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NÝSKÖPUNARÞING 2018

Innreið fjórðu iðnbyltingarinnar í heilbrigðis tækni. Ógnvaldur eða risavaxið tækifæri?

Pétur Már Halldórsson
Nox Medical

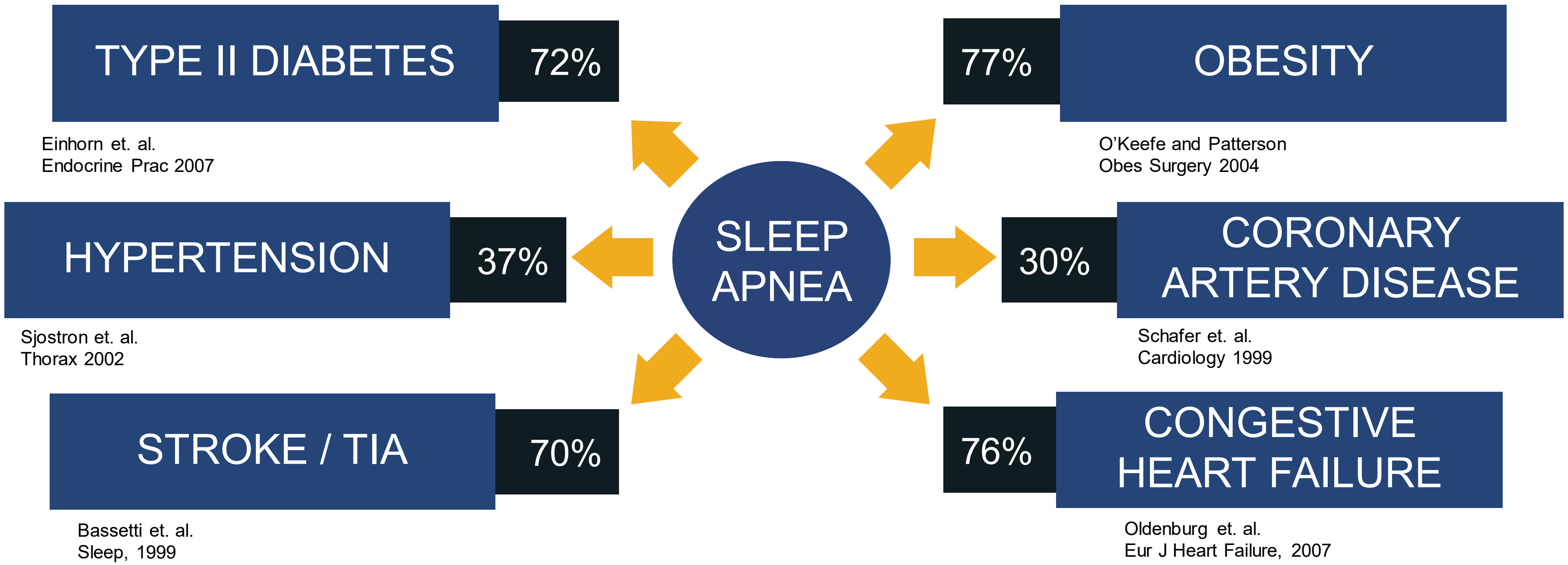
Vision & Mission

Our mission is to advance sleep diagnostics through simplification, increased efficiency, and comfort in all patient groups

Our vision is **Sleep for All**

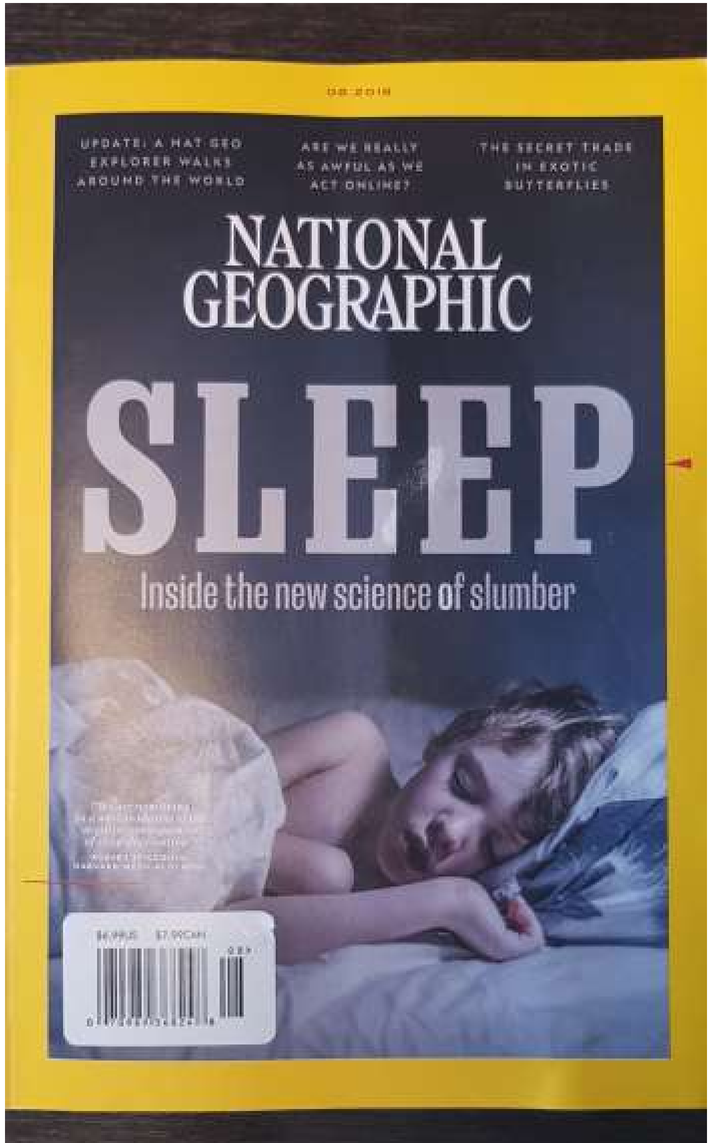
Sleep Apnea – The Silent Killer

Obstructive Sleep Apnea (OSA)
Public Health Problem of Epidemic Proportions



OSA and Sleep Related Chronic Diseases (SRCD)
Cost $1 Trillion Annually - OSA Alone Accounts for $165B

National Geographic (August issue 2018)



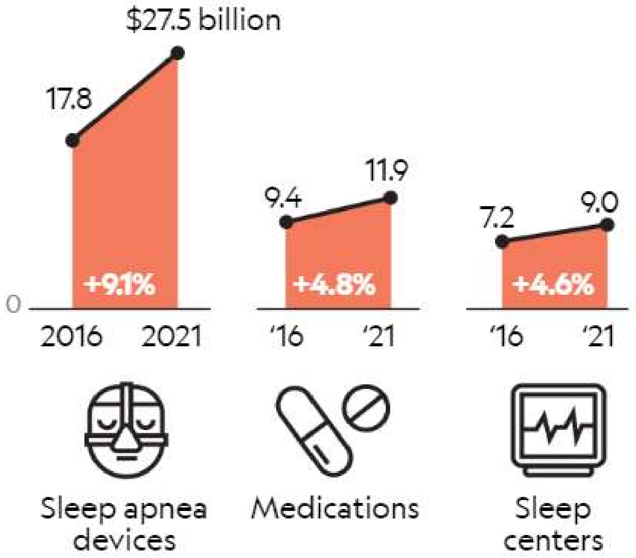
„We are now living in a worldwide test of the negative consequences of sleep deprivation“

Robert Stickgold, Harvard Medical School

National Geographic (August issue 2018) USA CDC

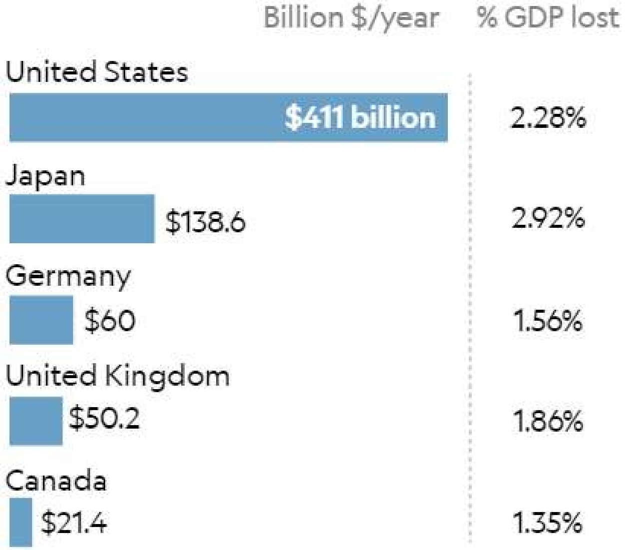
THE MARKET FOR SLEEP

Sleep-deprived consumers paid $66 billion in 2016 for devices, medications, and sleep studies. The figure could rise to $85 billion by 2021.



THE COST OF SLEEPLESSNESS

A 2017 Rand study found that lack of sleep can result in reduced productivity as well as more work absences, industrial and road accidents, health care expenses, and medical errors.



