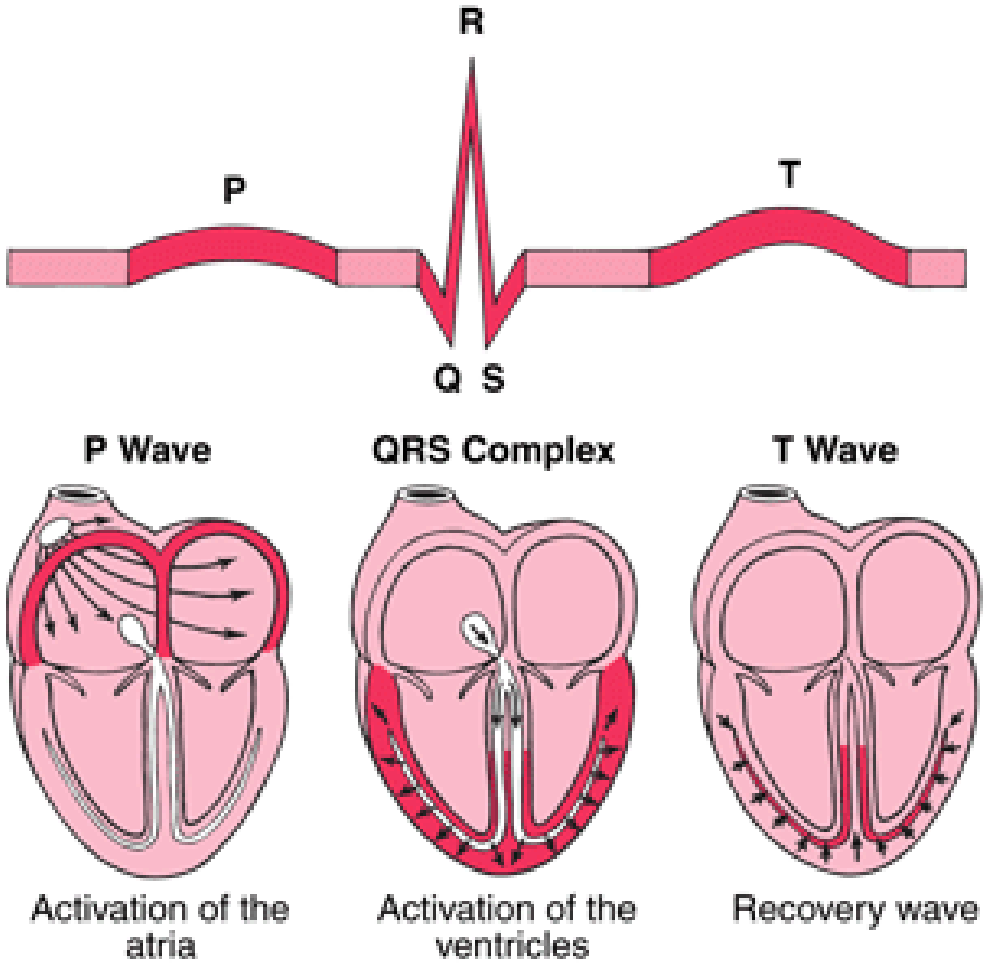


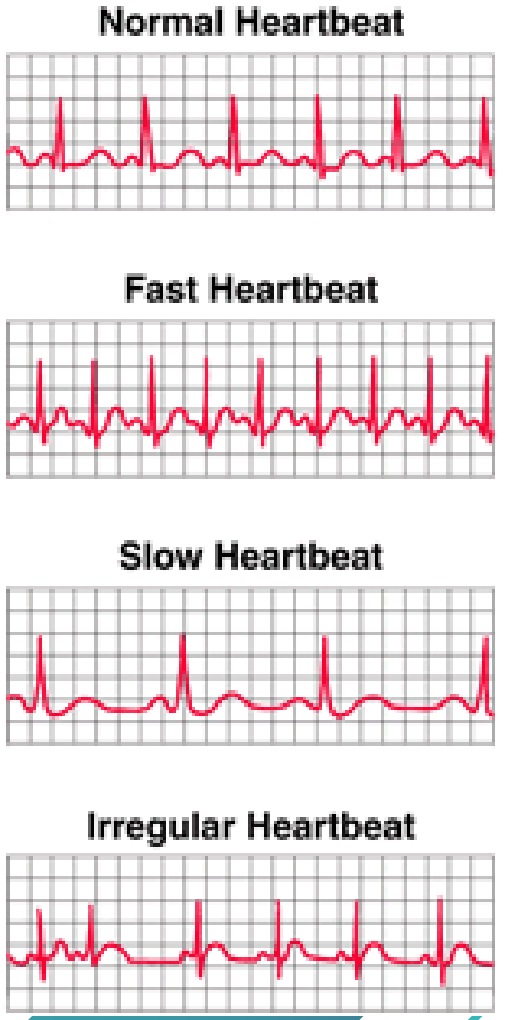


ECG

Source: https://www.sciencedirect.com/topics/medicine-and-dentistry/ecg-electrode

ECG

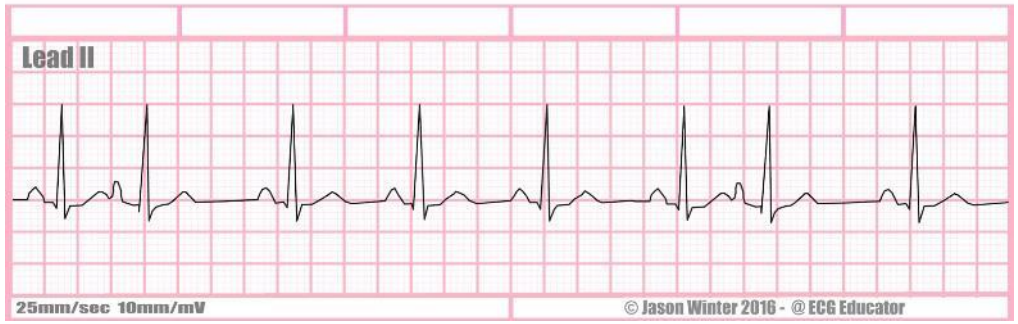




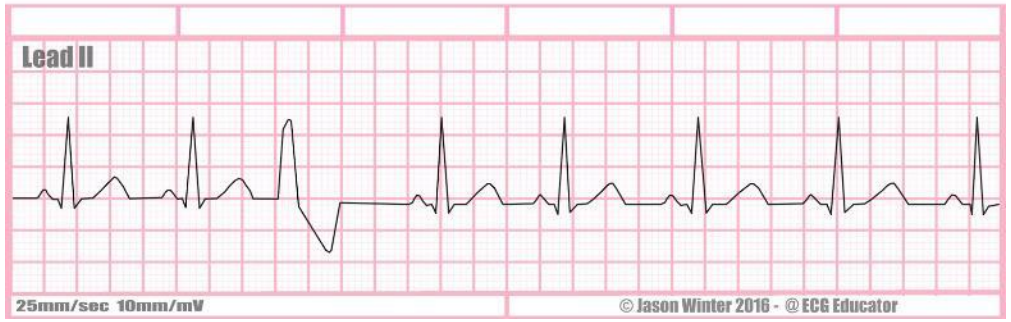
Source: https://www.msdmanuals.com/home/heart-and-blood-vessel-disorders/diagnosis-of-heart-and-blood-vessel-disorders/electrocardiography

Abnormal ECG

Premature Atrial Contraction (PAC)



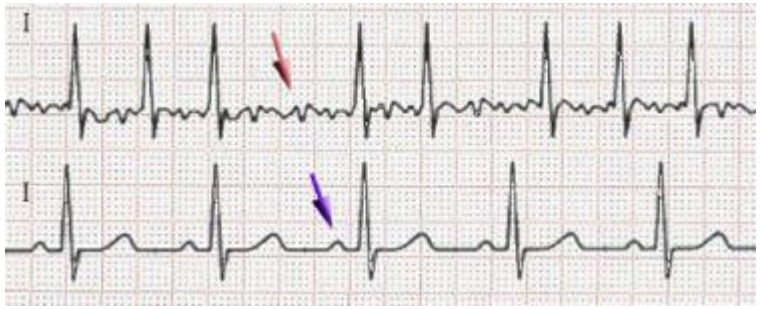
NSR with isolated PVC



Atrial fibrilation (AF)

AF

Normal



PVC: Premature vectricual contraction

PAC: Premature atrial contraction

Atrial fibrilation

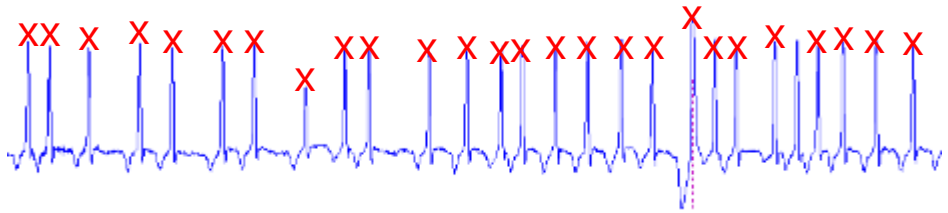
prevalence:

1% of world population,9% of people 80 years and older

Austria 2017: 8243 strokes/yrs, 55263 people after stroke

AF-associated stroke occurred in one third of all patients

Heartbeat Sequence Classification: Atrial fibrillation



modified Pan-Tompkins

Deep NN
Sequence classification

TensorFlow

1985, assembly code, Z80 microprocessor

230 IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. BME-32, NO. 3, MARCH 1985

A Real-Time *QRS* Detection Algorithm

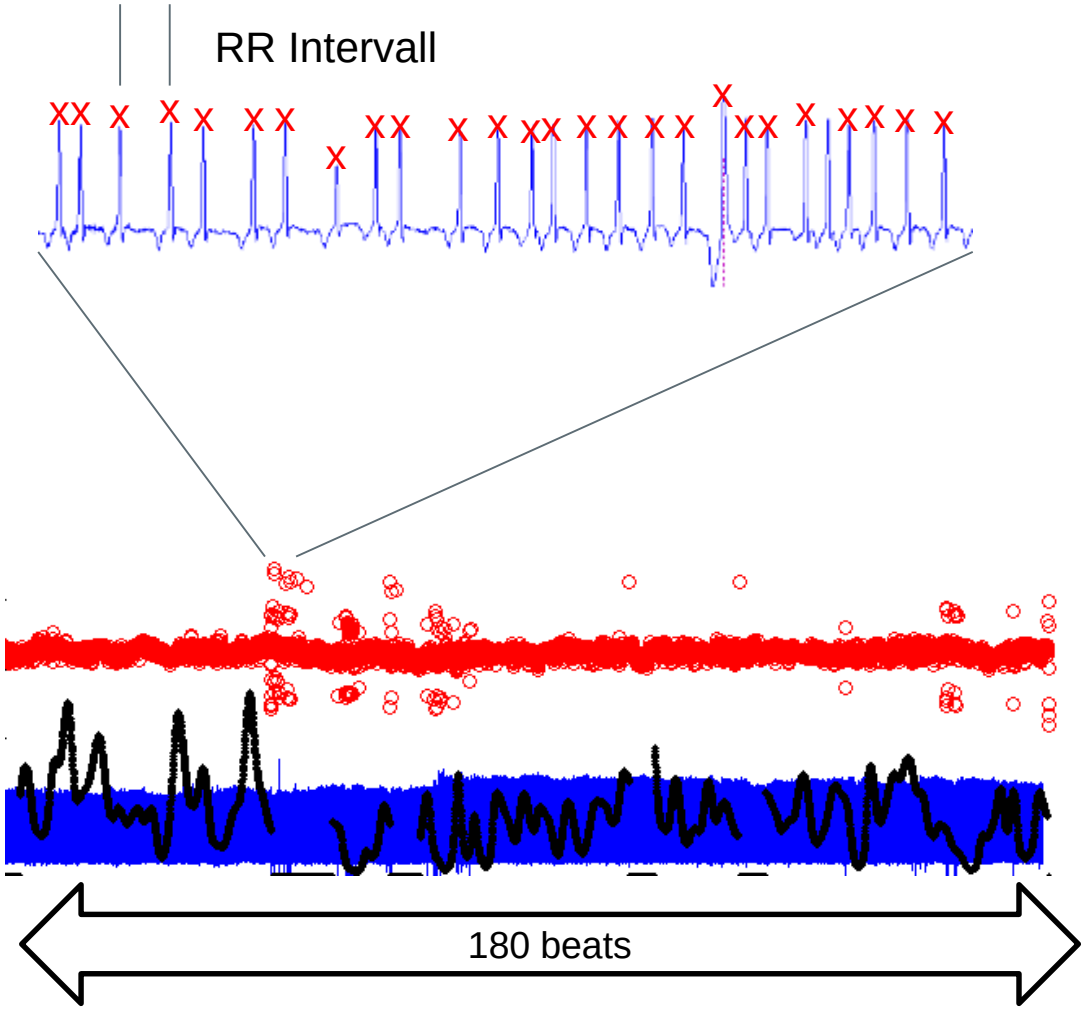
JIAPU PAN AND WILLIS J. TOMPKINS, SENIOR MEMBER, IEEE

***Abstract*—We have developed a real-time algorithm for detection of the *QRS* complexes of ECG signals. It reliably recognizes *QRS* complexes based upon digital analyses of slope, amplitude, and width. A special digital bandpass filter reduces false detections caused by the various types of interference present in ECG signals. This filtering permits use of low thresholds, thereby increasing detection sensitivity. The algorithm automatically adjusts thresholds and parameters periodically to adapt to such ECG changes as *QRS* morphology and heart rate. For the standard 24 h MIT/BIH arrhythmia database, this algorithm correctly detects 99.3 percent of the *QRS* complexes.**

a derivative, and a moving window integrator. The nonlinear transformation that we use is signal amplitude squaring. Adaptive thresholds and *T*-wave discrimination techniques provide part of the decision rule algorithm.