The Nox entrepreneur's

Our People

- More than 50 employees
- Expertise and experience in medical engineering and software development
- High level of domain knowledge
- Tight knit group with a diverse set of qualifications and skills

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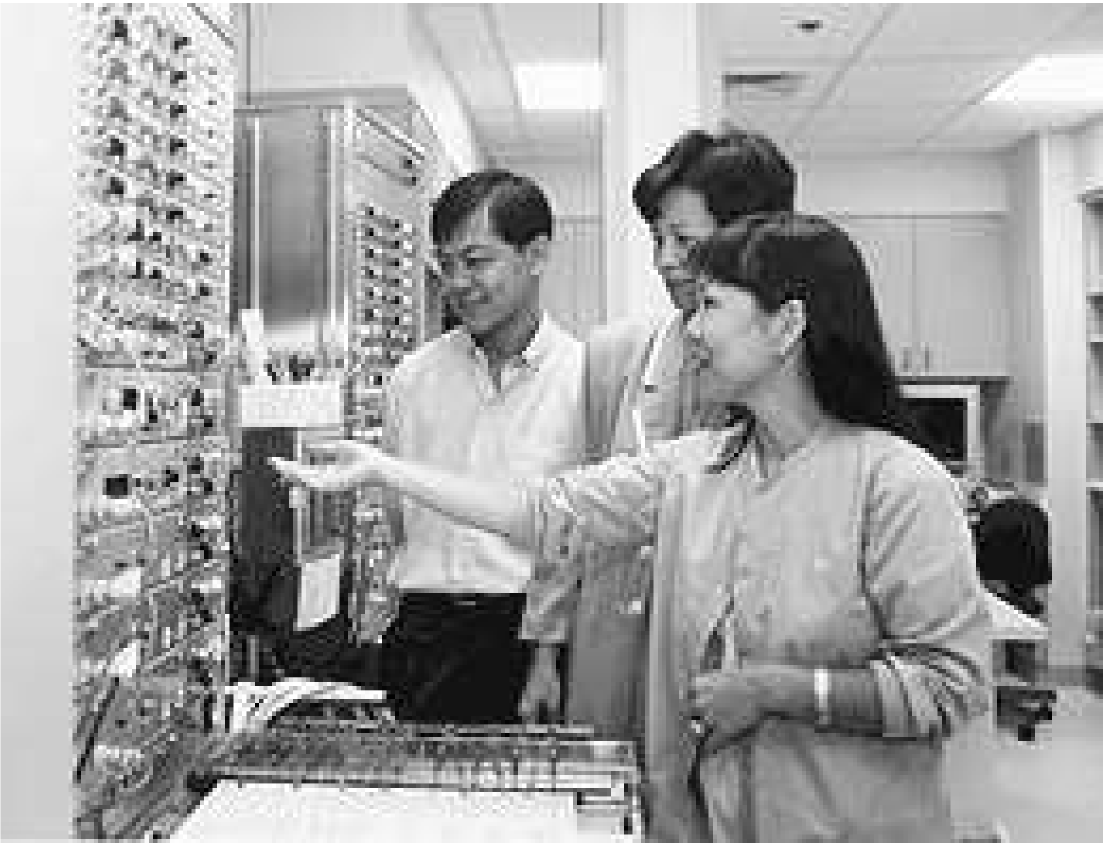
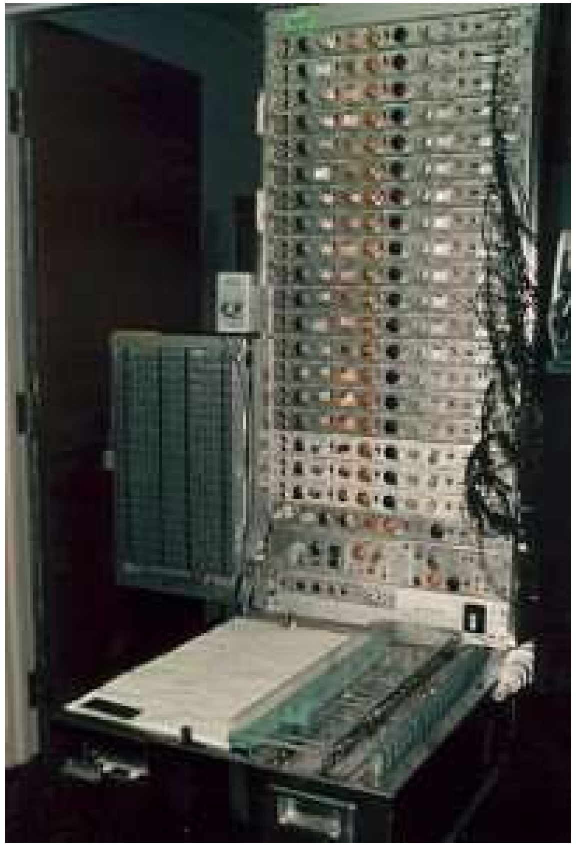
This is not from ancient times





The early days

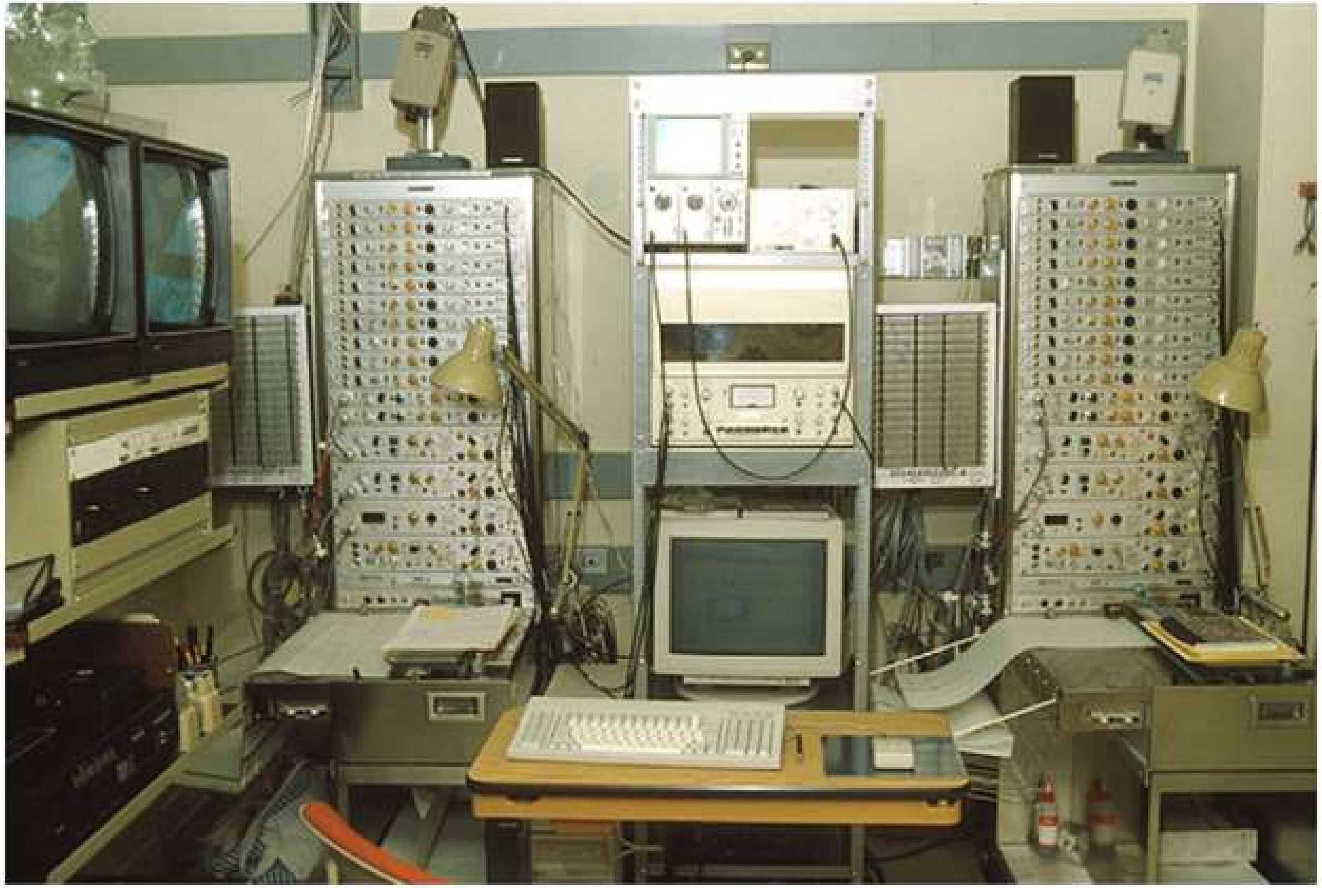


Fig. 5. Analog sleep system. Two-bed sleep laboratory at the University of Wisconsin, 1988. (*Courtesy of* S. Weber, Madison, WI.)

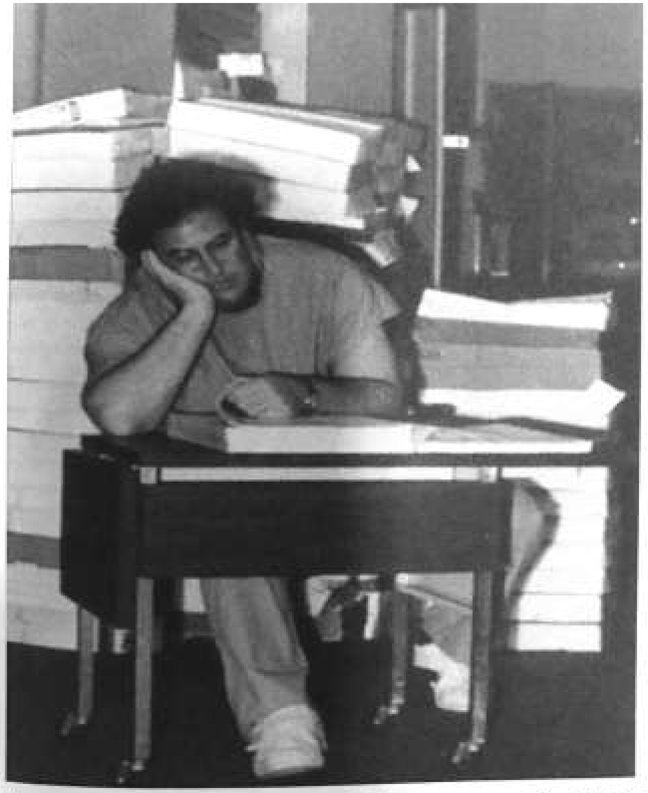


Fig. 4. Author surrounded by a sea of paper polysomnograms.