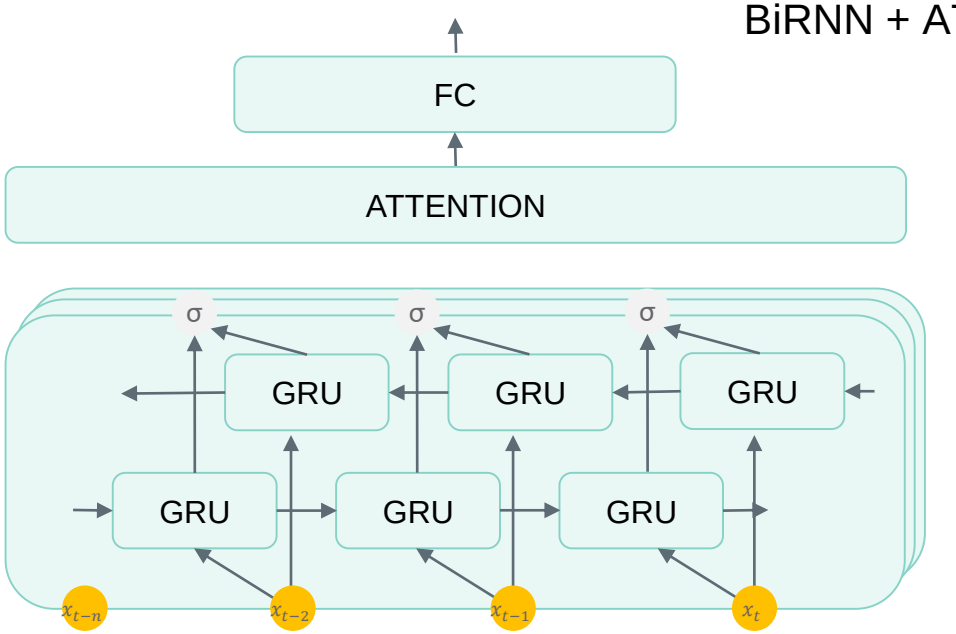
The slope of the *R* wave is a popular signal feature used to locate the *QRS* complex in many *QRS* detectors [5]. An analog circuit or a real-time derivative algorithm that provides slope information is straightforward to implement. However, by its very nature, a derivative amplifies the undesirable higher

Detection of Atrial Fibrillation (AF)

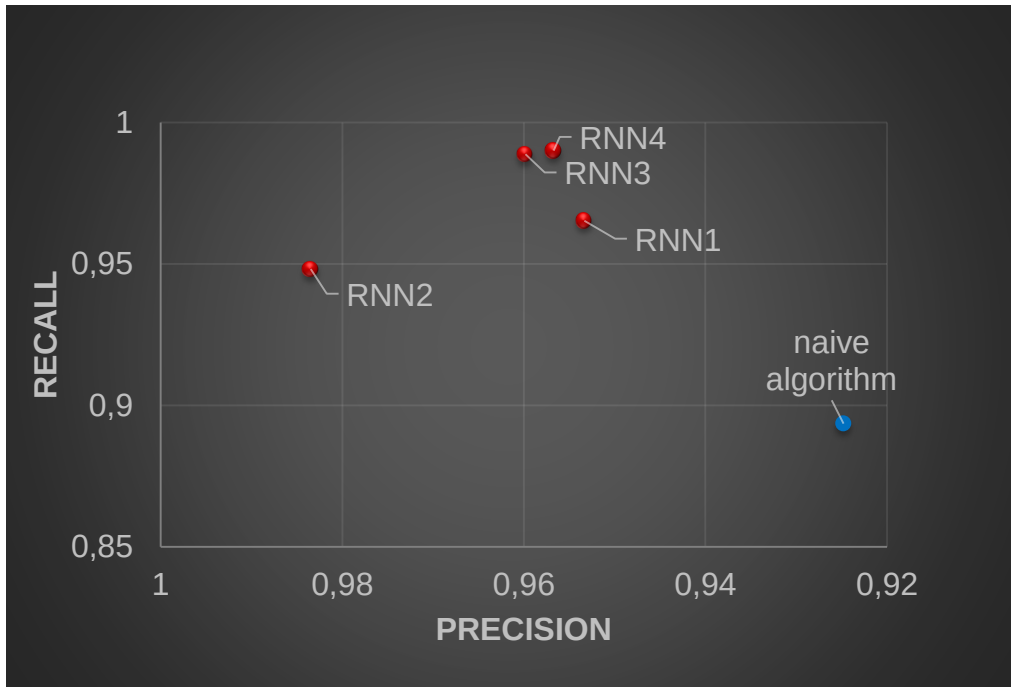


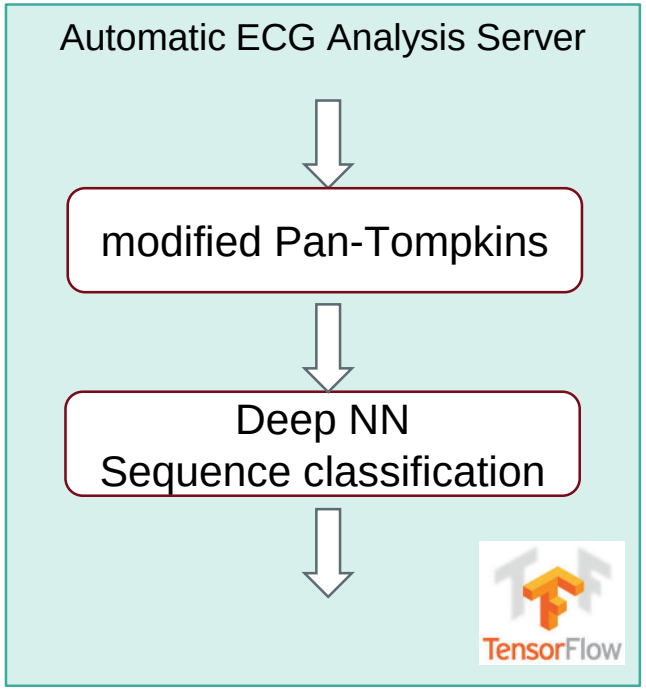
RR Intervalls

BiRNN + ATT



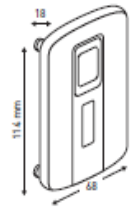
Automatic detection of atrial fibrillation with Deep Learning





CardioDSS Project

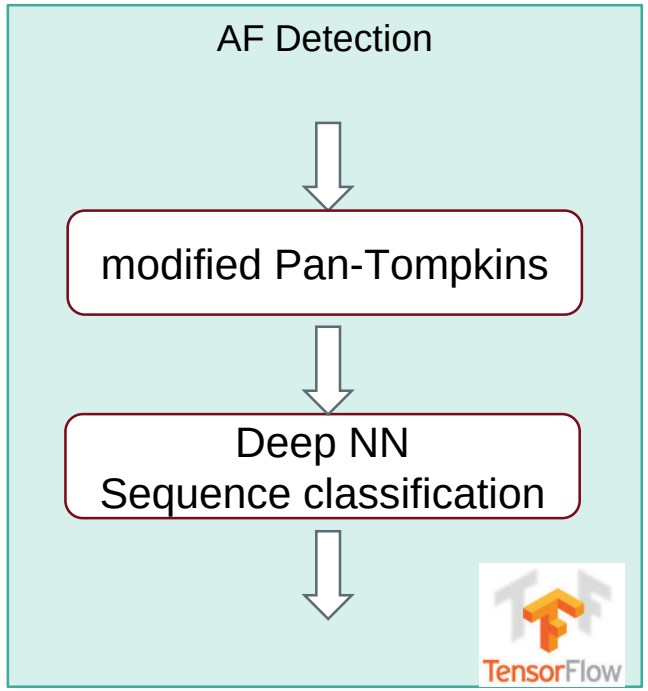
getemed



Merkmale

- 1-Knopf-Technik für einfachste Handhabung
- Integriertes GSM-Modul zur mobilen EKG-Übertragung
- 2-Kanal-EKG über vier Elektroden auf der Rückseite
- Induktives Aufladen der integrierten Batterie
- Staub- und spritzwassergeschütztes Gehäuse

Source: www.getemed.net



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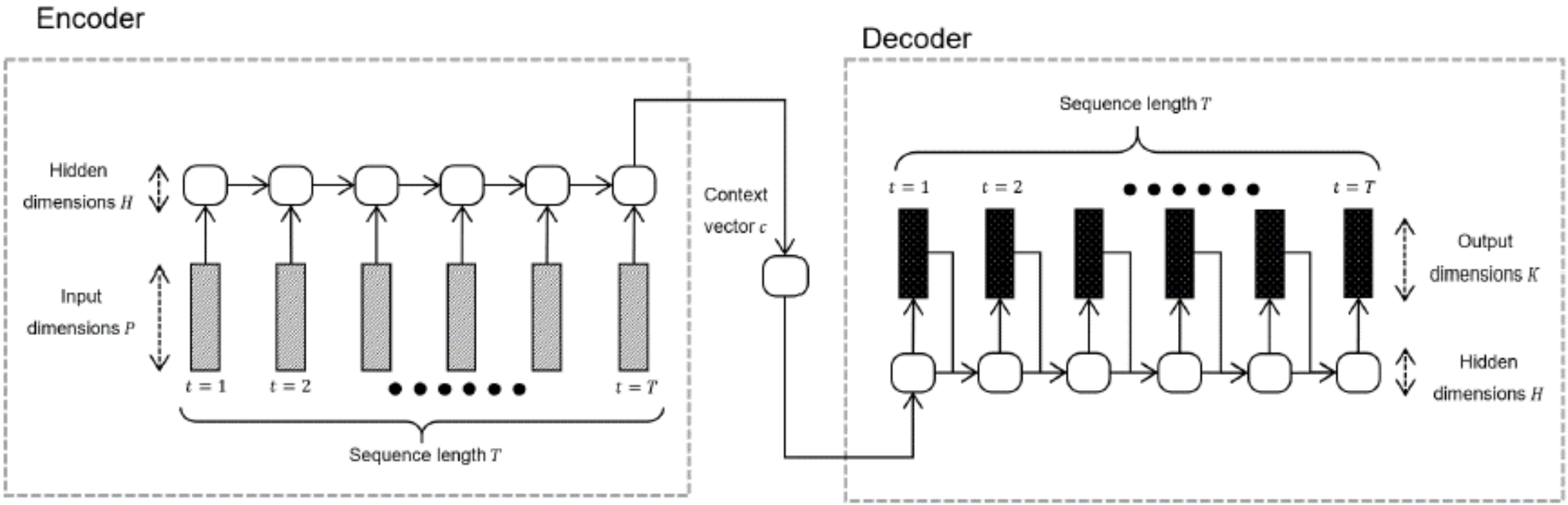
RECURRENT AUTOENCODER

Machine learning of Features

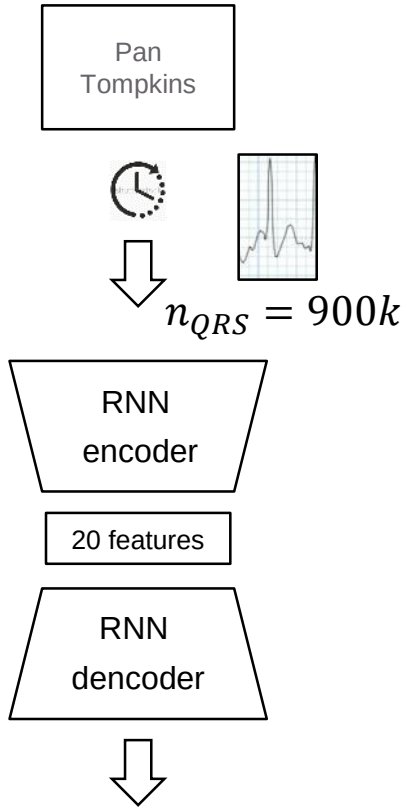
Recurrent Autoencoder: Capture times-series information



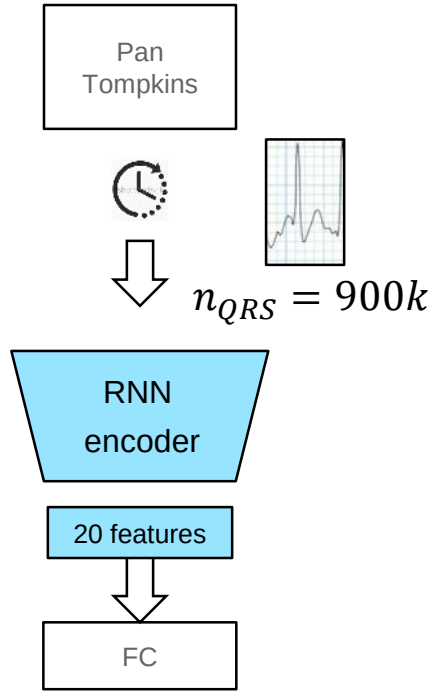
Detection of PVC with autoencoded features:

n_{PAT} =85, $n_{QRS} = 900k$

optimization: μ=0 σ=1



freeze

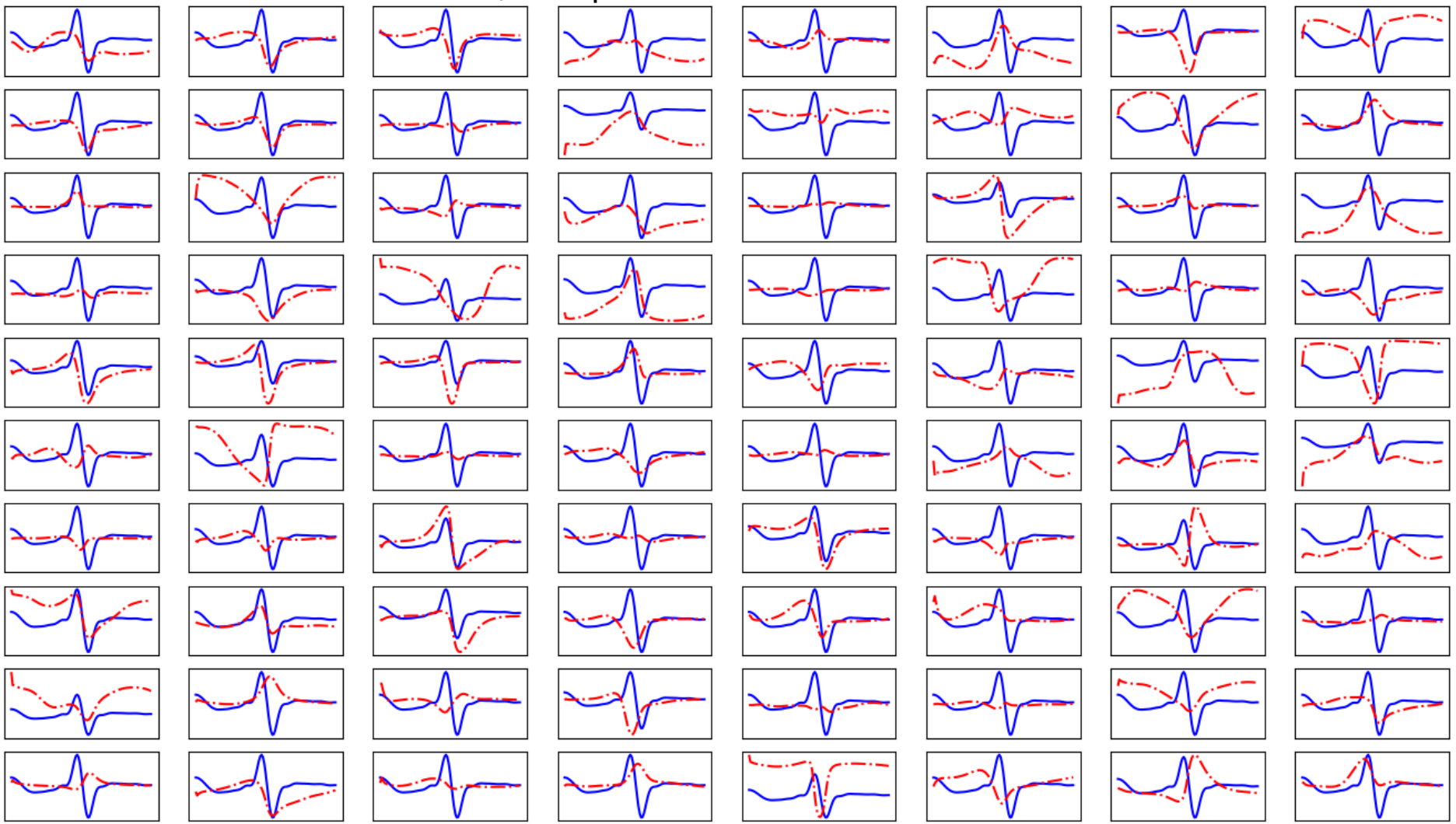


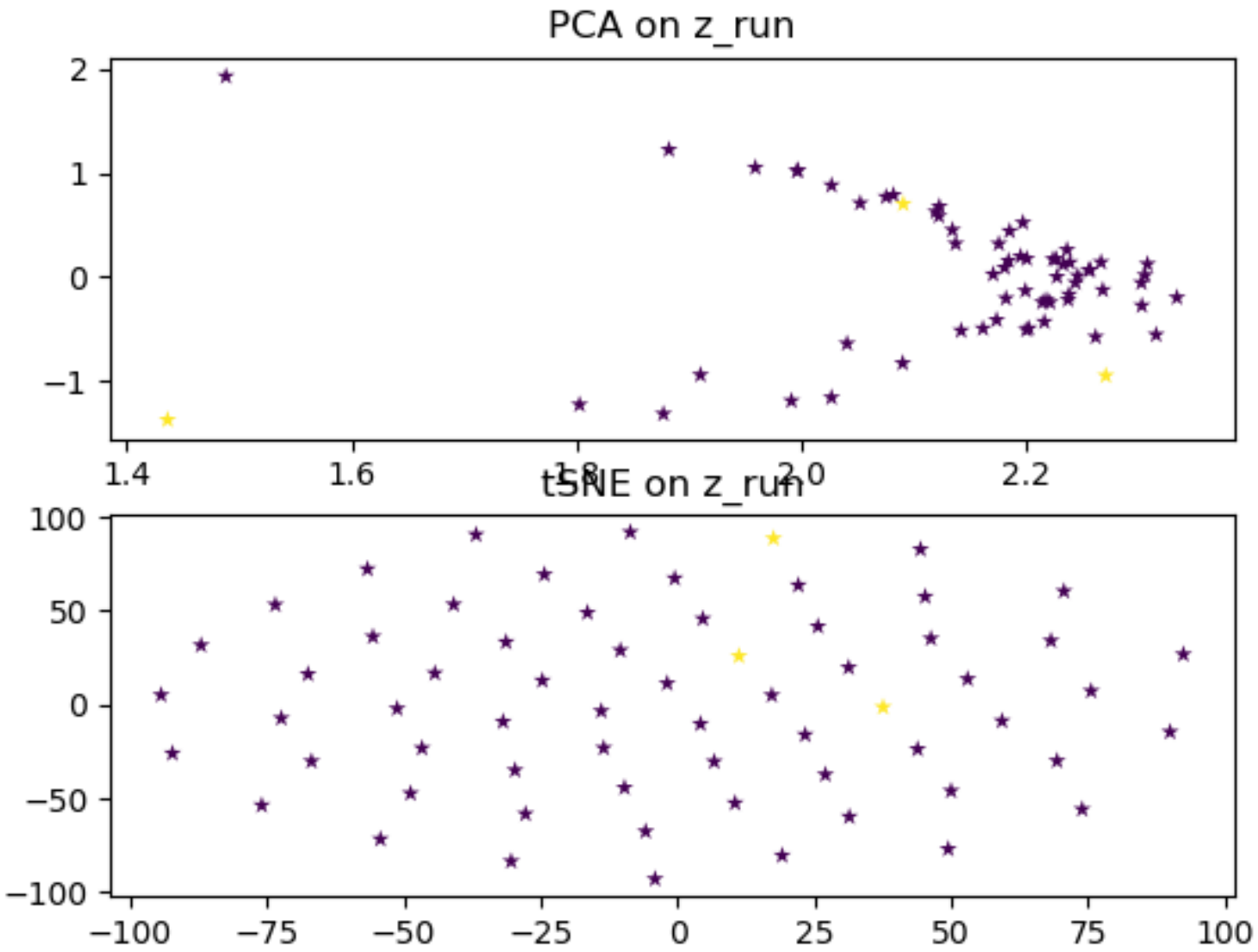
PVC / Normal

PHASE I

PHASE II

Autoencoder with 20 feature state, 80 representations




PCA on z_run
2
1
0
−1
1.4
1.6
1.8
2.0
2.2
tSNE on z_run
100
50
0
−50
−100
−100
−75
−50
−25
0
25
50
75
100

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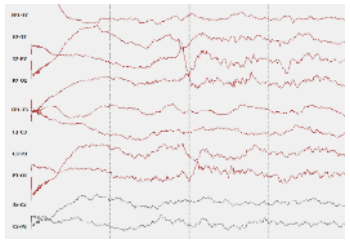
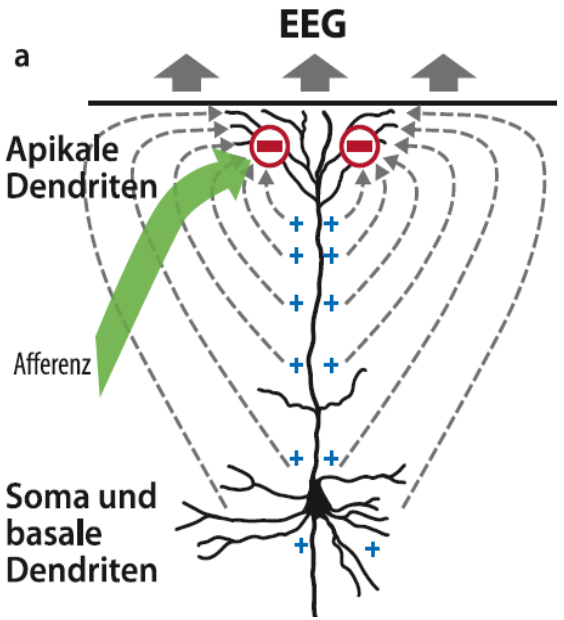
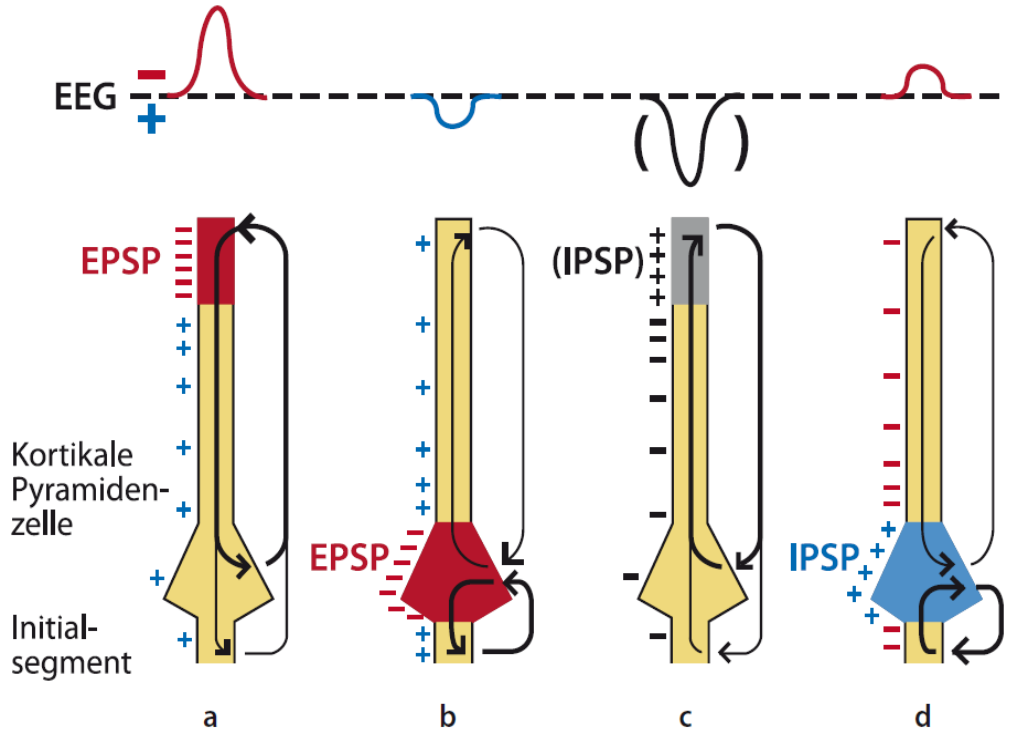
EEG



Electroencephalogram (EEG)



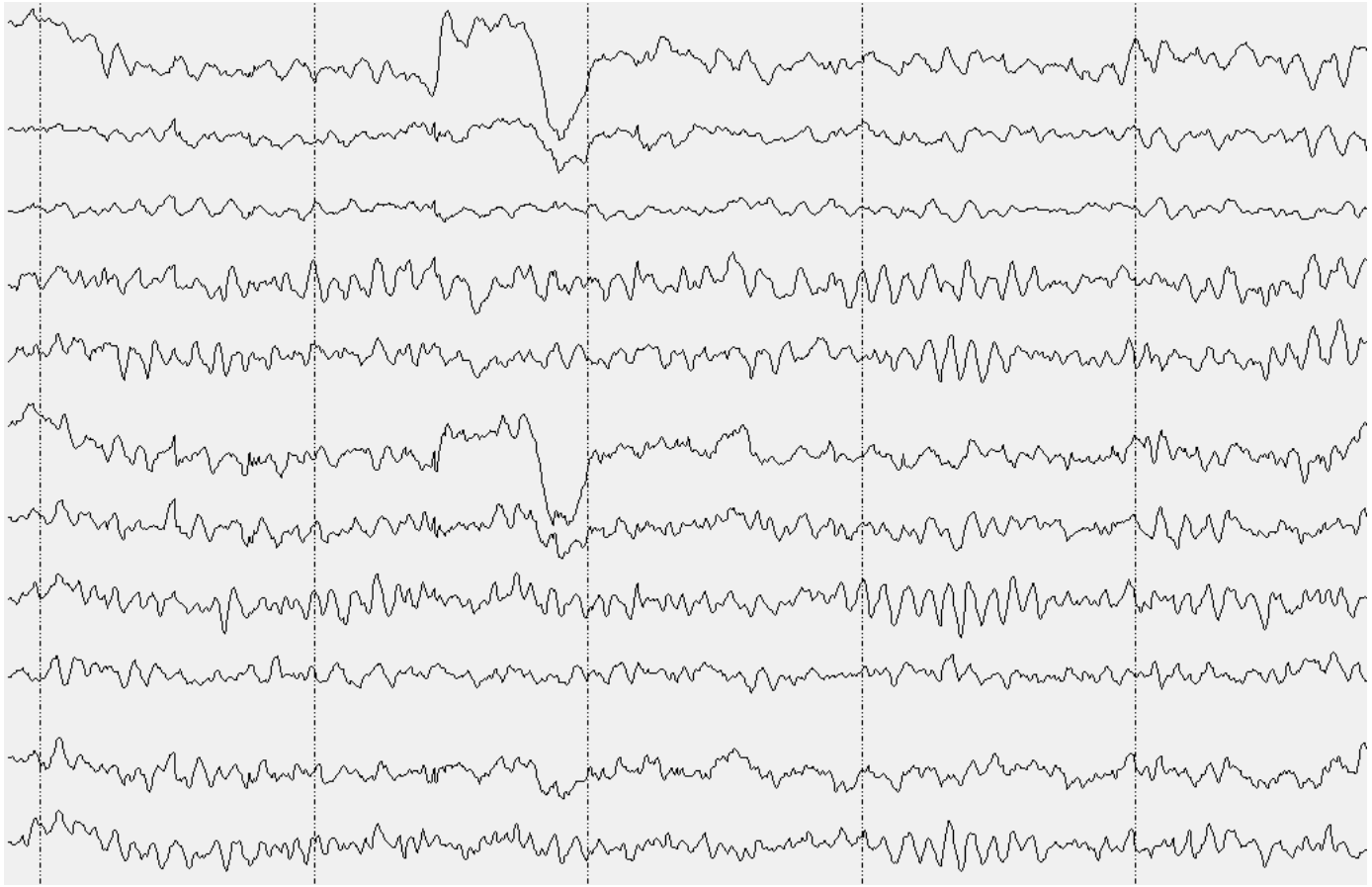


- Non invasively measured on scalp
- Small signal amplitude (~100µV)

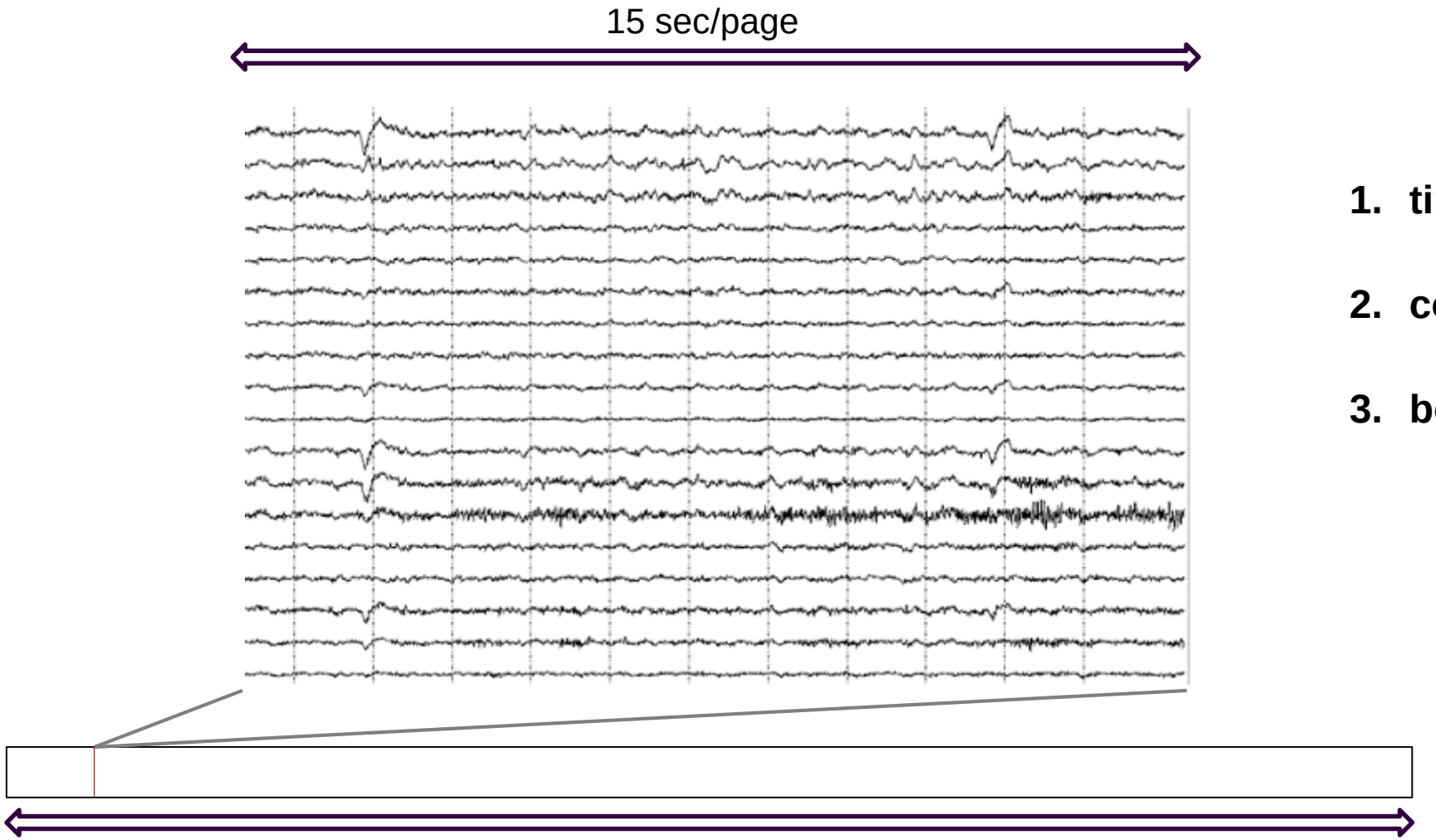
- Potential changes over time -> time series data
- Visually usable frequency band: 0.5 - 16 Hz

Source: Zschoke u. Hansen, 2011: Klinische Elektroenzephalographie

Electroencephalogram (EEG)



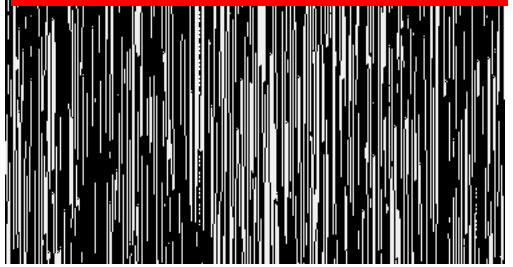
One page of EEG



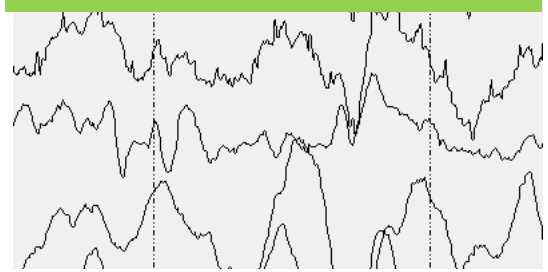
1. **time consuming**
2. **confusing**
3. **boring**