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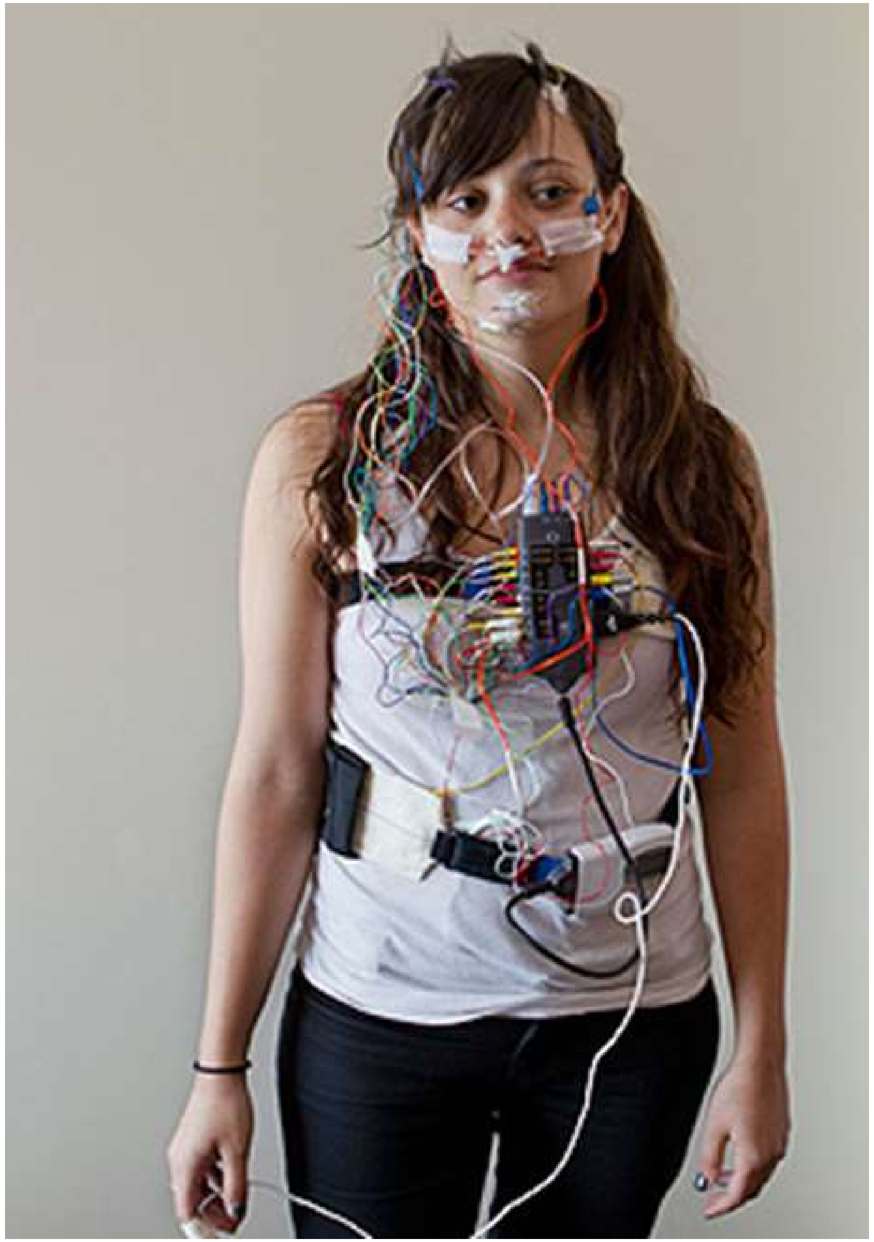

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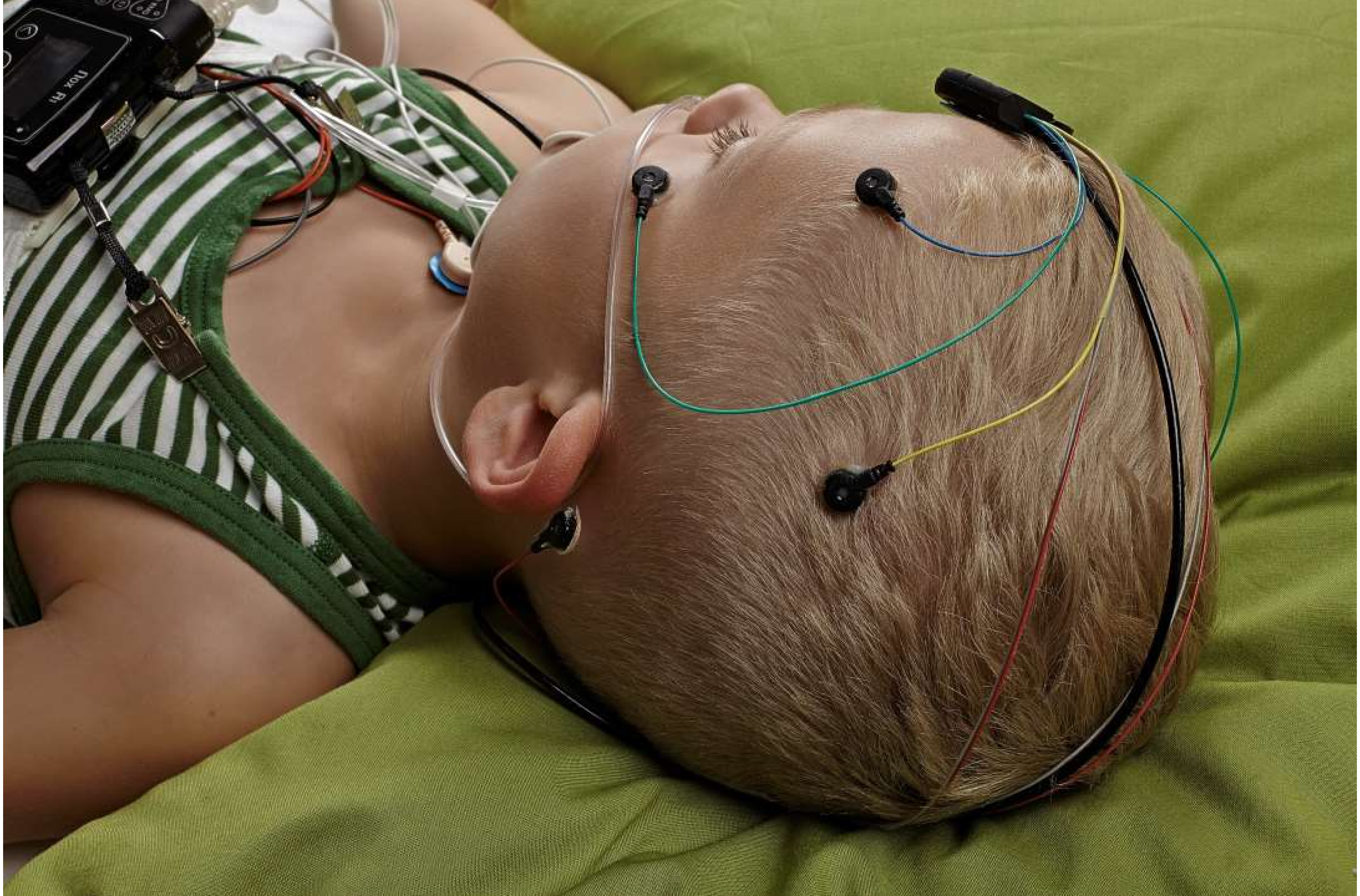