Examples of Electroencephalogram (EEG)

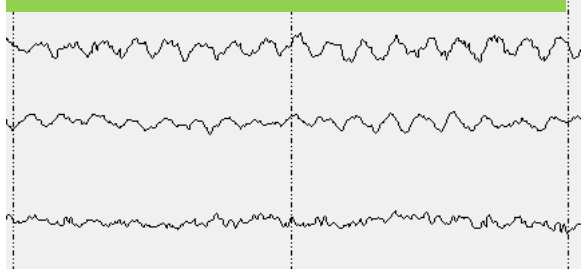
epileptic seizure:
time: < 3 minutes to ensure life support



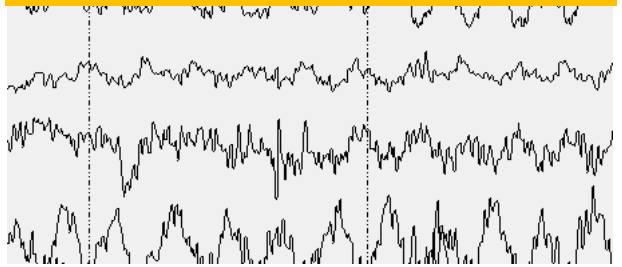
deep sleep, all well



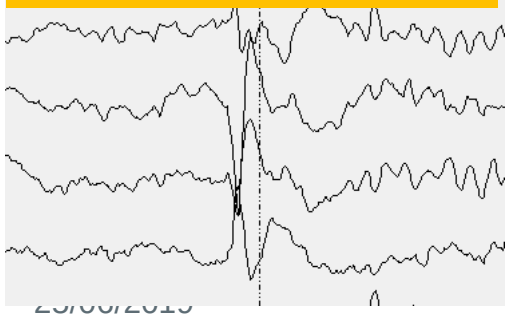
eyes closed. OK



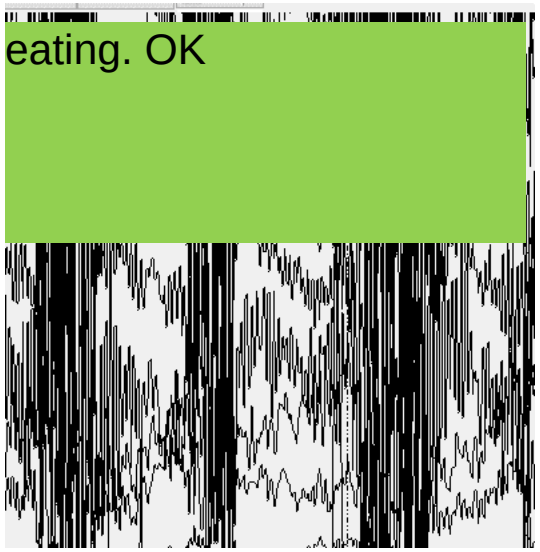
focal seizure:
time: < 3 min. for neuro tests medication or brain surgery



lateral focal spike
medication or
sugical intervetion

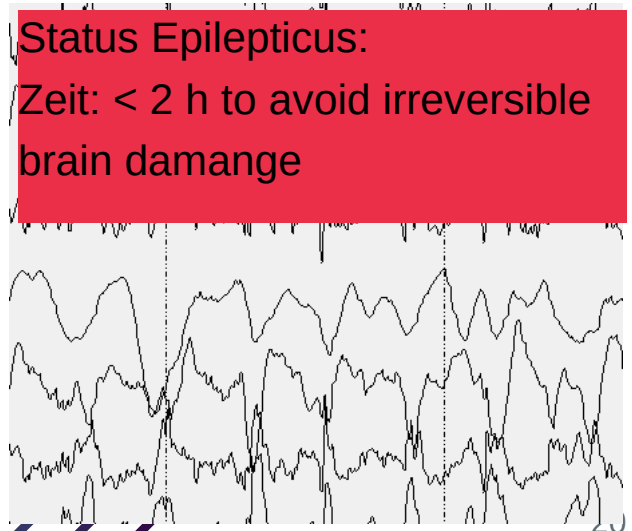


eating. OK



wake up: OK

Status Epilepticus:
Zeit: < 2 h to avoid irreversible brain damange



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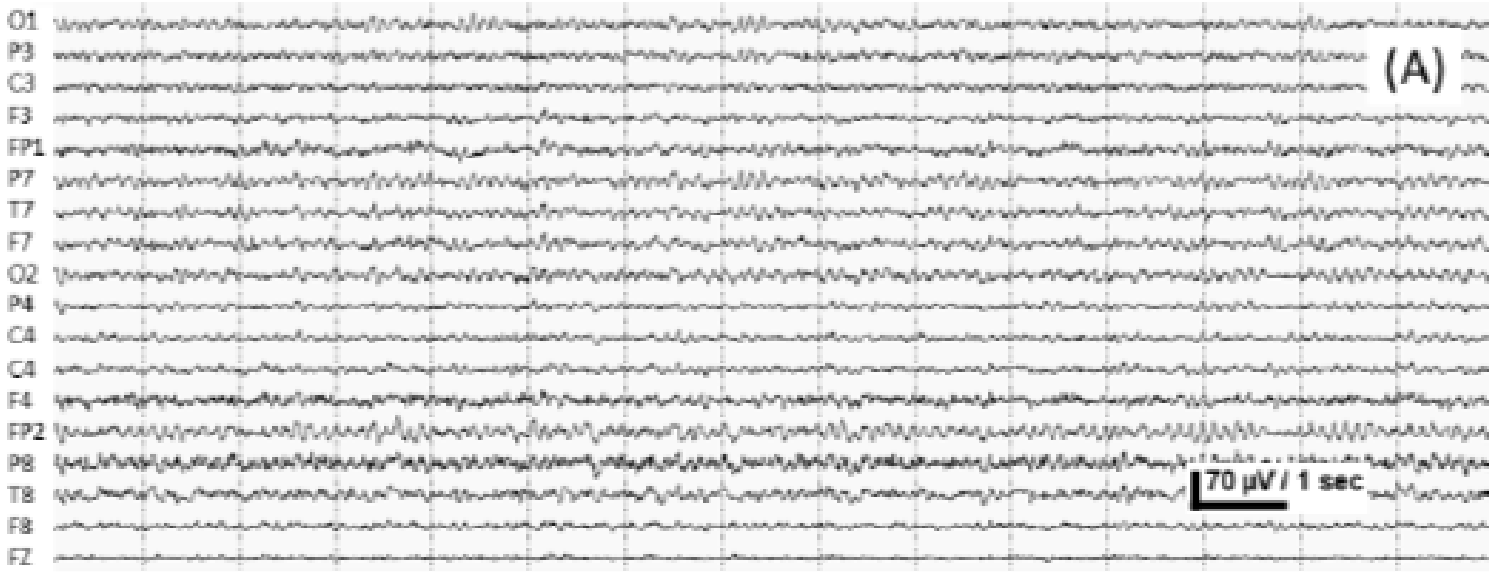
PROBLEMS IN EEG ANALYSIS

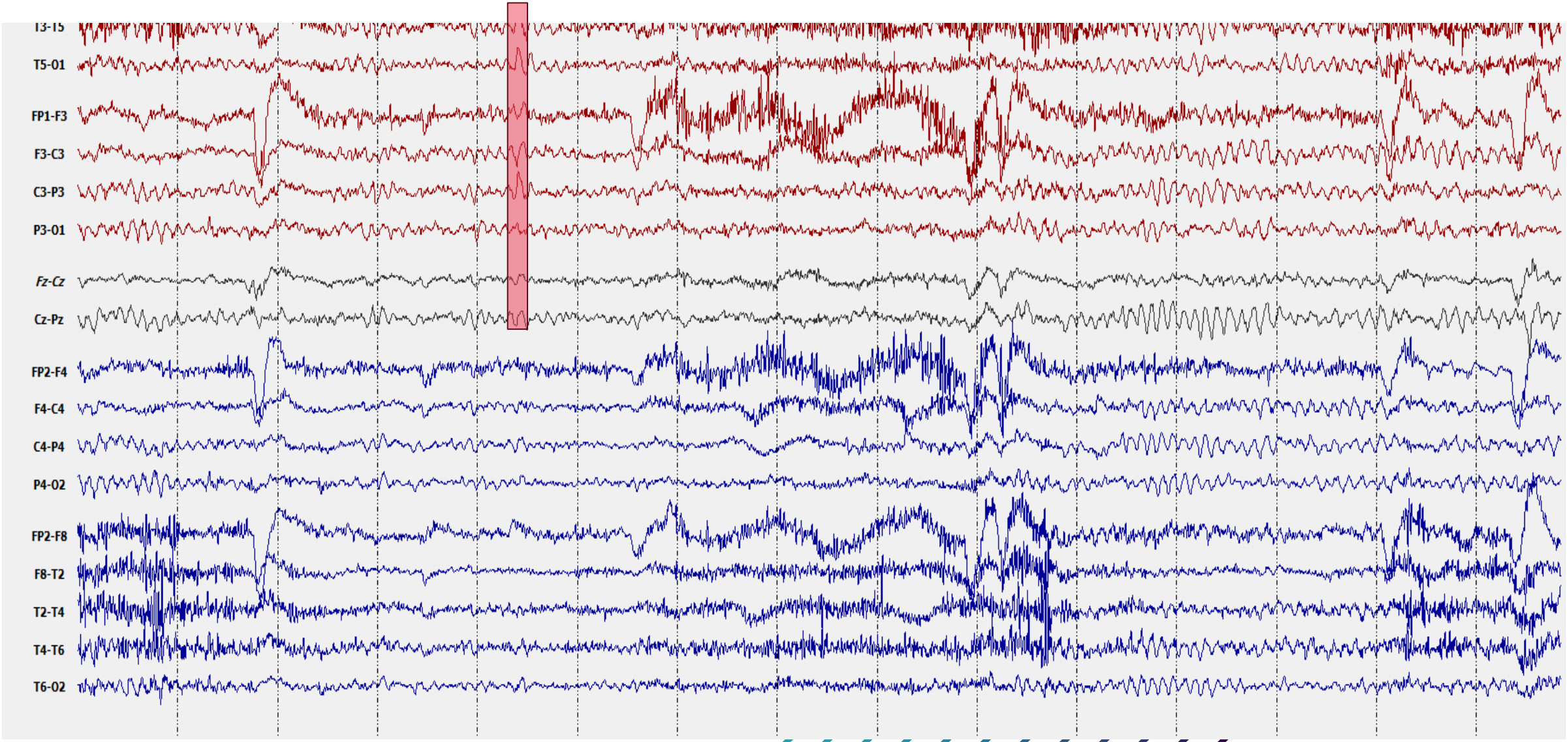
EEG Seizure Detection: Adults



Epilepsy:
~1% of world population

0.9 million with active epilepsy in Europe

Epileptic spike detection in EEG

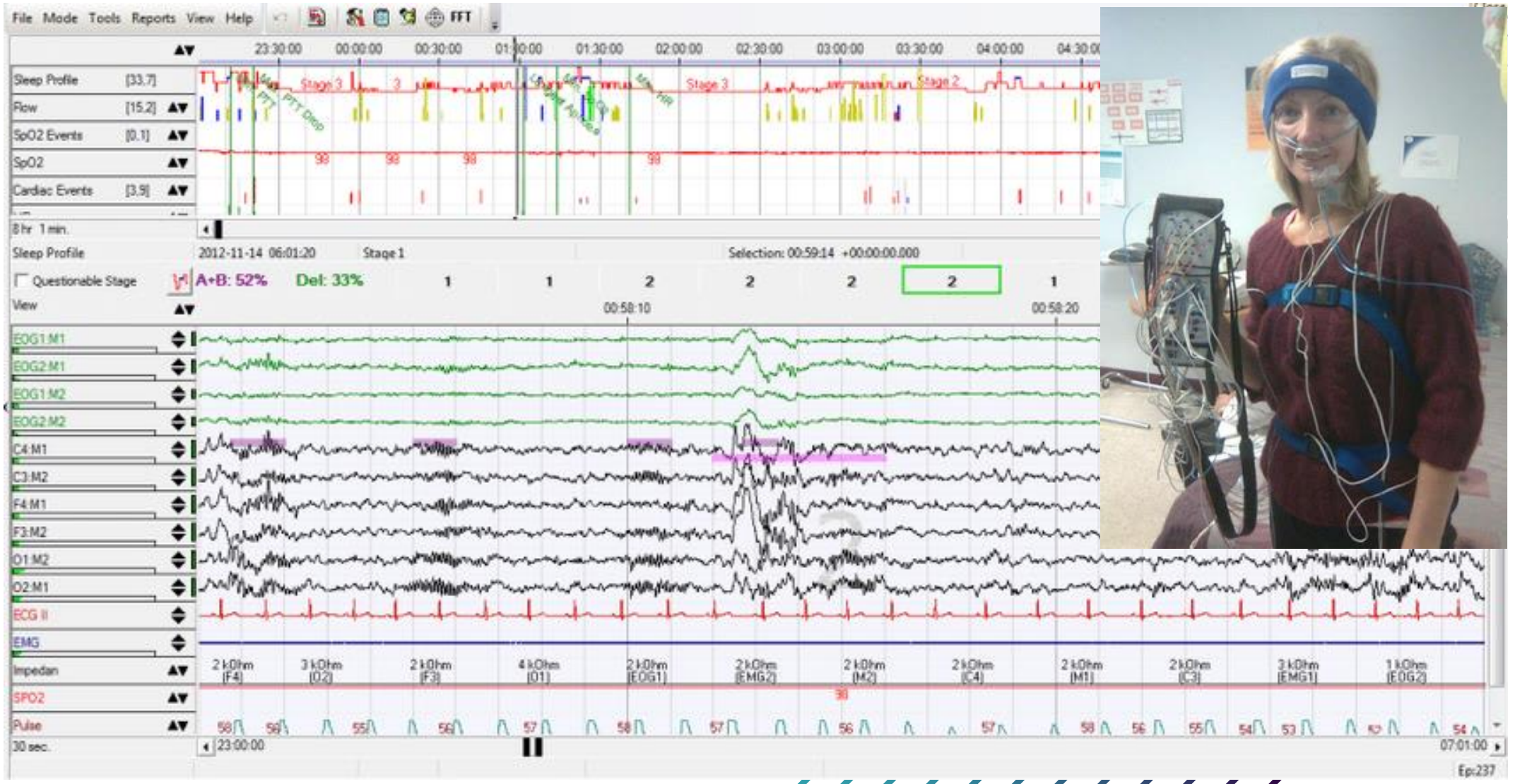


Intensive Care: EEG Seizure Detection / Classification

EEG Seizure Detection / Classification: Neonatal ICU

Source: www.cephalon.eu/products/eeg-erp/neon-cap/

Polysomnography: Sleep Staging



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Model Epileptic Spikes with Deep Learning

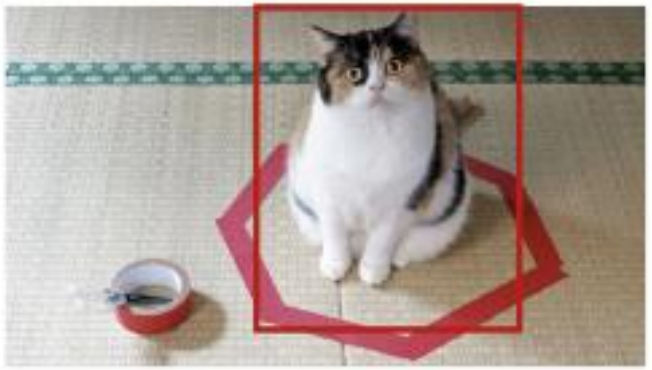
How to approach?

1

Is this image of Cat or not?

Image classification problem

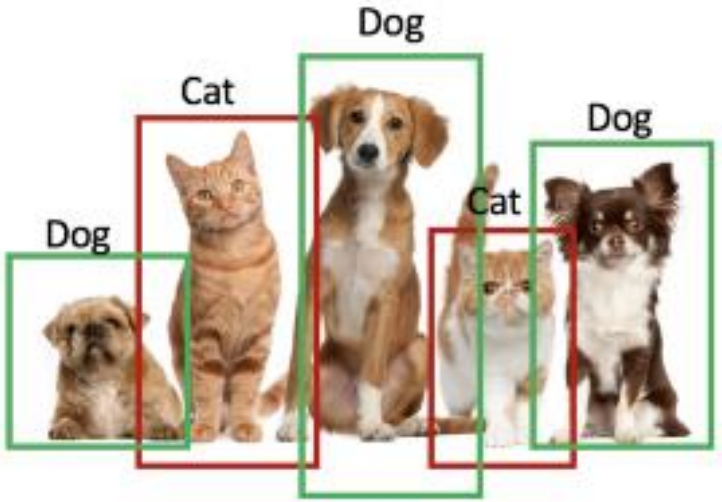
2



Where is Cat?

Classification with localization problem

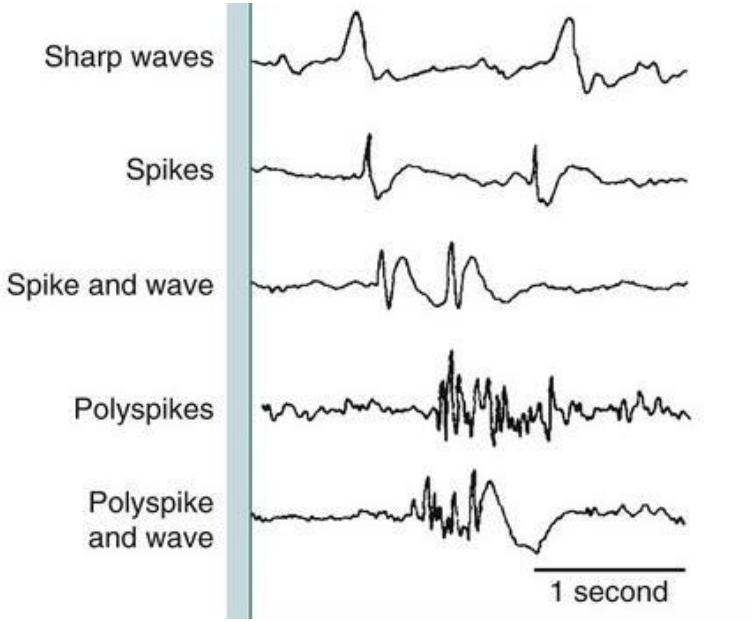
3

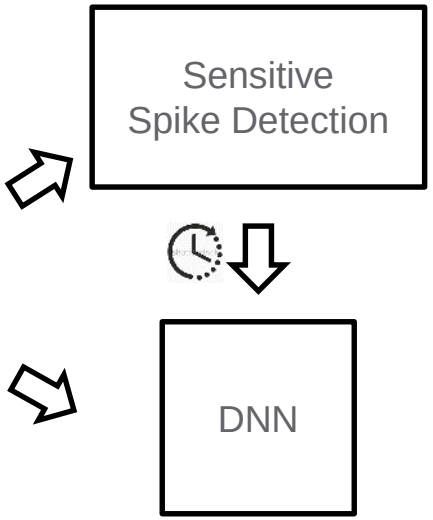


Which animals are there in image and where?

Object detection problem

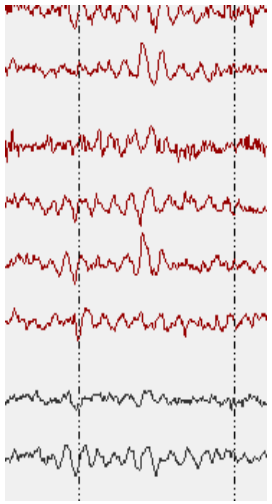
Spike classification for EEG: Pre-detector needed