lical

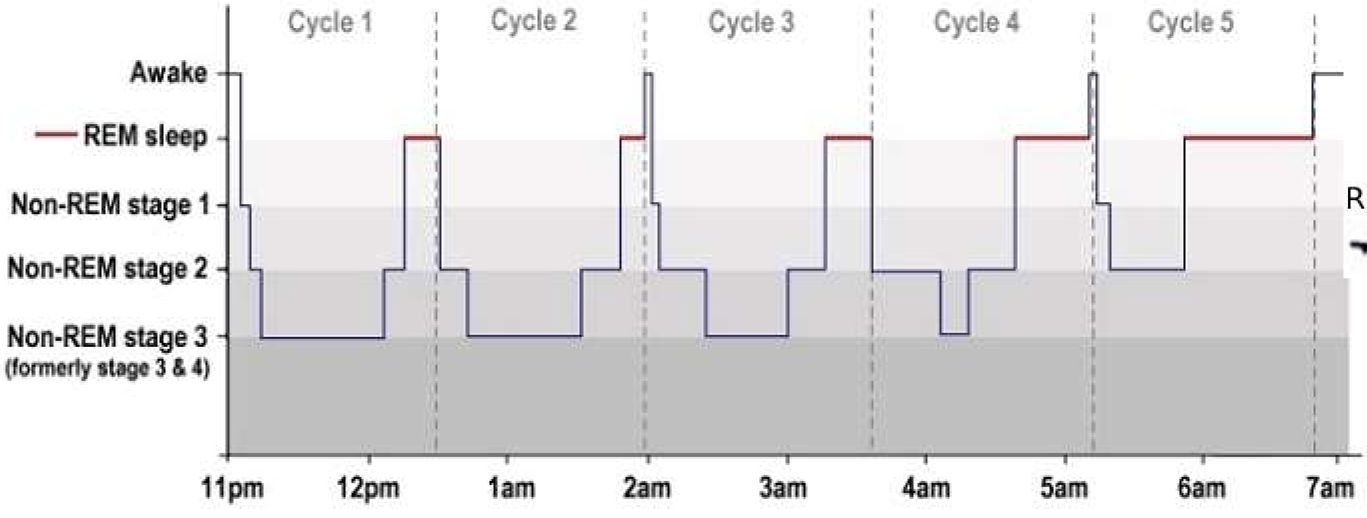
up until 2018

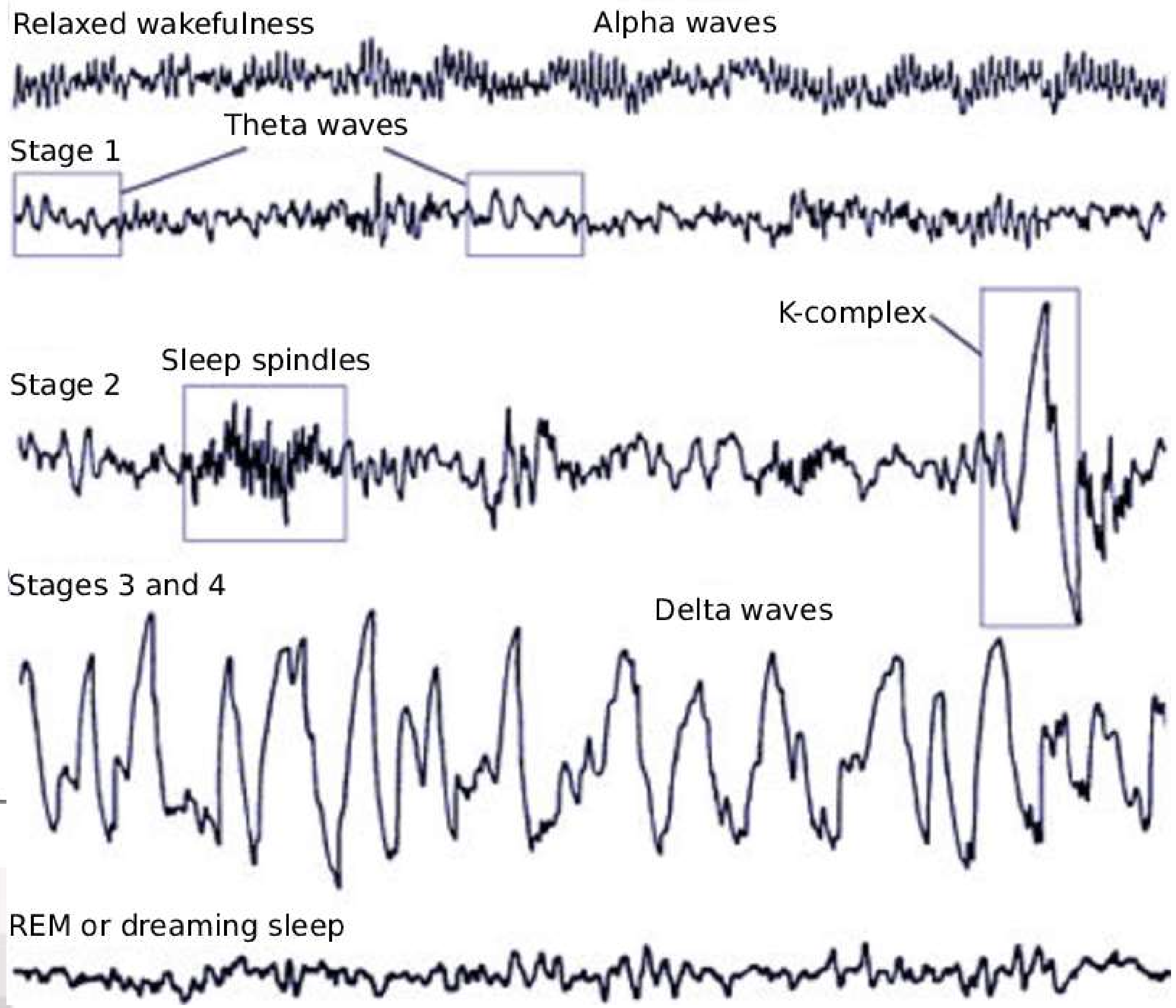
5 Million lives

Affected with Nox Medical technology world wide

Sleep stages

Classify every 30 seconds
5 Sleep stages
Classification rules
Human experts agree





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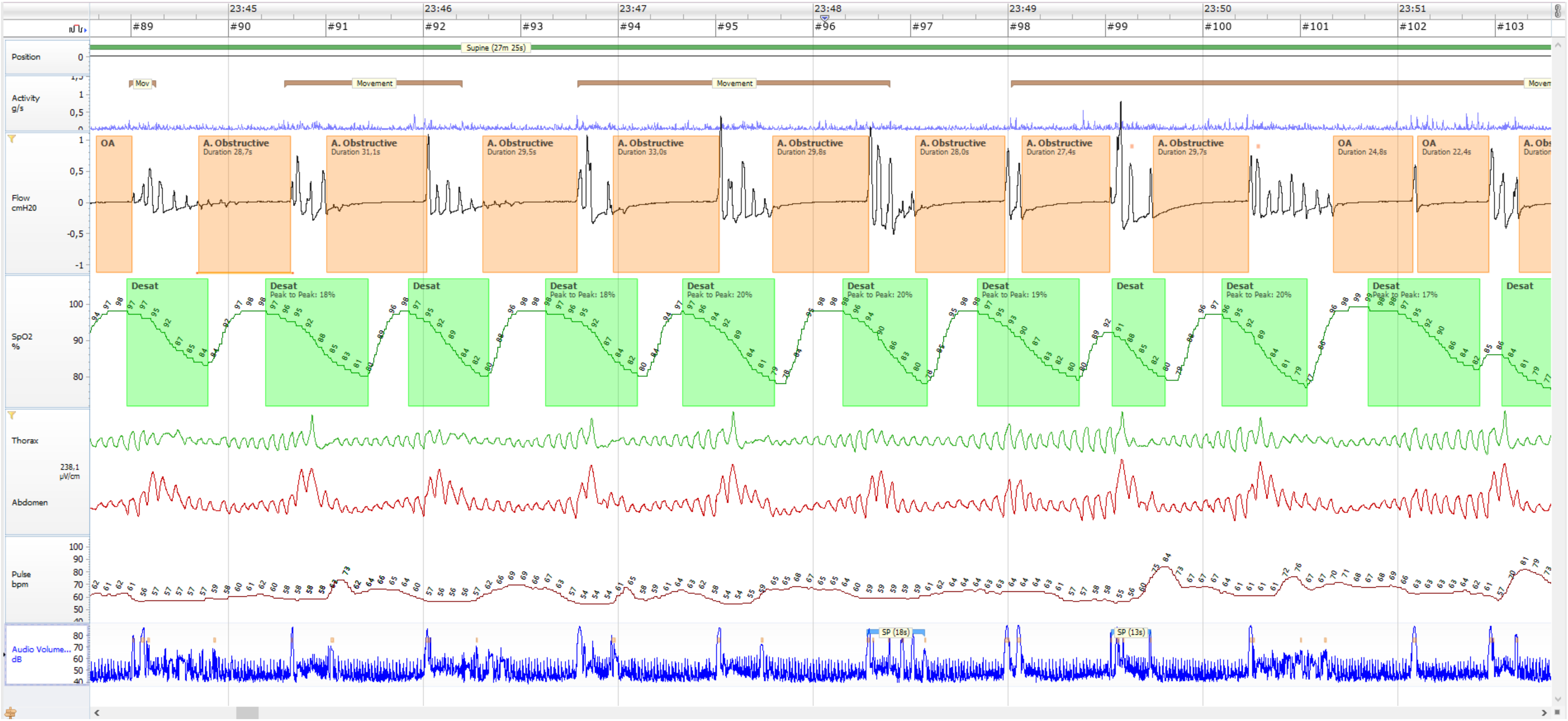

23:45
23:46
23:47
23:48
23:49
23:50
23:51
#89 #90 #91 #92 #93 #94 #95 #96 #97 #98 #99 #100 #101 #102 #103
Position
Supine (27m 25s)
Activity g/s
Movement
Flow cmH20
OA
A. Obstructive
Duration 28,7s
Duration 31,1s
Duration 29,5s
Duration 33,0s
Duration 29,8s
Duration 28,0s
Duration 27,4s
Duration 29,7s
Duration 24,8s
Duration 22,4s
SpO2 %
Desat
Peak to Peak: 18%
Peak to Peak: 20%
Peak to Peak: 19%
Peak to Peak: 17%
Thorax
238,1 µV/cm
Abdomen
Pulse bpm
Audio Volume... dB
SP (18s)
SP (13s)

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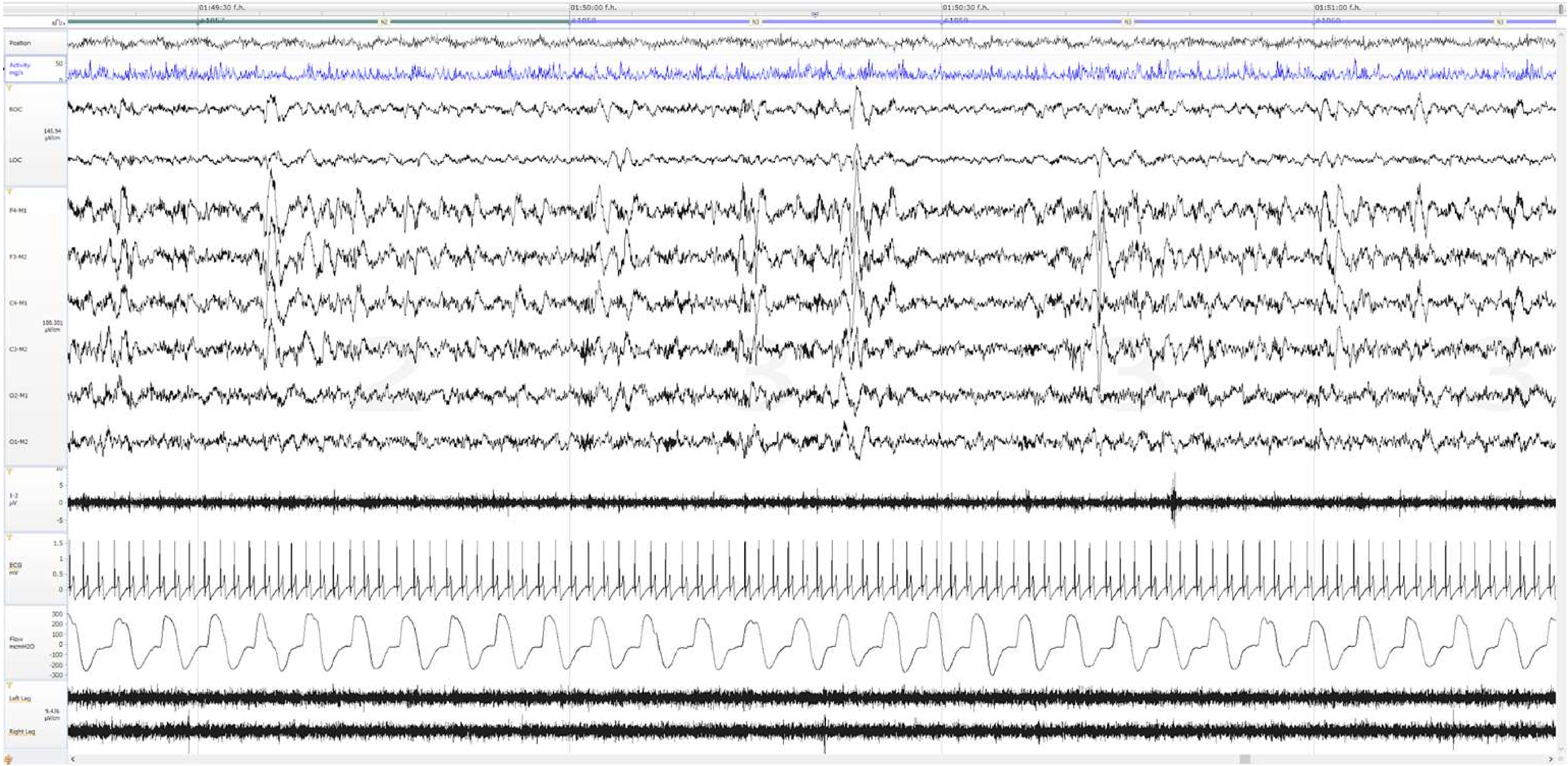
01:49:30 f.h.
01:50:00 f.h.
01:50:30 f.h.
01:51:00 f.h.
Position
Activity
mg/s
ROC
LOC
F4-M1
F3-M2
C4-M1
C3-M2
O2-M1
O1-M2
ECG
mV
Flow
Left Leg
Right Leg

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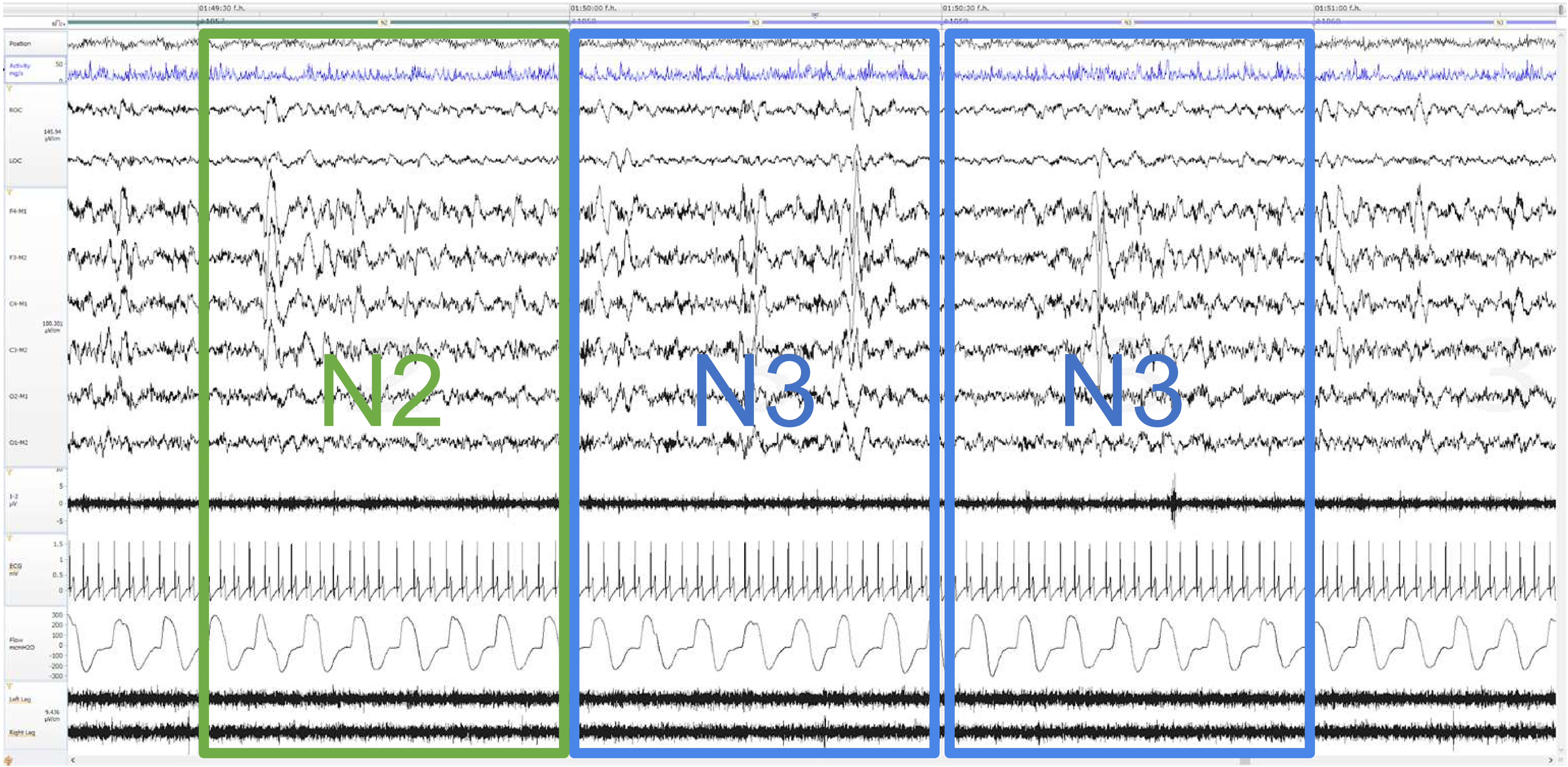

01:49:30 f.h.
01:50:00 f.h.
01:50:30 f.h.
01:51:00 f.h.
Position
Activity
ROC
LOC
F4-M1
F3-M2
C4-M1
C3-M2
O2-M1
O1-M2
ECG
Flow
Left Leg
Right Leg
N2
N3
N3

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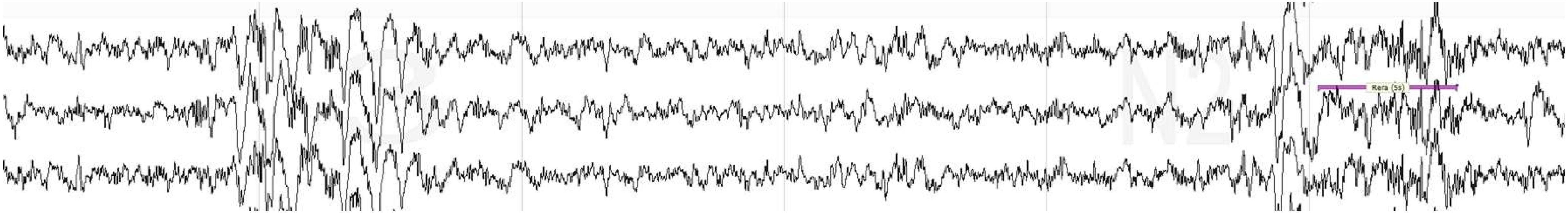
Scoring arousals - challenges

- Manual scoring, challenges
  - Time consuming
  - Variance across patients
  - Human error
- Automatic scoring, challenges
  - Lack of well manually scored data
  - Imbalanced data set
    - 2-7% arousals
    - > 93% non-arousals
  - Fuzzy definition, easy to confuse to noise

Important to find a solution to the automatic arousal scoring problem



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Nox Research

Team of scientists

- Self funded
- External collaborations
- Internal projects

Mission

- Automation
- Enabling Research

Ambition

- Convert data to information
- Improve patient health

European Commission

Horizon 2020
European Union funding
for Research & Innovation

Tækniþróunarsjóður

eurostars™ dical

EEG setup - Big DATA

Conventional EEG

8 EEG channels

2 EOG channels

2 EMG chin channels

Frontal EEG

9 channels recording EEG and EOG

RIP belts detect muscle tone

MACS cohort

2000 people in 1 year

Self-Applied Somnography
Data quality pipeline
Customized data analysis
Technical support
Knowledge transfer

JOHNS HOPKINS MEDICINE
THE JOHNS HOPKINS HOSPITAL

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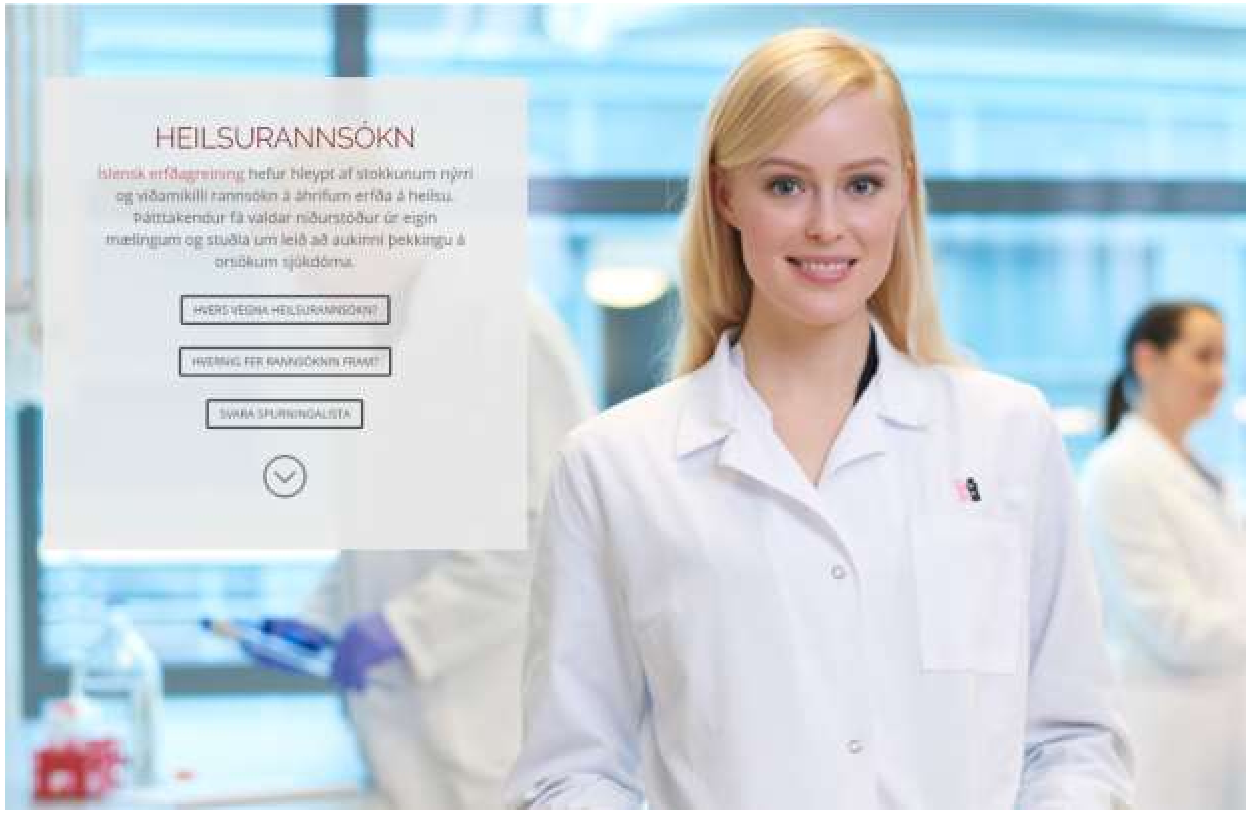
deCode HERA