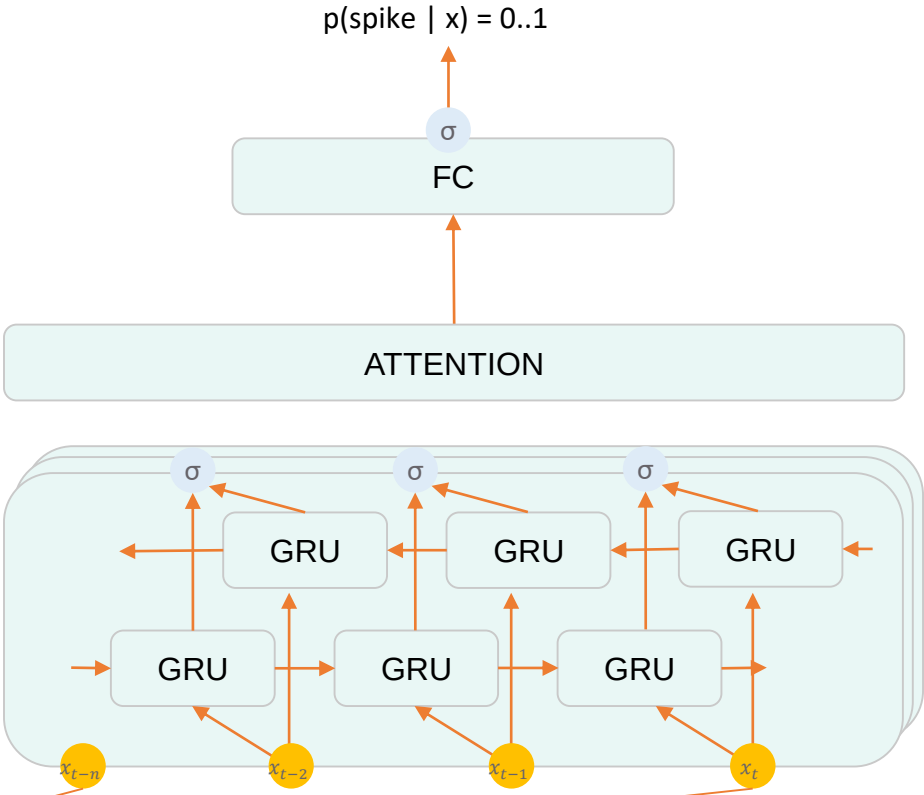


1. Spike
2. Polyspike, …
3. Normal

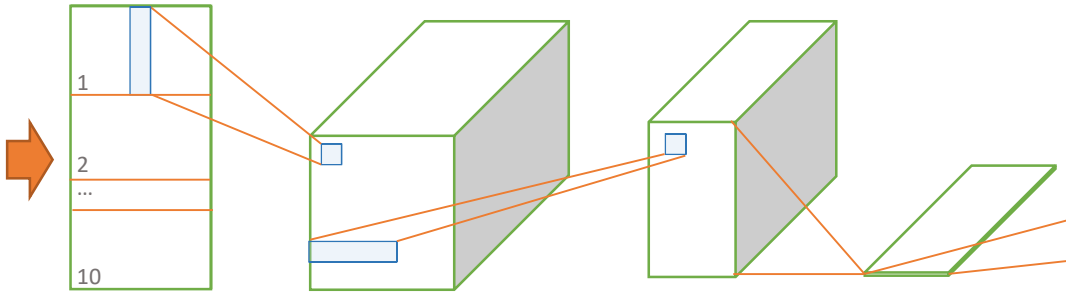
deepSpike (V1): CNN->RNN->ATT->FC



II) Sequence classifcation

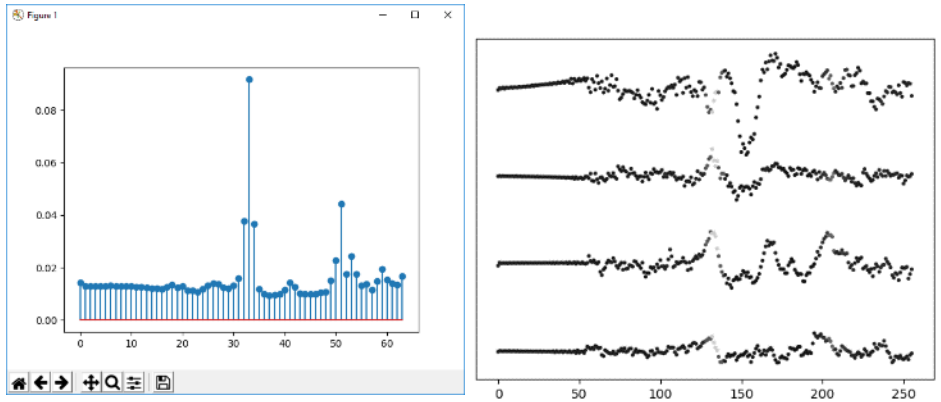


I) Reduce n-channel EEG to 1-channel

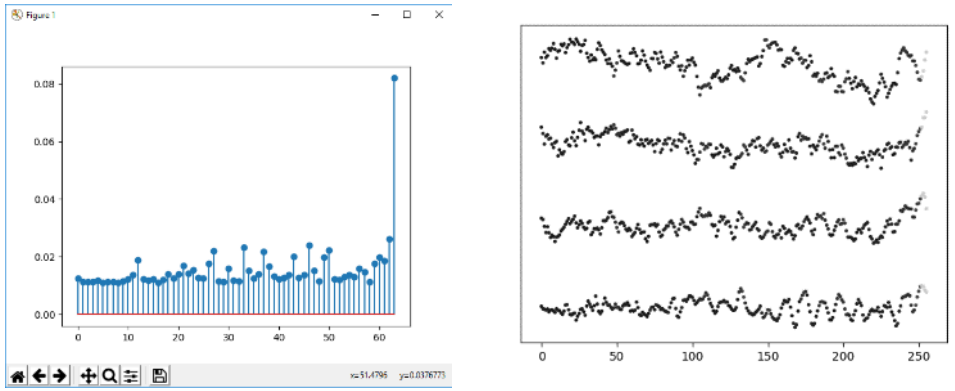


CNN -> Attention -> RNN

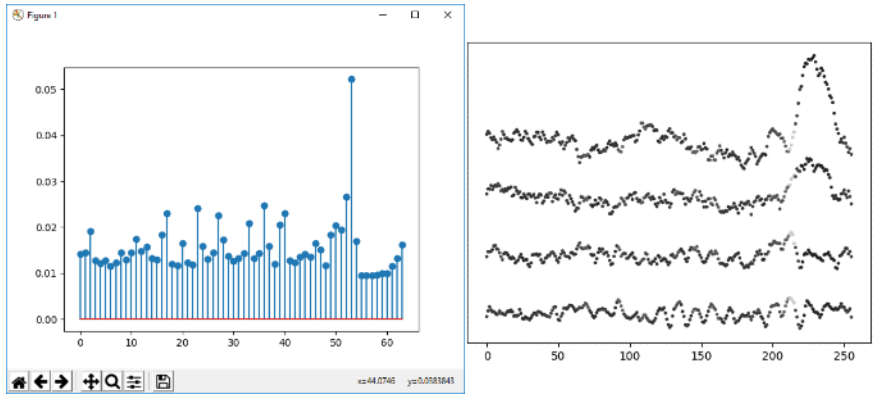
TP -> Spike Detektion



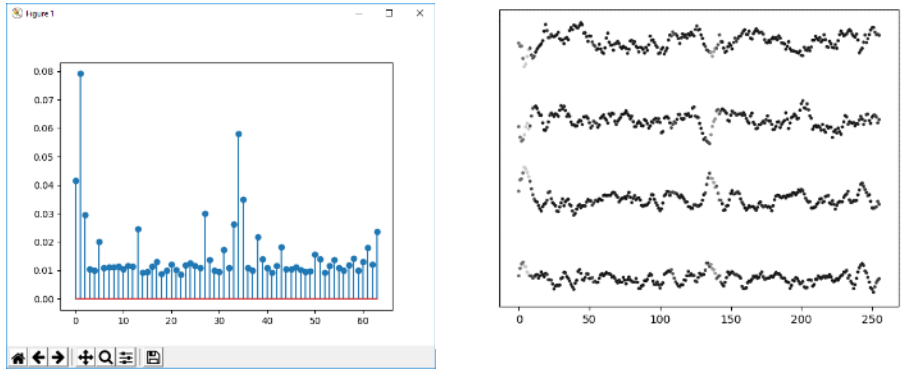
FP -> falsche Detektion



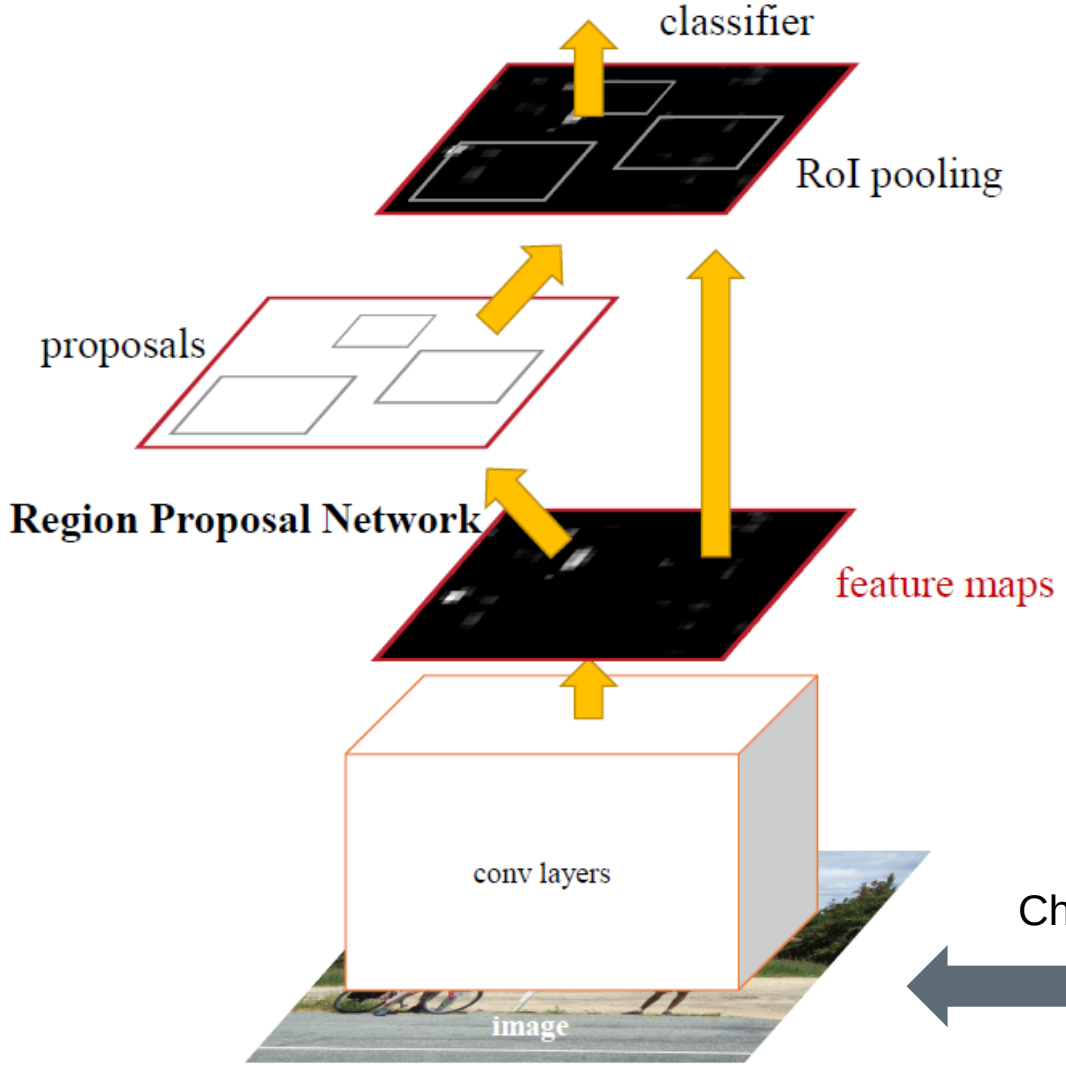
TN -> keine Detektion



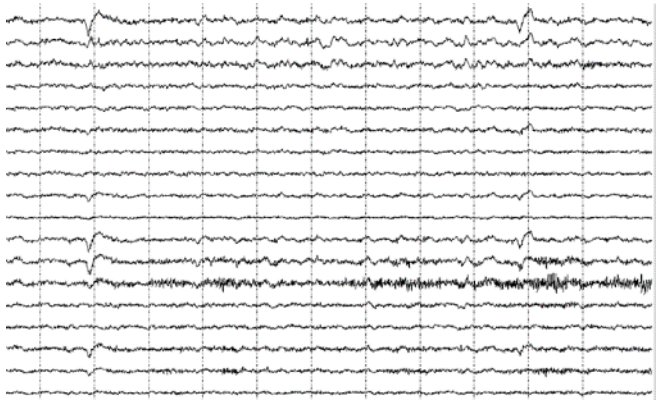
FN -> Nicht detektiert



End-to-End: Faster R-CNN for spike object detection

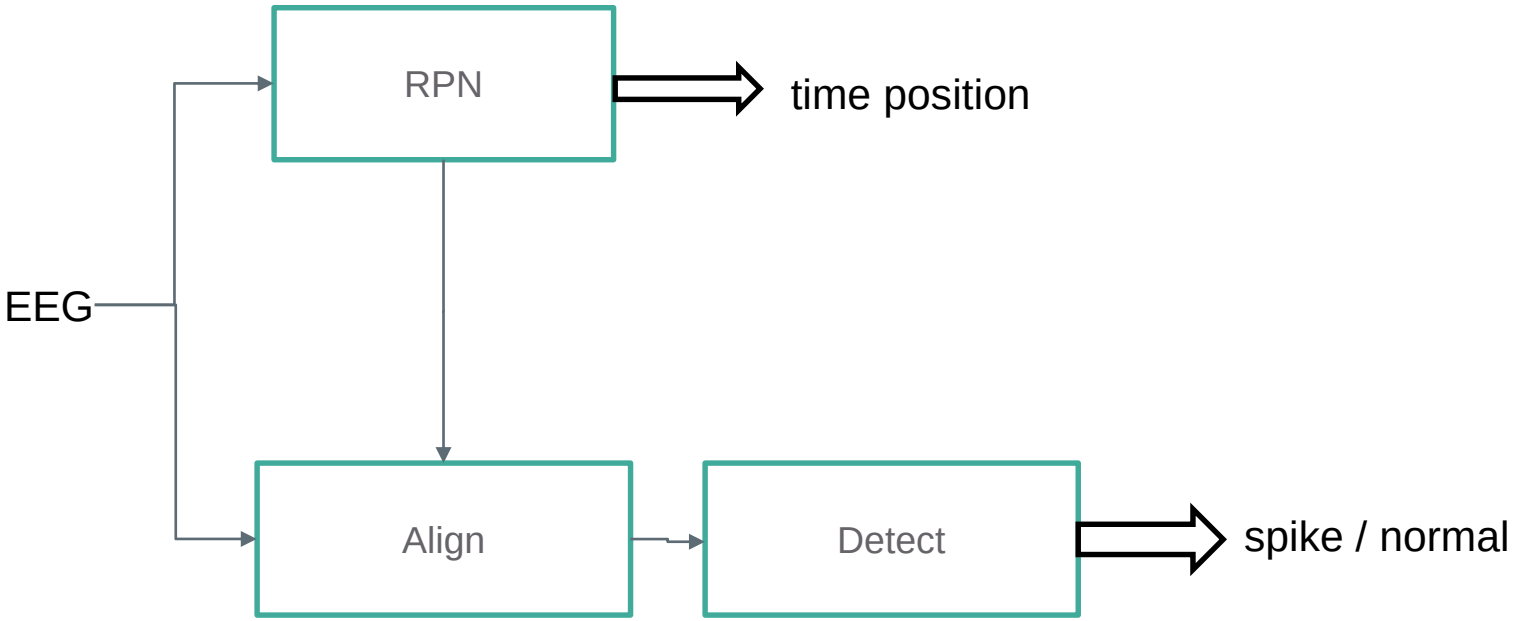


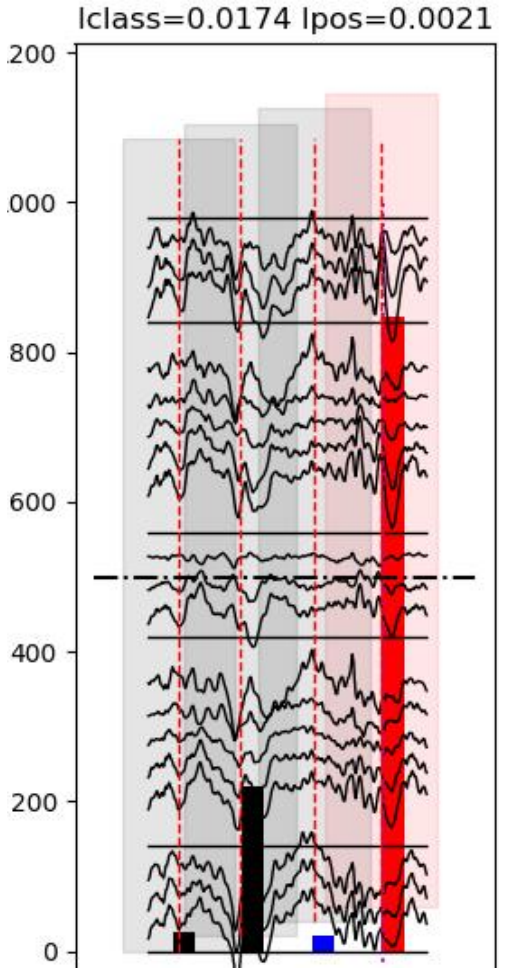
Change here!



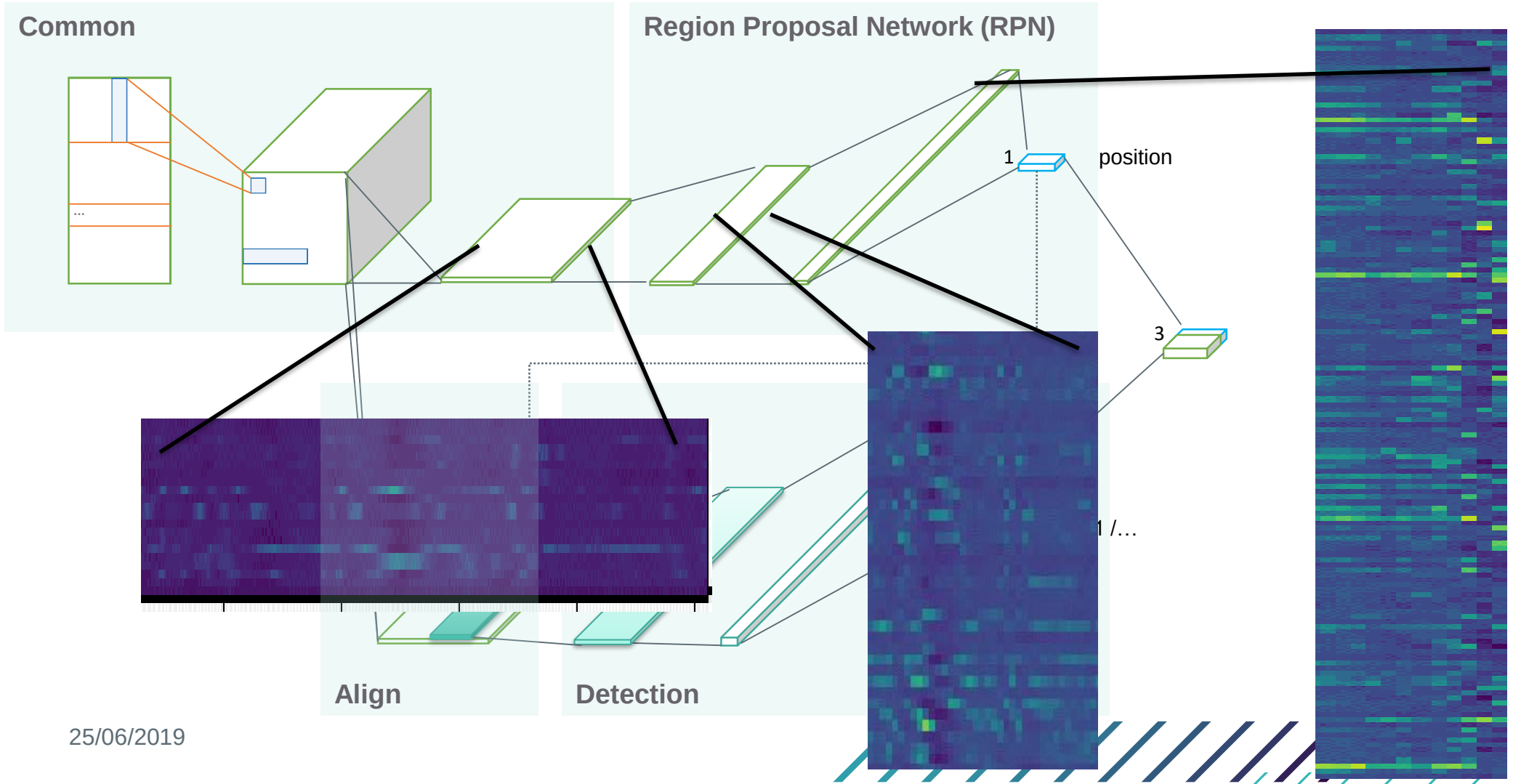
Source: https://arxiv.org/pdf/1506.01497.pdf

EEG R-CNN: deepSpike

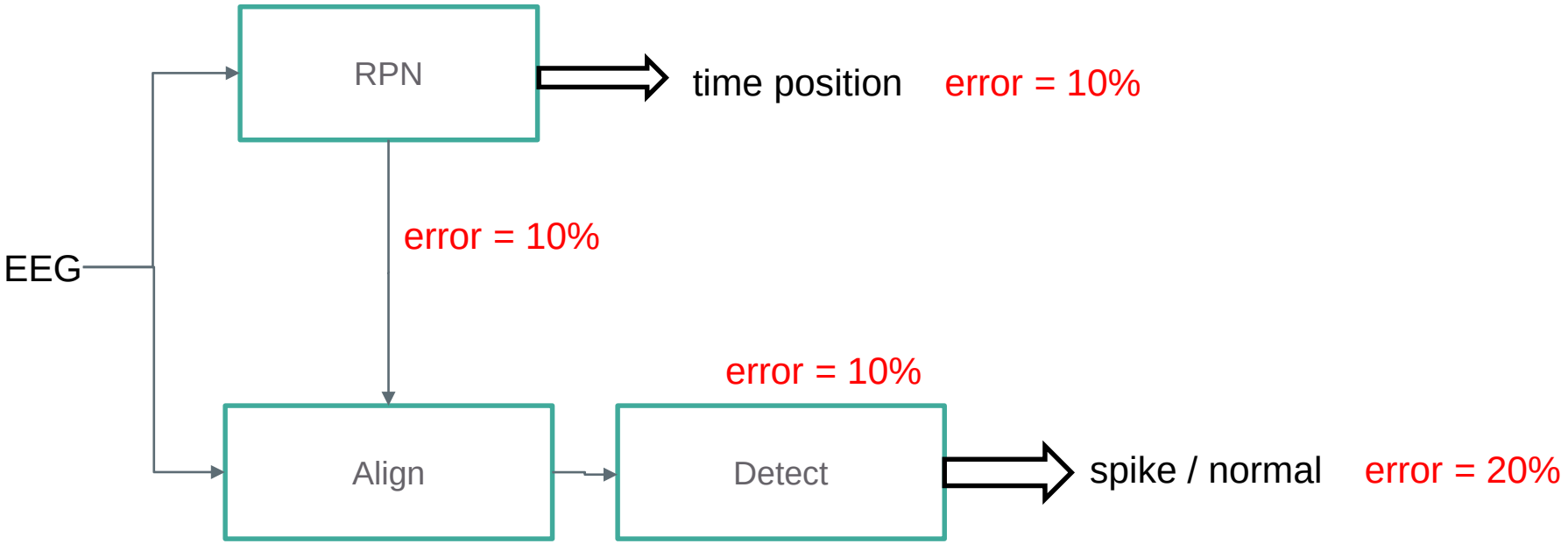




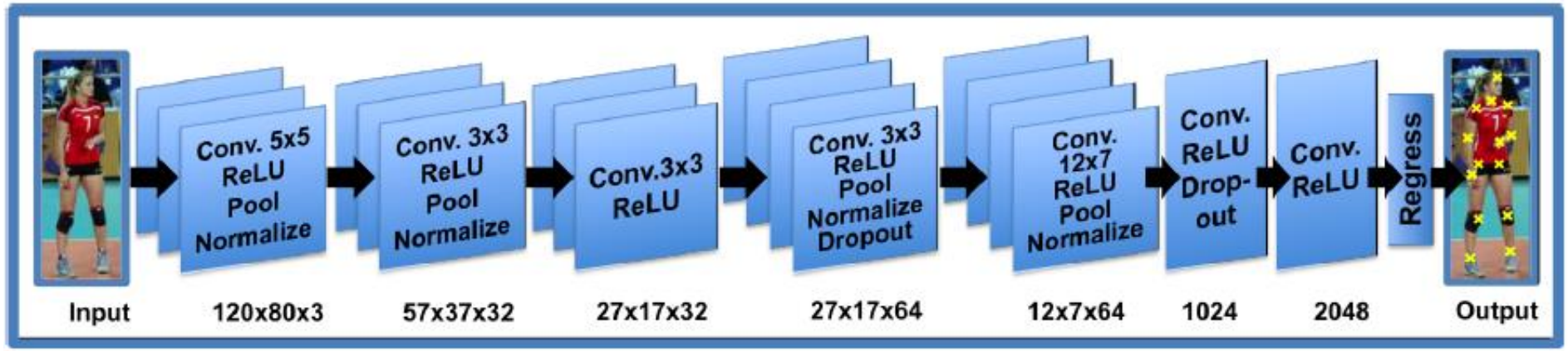
deepSpike


Common
Region Proposal Network (RPN)
...
1
position
3
1 /…
Align
Detection

deepSpike: error propagation

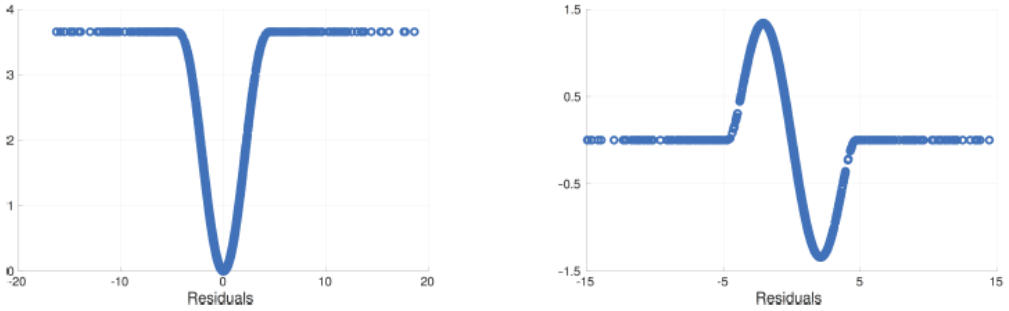


ROI estimation: Deep Regression Network



Network Architecture

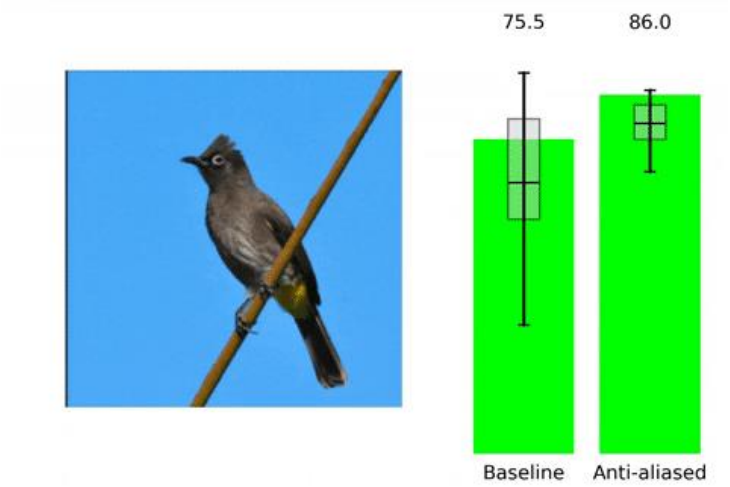
Tukey's biweight loss function and the derivative