3000 People per year
Sleep measurement
Extensive clinical and health data

Self-Applied Somnography
Data quality pipeline
Customized data analysis
Technical support



Big Data → Big Dating

Yale University
School of Medicine

Health

HARVARD
UNIVERSITY

Stanford
University

Penn
UNIVERSITY of PENNSYLVANIA

BRIGHAM HEALTH
BWH BRIGHAM AND WOMEN'S HOSPITAL
BRIGHAM RESEARCH INSTITUTE

THE UNIVERSITY OF SYDNEY

LANDSPÍTALI
UNIVERSITY HOSPITAL

JOHNS HOPKINS
MEDICINE
THE JOHNS HOPKINS HOSPITAL

The Icelandic Institute for Intelligent Machines

THE UNIVERSITY OF CHICAGO

AMGEN®

HÁSKÓLINN Í REYKJAVÍK
REYKJAVIK UNIVERSITY

COLUMBIA UNIVERSITY

deCODE genetics

REMOTE
SmartECG

Imperial College London

Scoring arousals - challenges

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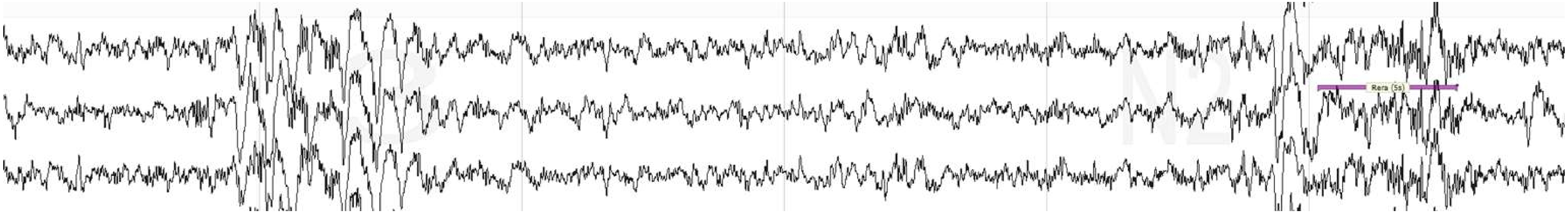

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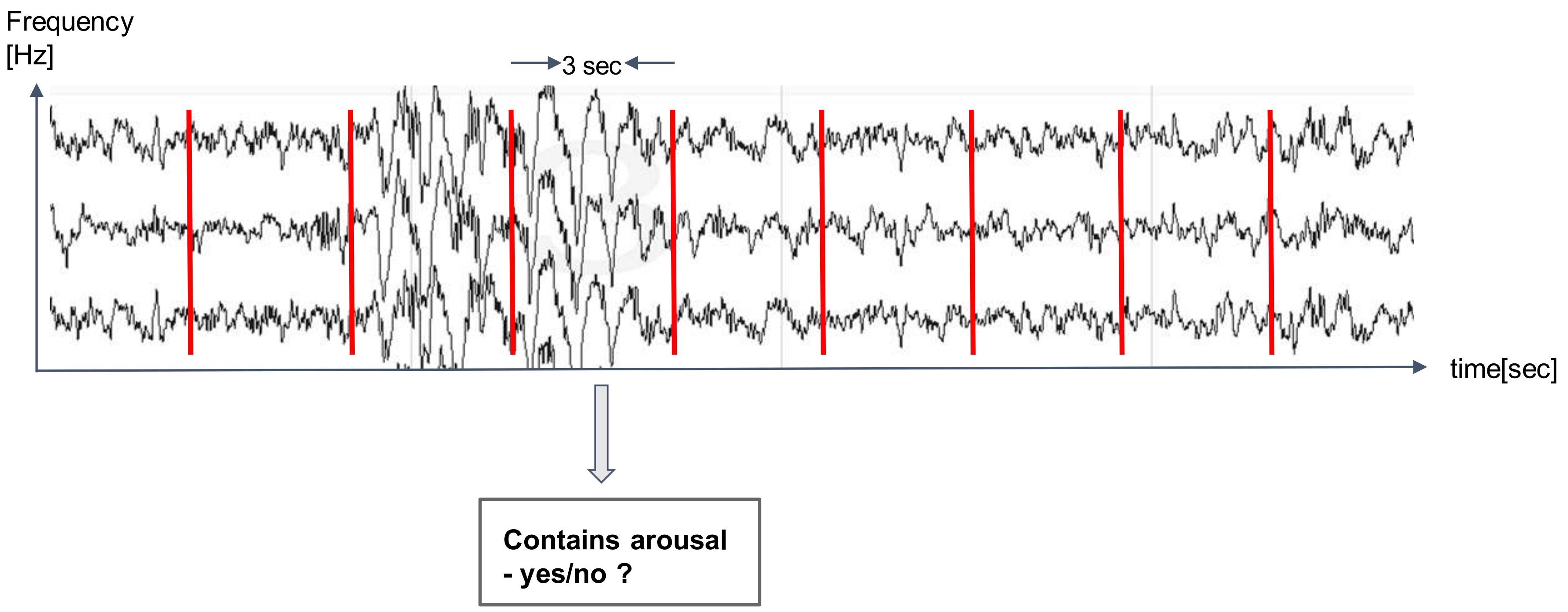
To automatically detect arousals in EEG using supervised learning (classification)



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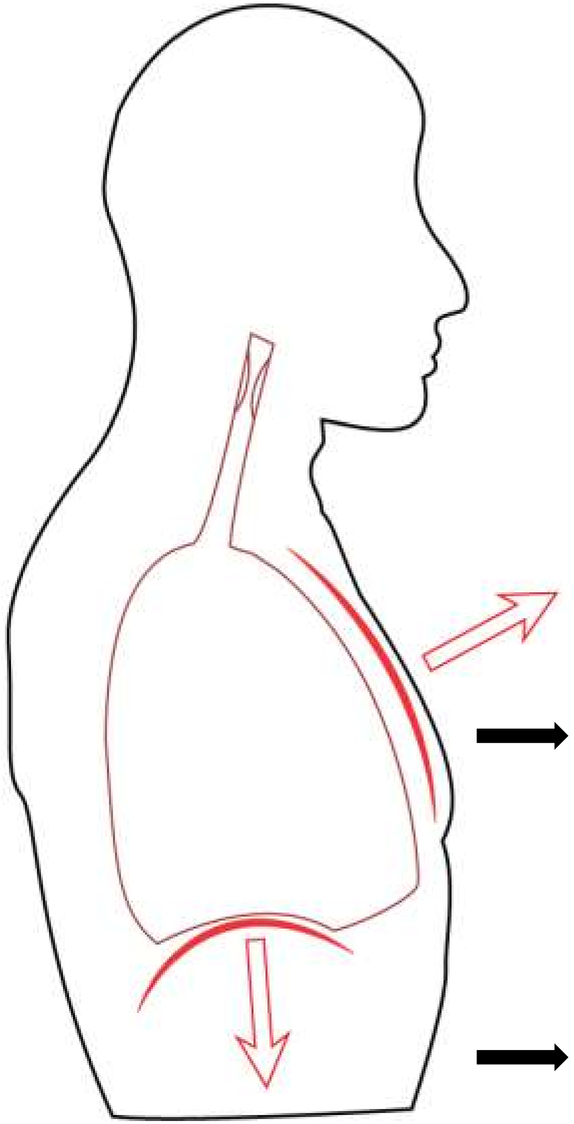
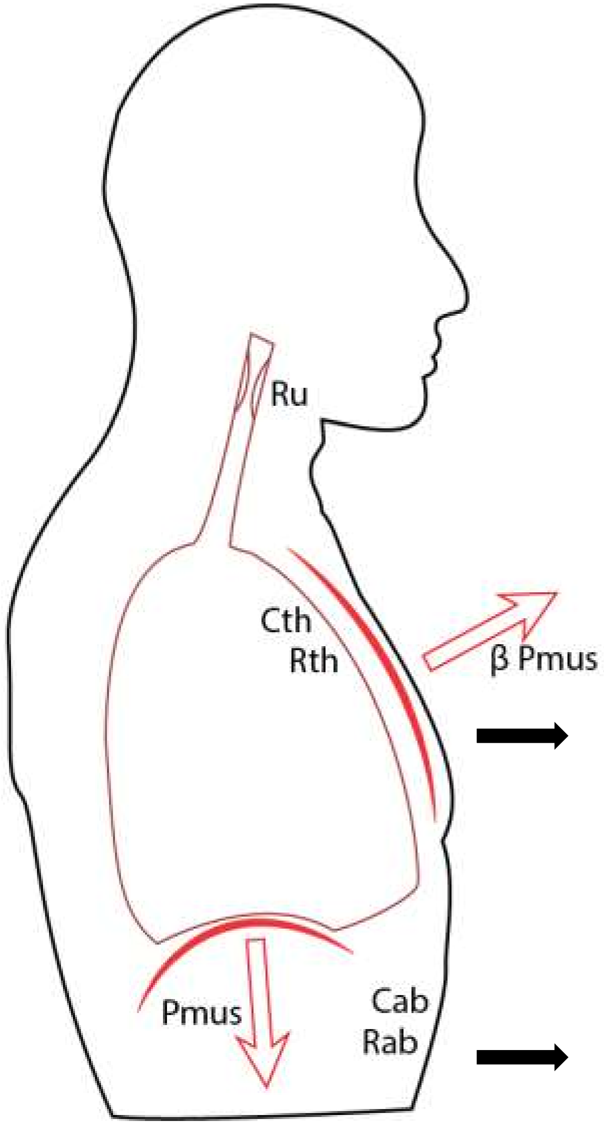
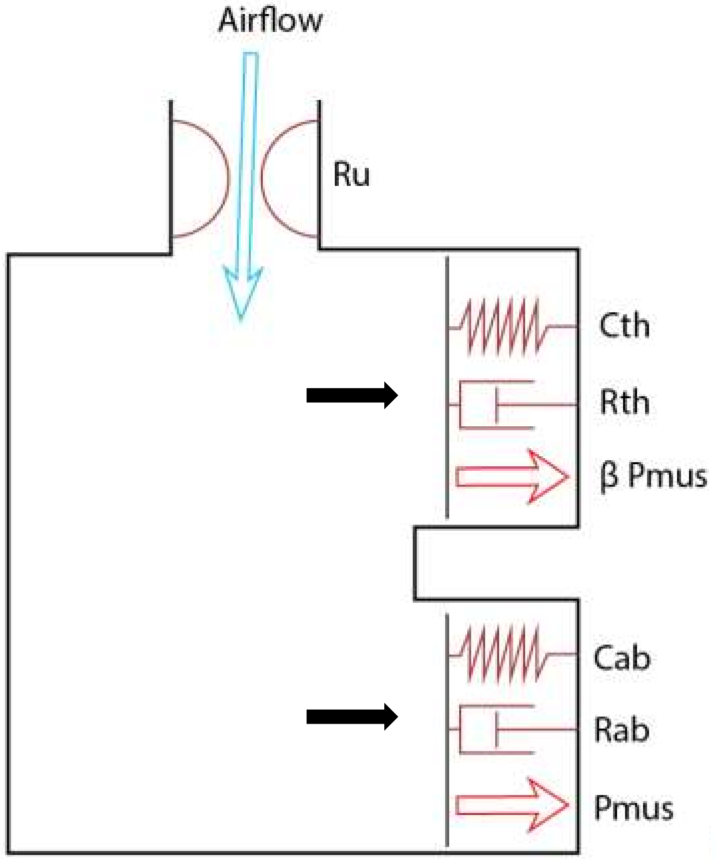
Modelling breathing



Modelling breathing





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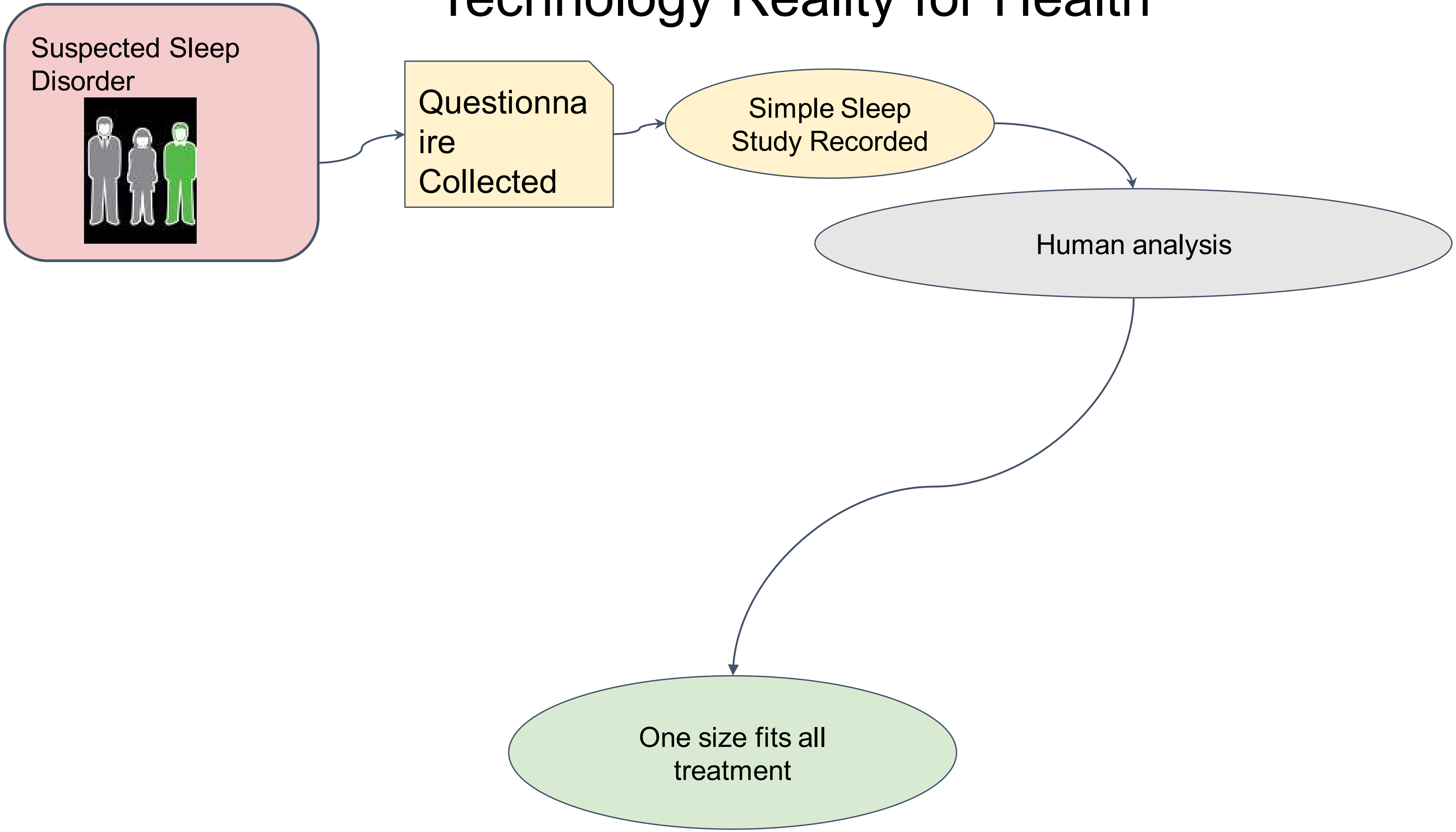
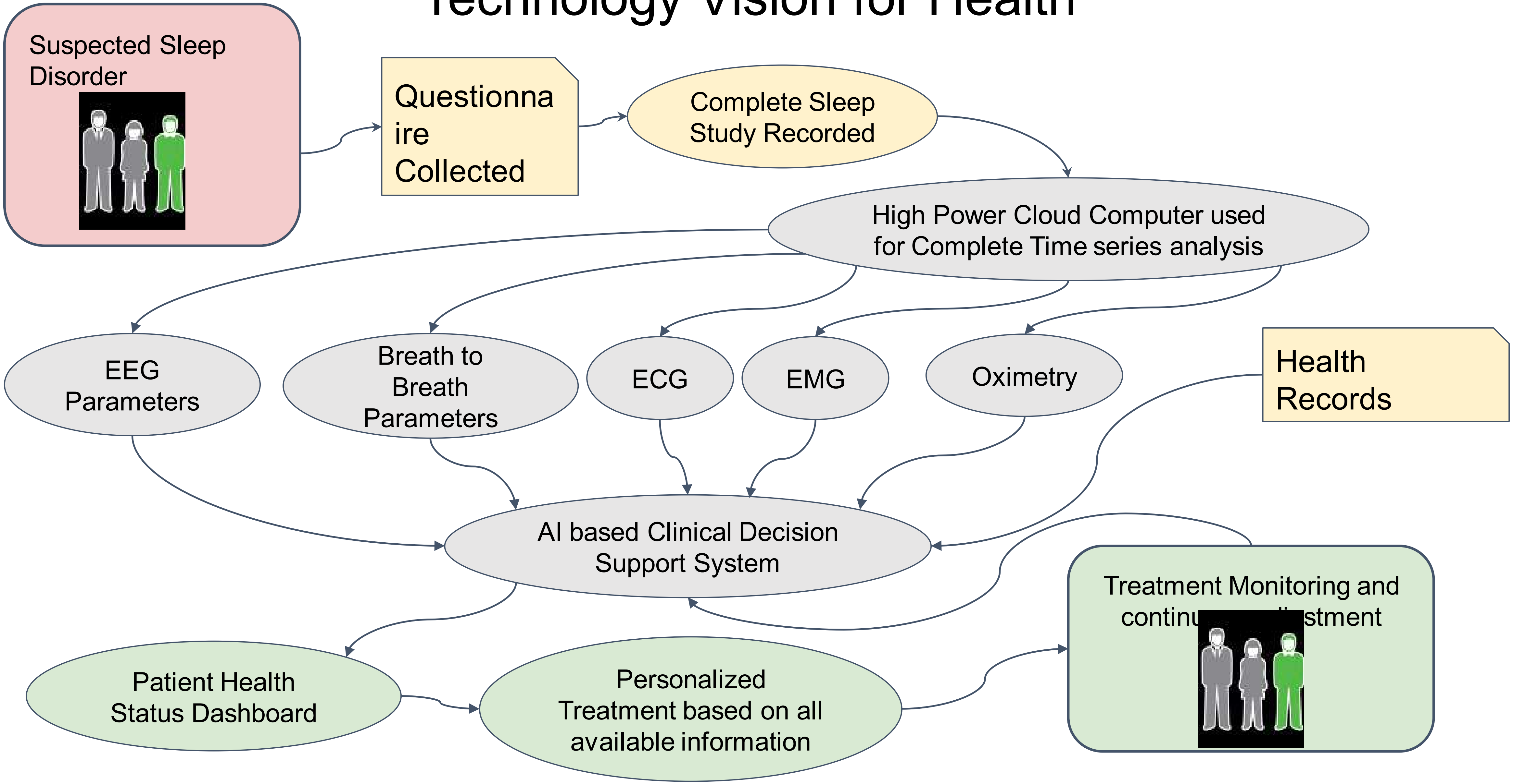
Technology Reality for Health