Source: Robust Optimization for Deep Regression, Vasileios Belagiannis1,2, Christian Rupprecht1,3, Gustavo Carneiro4 , and Nassir Navab1,3, https://arxiv.org/pdf/1505.06606.pdf

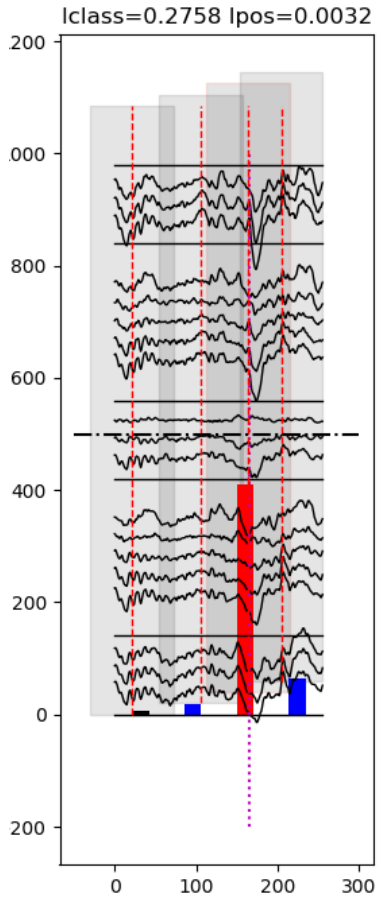
Making Convolutional Networks Shift-Invariant Again

(1) Richard Zhang, Adobe Research, San Francisco, CA. Correspondence to: Richard Zhang .

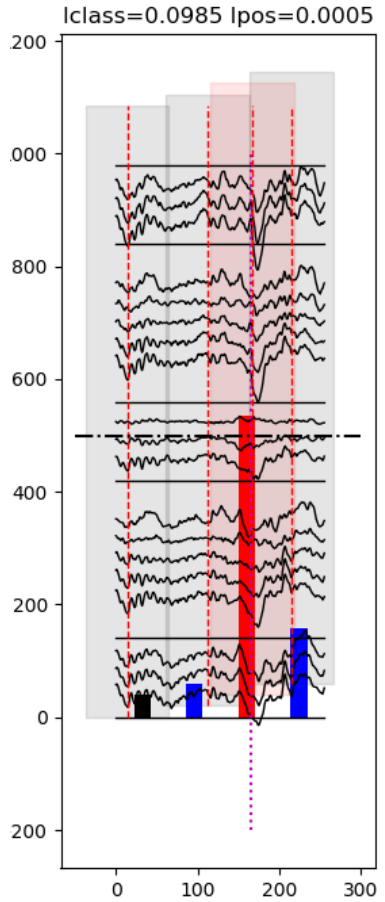


Source: https://richzhang.github.io/antialiased-cnns/

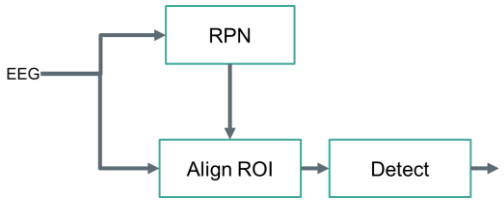
Max pooling

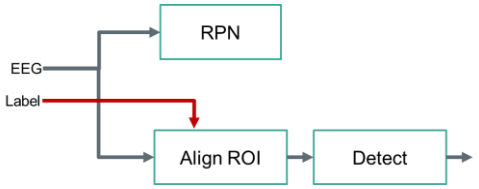


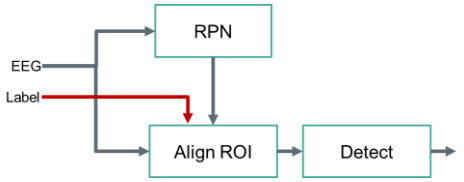
Blur pooling

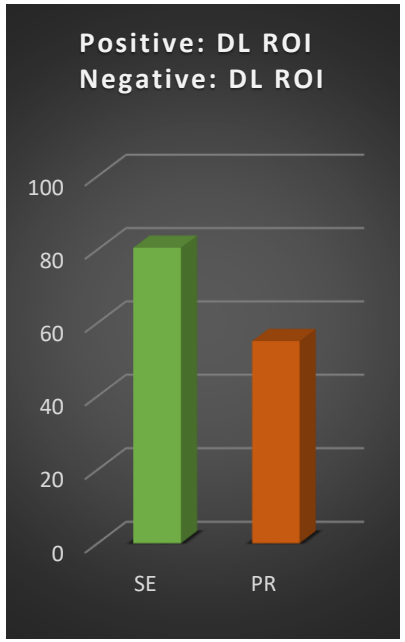


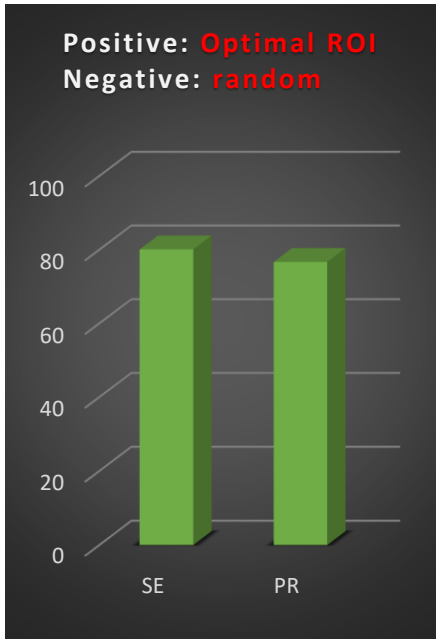
Detector Performance Insights

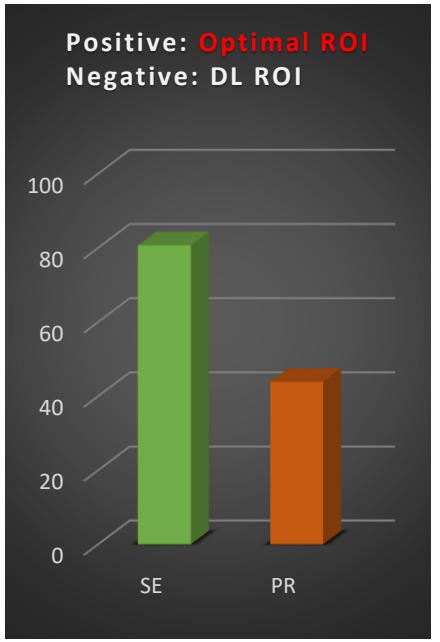


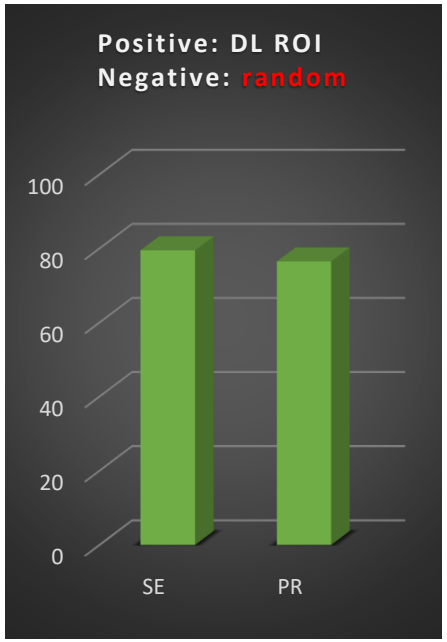




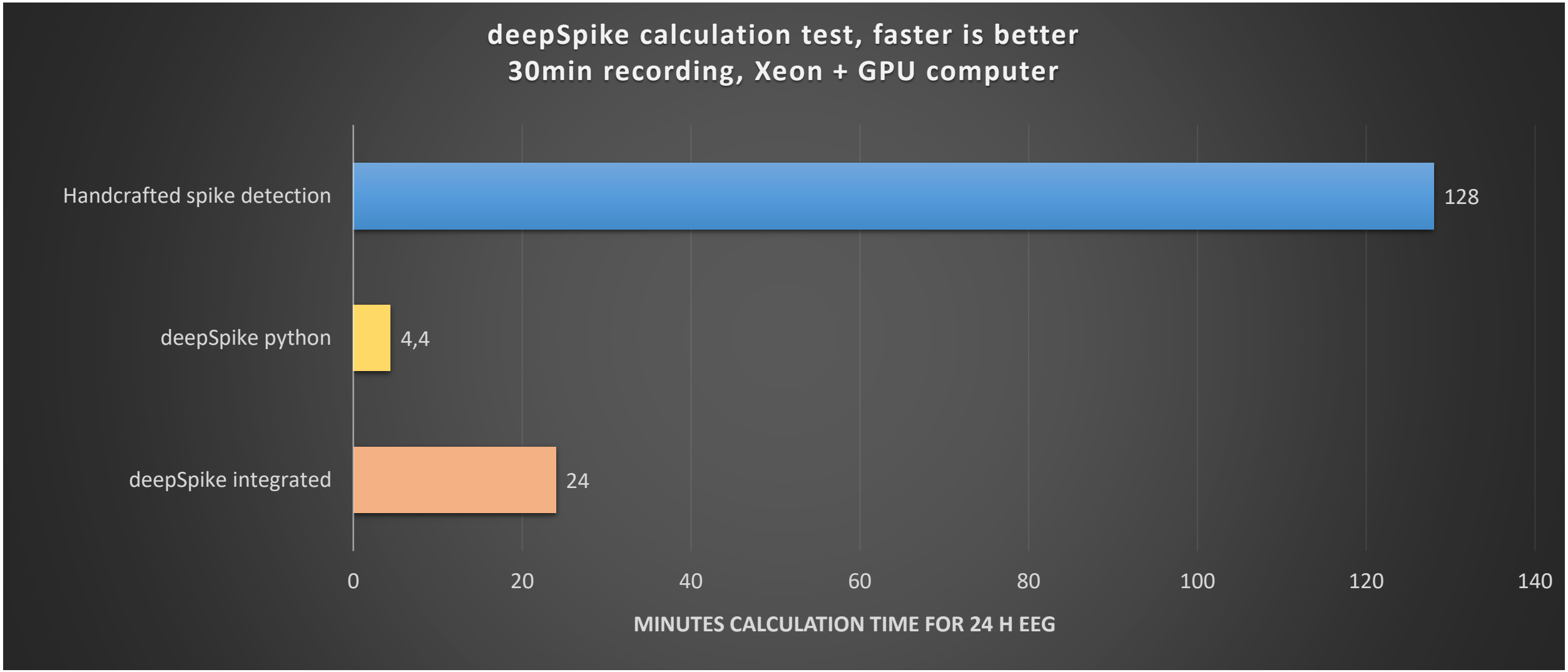


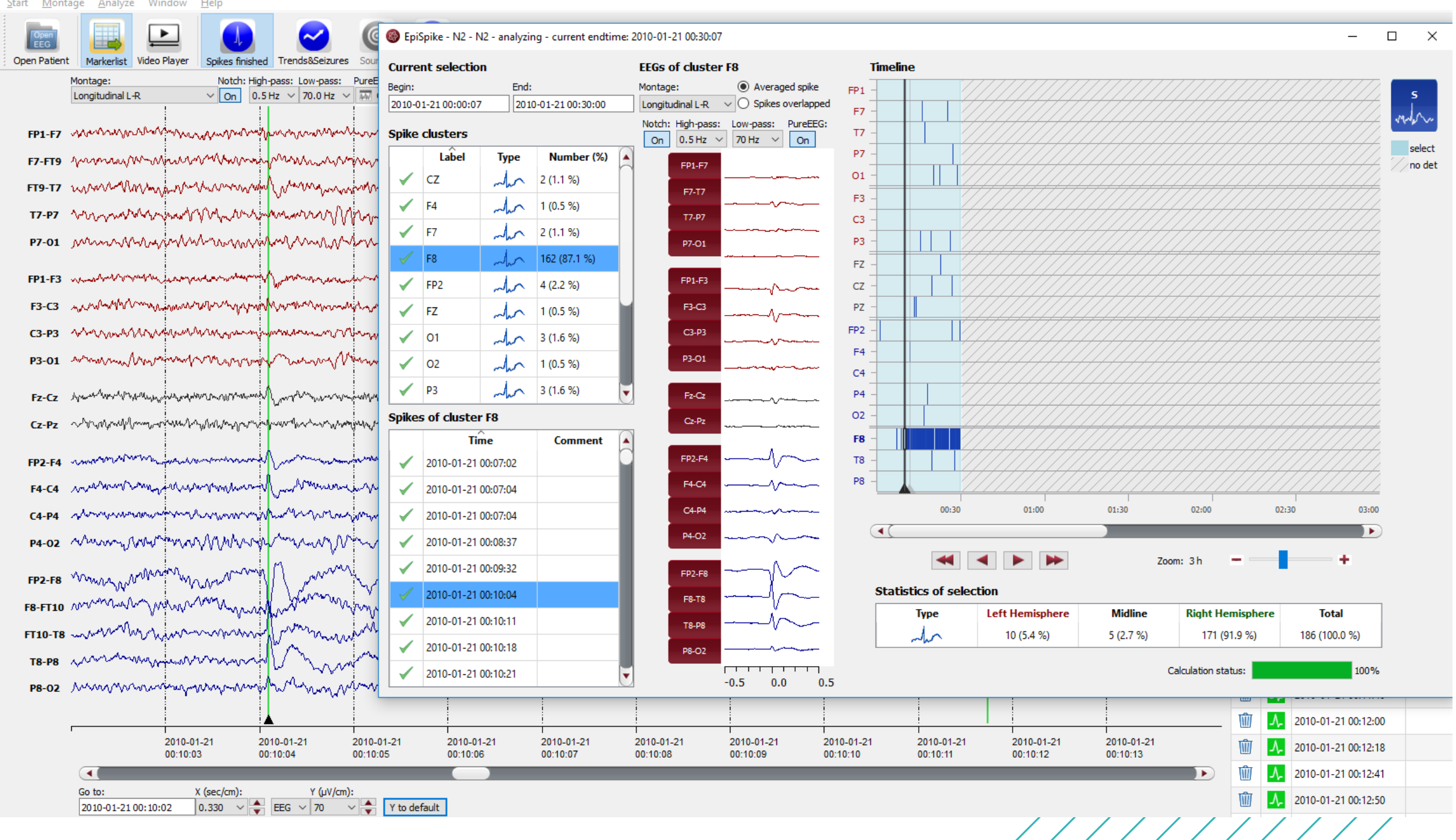






Runtime performance: handcrafted vs. DL

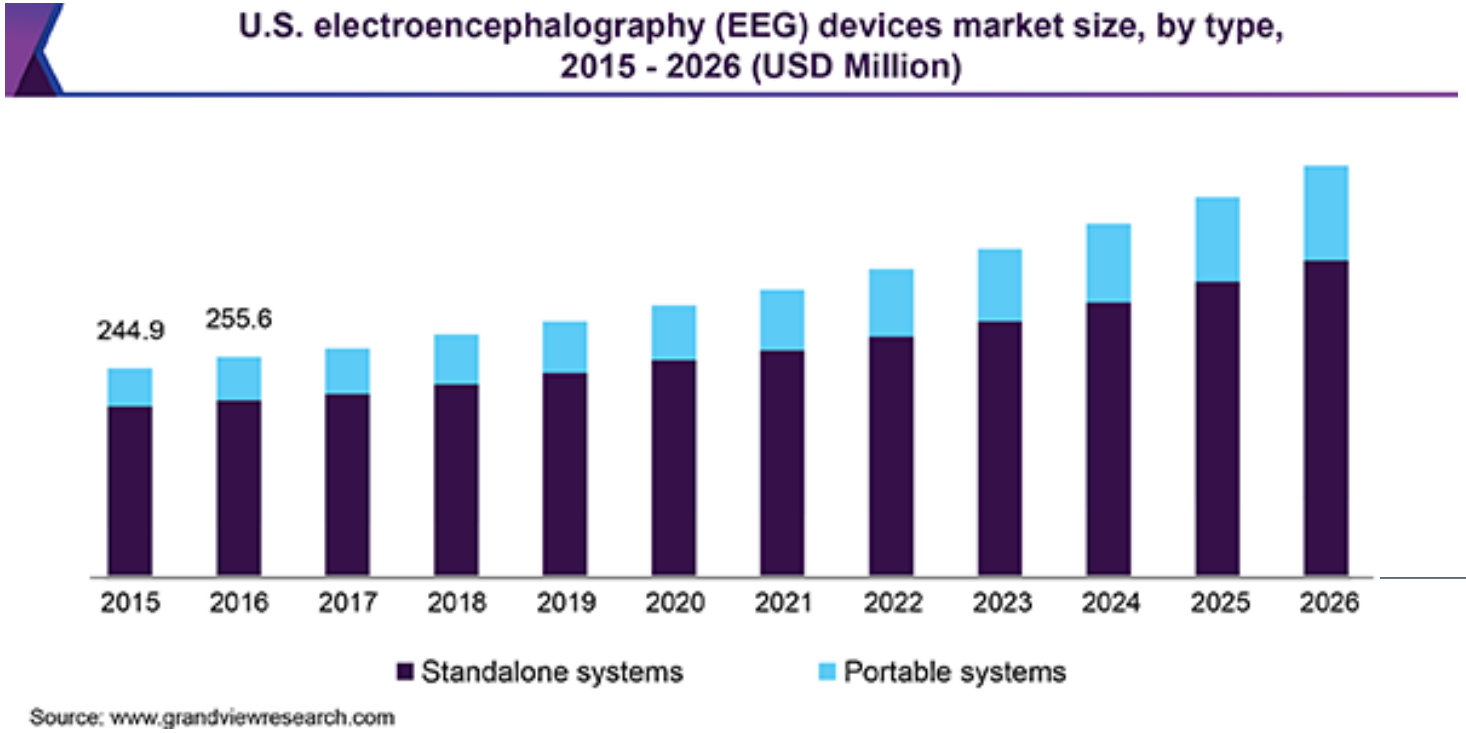


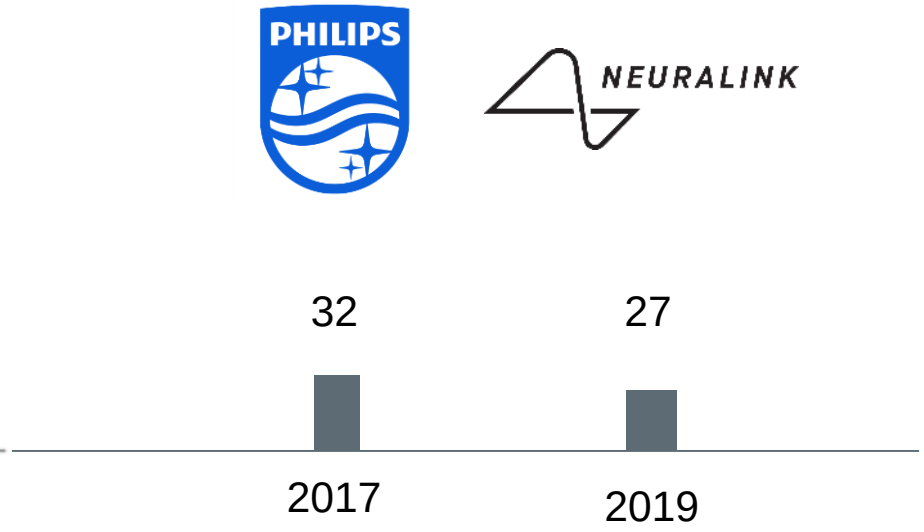

Start
Montage
Analyze
Window
Help
Open Patient
Markerlist
Video Player
Spikes finished
Trends&Seizures
Montage:
Notch:
High-pass:
Low-pass:
Longitudinal L-R
On
0.5 Hz
70.0 Hz
FP1-F7
F7-FT9
FT9-T7
T7-P7
P7-O1
FP1-F3
F3-C3
C3-P3
P3-O1
Fz-Cz
Cz-Pz
FP2-F4
F4-C4
C4-P4
P4-O2
FP2-F8
F8-FT10
FT10-T8
T8-P8
P8-O2
2010-01-21 00:10:03
2010-01-21 00:10:04
2010-01-21 00:10:05
2010-01-21 00:10:06
2010-01-21 00:10:07
2010-01-21 00:10:08
2010-01-21 00:10:09
2010-01-21 00:10:10
2010-01-21 00:10:11
2010-01-21 00:10:12
2010-01-21 00:10:13
Go to:
2010-01-21 00:10:02
X (sec/cm):
0.330
Y (µV/cm):
EEG
70
Y to default
EpiSpike - N2 - N2 - analyzing - current endtime: 2010-01-21 00:30:07
Current selection
Begin:
2010-01-21 00:00:07
End:
2010-01-21 00:30:00
Spike clusters
Label
Type
Number (%)
CZ
2 (1.1 %)
F4
1 (0.5 %)
F7
2 (1.1 %)
F8
162 (87.1 %)
FP2
4 (2.2 %)
FZ
1 (0.5 %)
O1
3 (1.6 %)
O2
1 (0.5 %)
P3
3 (1.6 %)
Spikes of cluster F8
Time
Comment
2010-01-21 00:07:02
2010-01-21 00:07:04
2010-01-21 00:07:04
2010-01-21 00:08:37
2010-01-21 00:09:32
2010-01-21 00:10:04
2010-01-21 00:10:11
2010-01-21 00:10:18
2010-01-21 00:10:21
EEGs of cluster F8
Montage:
Averaged spike
Spikes overlapped
Notch:
High-pass:
Low-pass:
PureEEG:
On
0.5 Hz
70 Hz
On
FP1-F7
F7-T7
T7-P7
P7-O1
FP1-F3
F3-C3
C3-P3
P3-O1
Fz-Cz
Cz-Pz
FP2-F4
F4-C4
C4-P4
P4-O2
FP2-F8
F8-T8
T8-P8
P8-O2
-0.5
0.0
0.5
Timeline
FP1
F7
T7
P7
O1
F3
C3
P3
FZ
CZ
PZ
FP2
F4
C4
P4
O2
F8
T8
P8
00:30
01:00
01:30
02:00
02:30
03:00
select
no det
Zoom: 3 h
Statistics of selection
Type
Left Hemisphere
Midline
Right Hemisphere
Total
10 (5.4 %)
5 (2.7 %)
171 (91.9 %)
186 (100.0 %)
Calculation status:
100%
2010-01-21 00:12:00
2010-01-21 00:12:18
2010-01-21 00:12:41
2010-01-21 00:12:50

AUSTRIAN INSTITUTE OF TECHNOLOGY
TOMORROW TODAY

Market changes

Electrodiagnostic market is growing





Royal Phillips aquired Electrical Geostatics Inc (EGI) for € 32 M

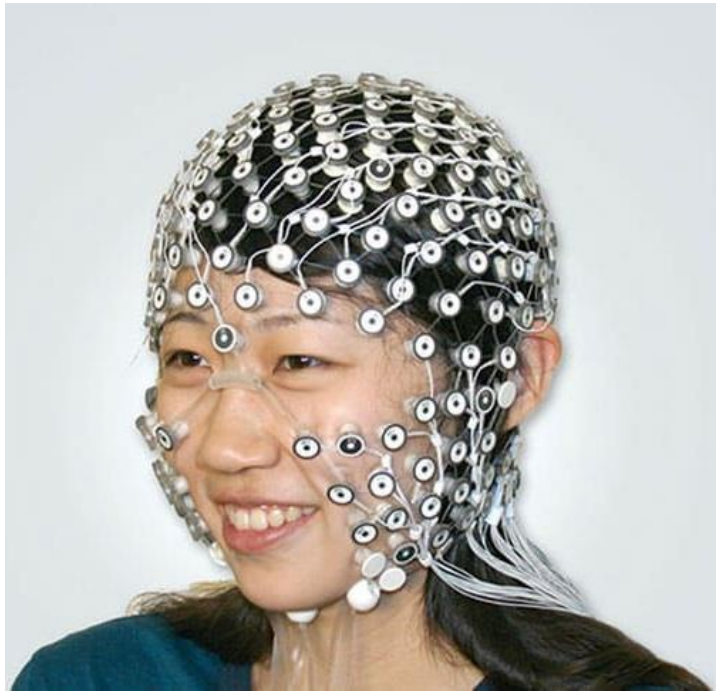
Alan Musk raised $27 M for Neuralink (neuralink.com)

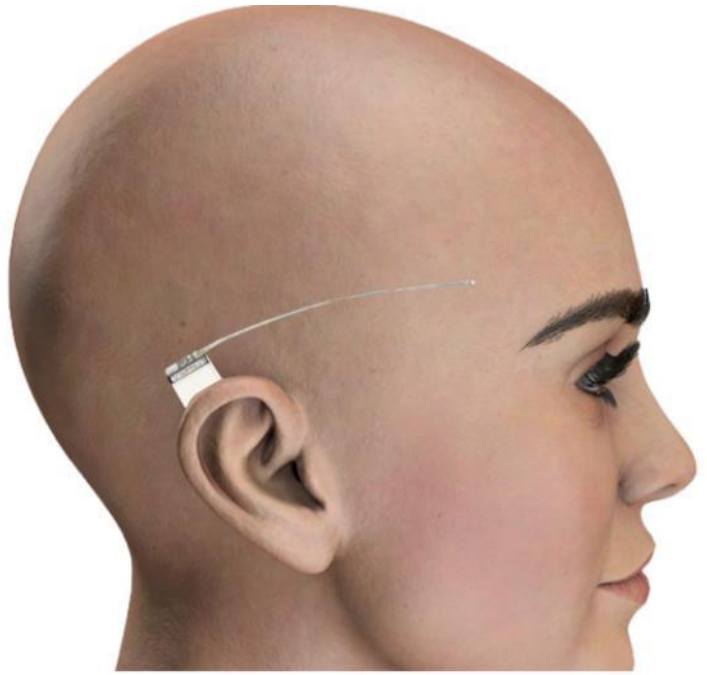
New ways to do EEG

ZETO

PHILIPS Healthcare

UNEEG medical





Fast setup

High spatial resolution

Ultra long-term

Measures

- heart rate (sine rhythm)
- warns about atrial fibrillation
- tachycardia
- FDA approved for SW only

Source: www.apple.com/at/watch/

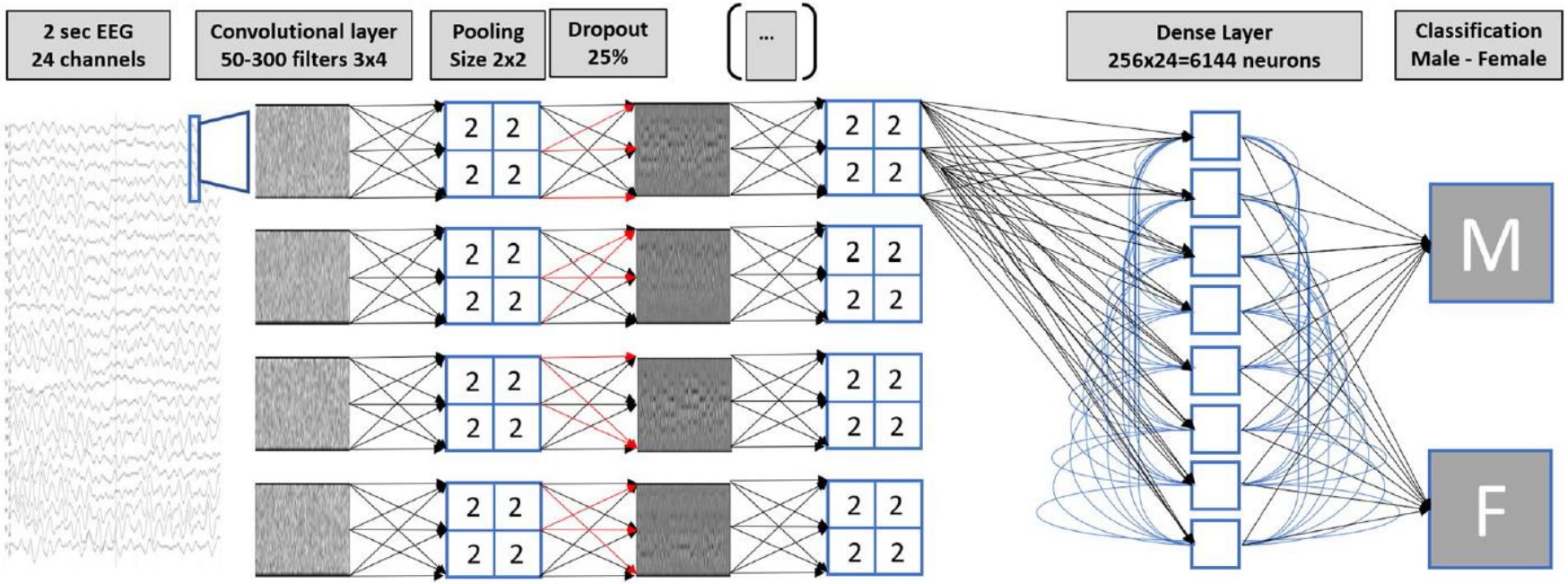
Things that were impossible before DL

SCIENTIFIC REPORTS

OPEN

Predicting sex from brain rhythms with deep learning

Michel J. A. M. van Putten[1], Sebastian Olbrich[2] & Martijn Arns[3]



accuracy = 83%

Source: https://www.nature.com/articles/s41598-018-21495-7.pdf

CONCLUSION

- ECG and EEG electrial biosignals and how to interpret them
- Atrial fibrillation and epilepsy
- RR Sequence Analysis, recurrent ECG Autoencoder, EEG R-CNN object detector
- EEG/ECG medical devices

THANK YOU!

Dr. Franz Fürbass
franz.fuerbass@ait.ac.at

encevis

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The AIT team behind encevis

The basis of our success

Our team at AIT is working on outstanding solutions for computational EEG analysis. We develop both the algorithms and the software to run it. We offer fast response time should you ever experience problems.