Technology Vision for Health



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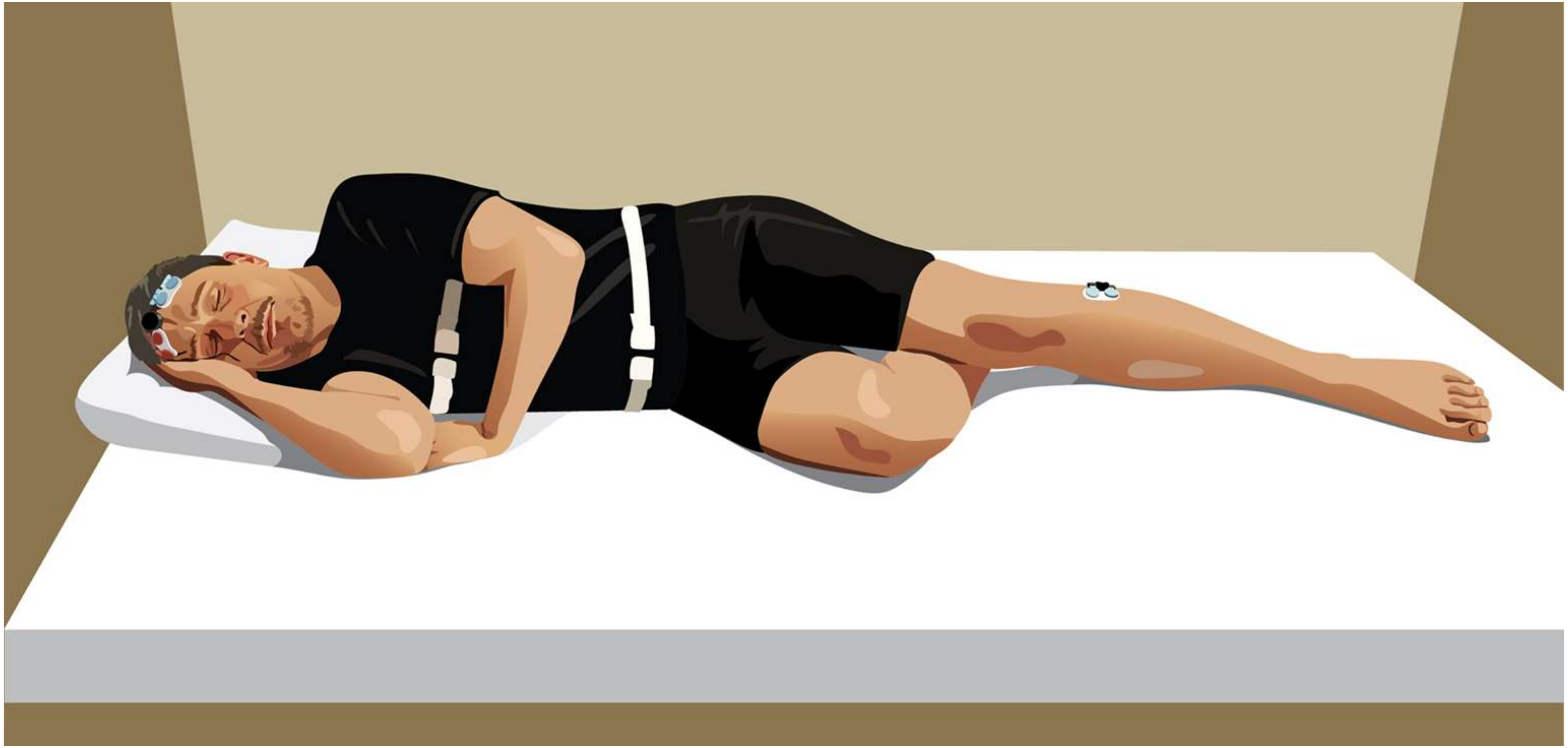
Smart-Sensor Nox System view -

Wireless miniature smart sensors using Bluetooth 5 streaming can be post-delivered to patient home



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PhysioNet
the research resource for
complex physiologic signals

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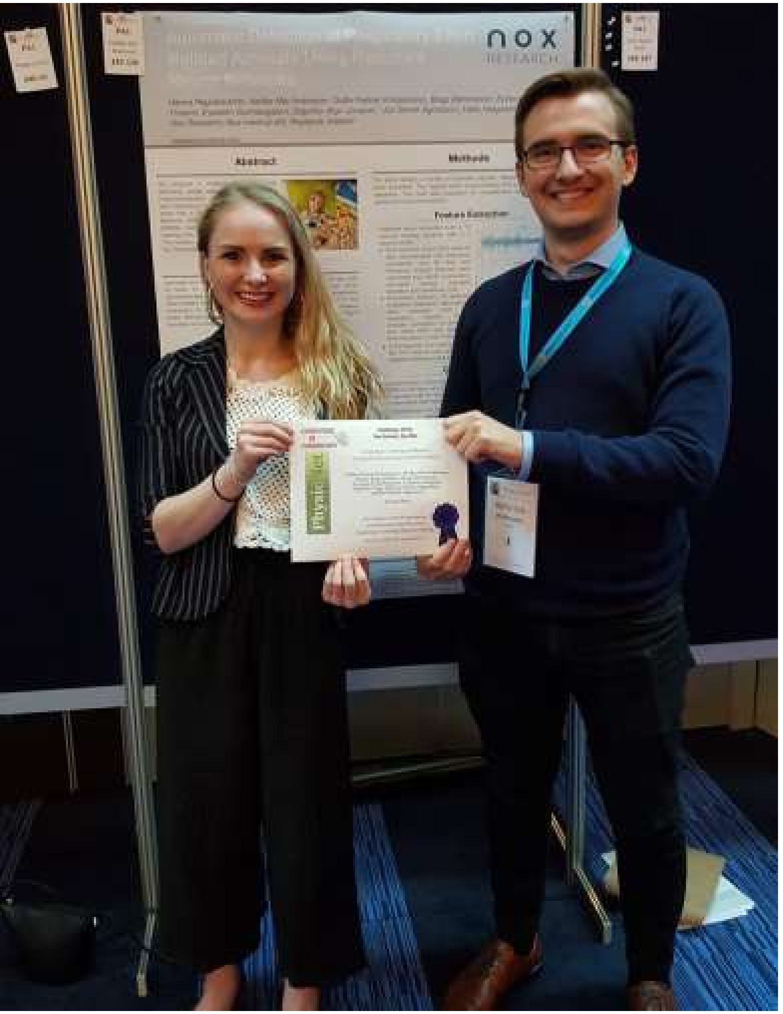

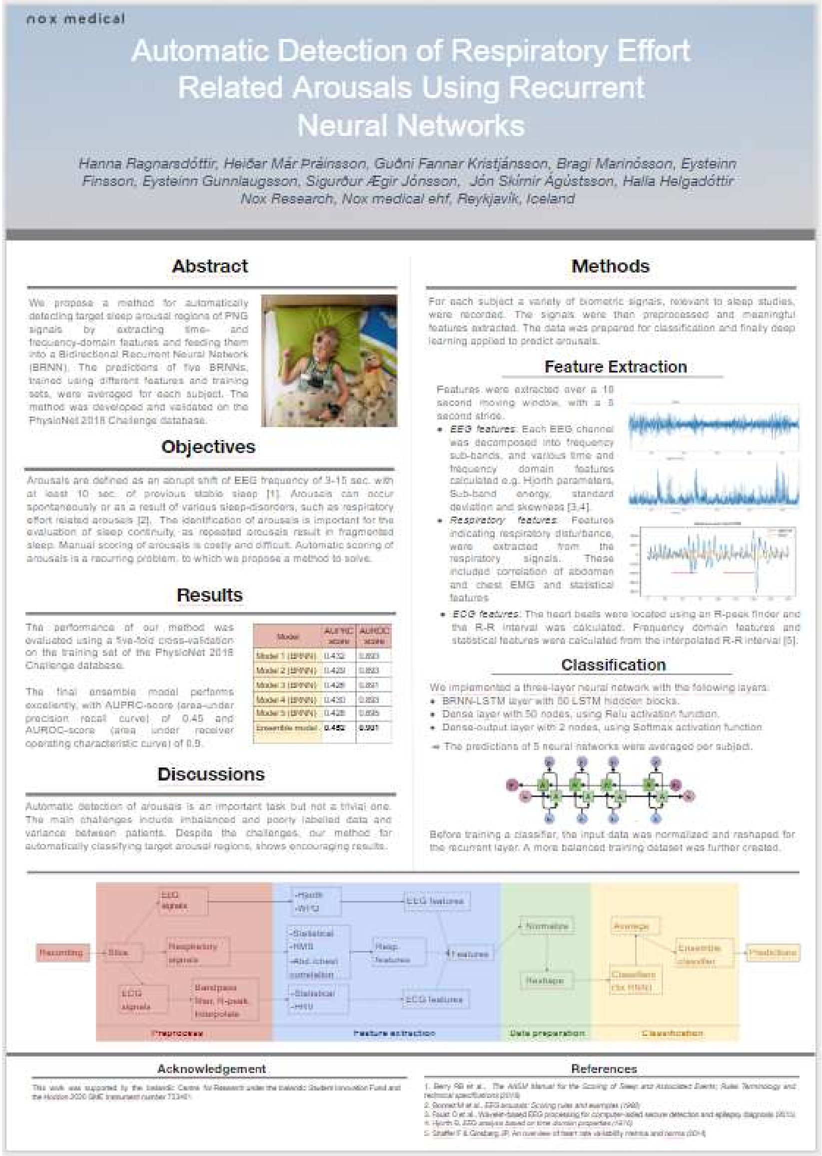
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Automatic Detection of Respiratory Effort Related Arousals Using Recurrent Neural Networks
Hanna Ragnarsdóttir, Heiðar Már Þráinsson, Guðni Fannar Kristjánsson, Bragi Marinósson, Eysteinn Finnsson, Eysteinn Gunnlaugsson, Sigurður Ægir Jónsson, Jón Skírnir Ágústsson, Halla Helgadóttir
Nox Research, Nox medical ehf, Reykjavík, Iceland
Abstract
We propose a method for automatically detecting target sleep arousal regions of PNG signals by extracting time- and frequency-domain features and feeding them into a Bidirectional Recurrent Neural Network (BRNN). The predictions of five BRNNs, trained using different features and training sets, were averaged for each subject. The method was developed and validated on the PhysioNet 2018 Challenge database.
Objectives
Arousals are defined as an abrupt shift of EEG frequency of 3-15 sec. with at least 10 sec. of previous stable sleep [1]. Arousals can occur spontaneously or as a result of various sleep-disorders, such as respiratory effort related arousals [2]. The identification of arousals is important for the evaluation of sleep continuity, as repeated arousals result in fragmented sleep. Manual scoring of arousals is costly and difficult. Automatic scoring of arousals is a recurring problem, to which we propose a method to solve.
Results
The performance of our method was evaluated using a five-fold cross-validation on the training set of the PhysioNet 2018 Challenge database.
The final ensemble model performs excellently, with AUPRC-score (area-under precision recall curve) of 0.45 and AUROC-score (area under receiver operating characteristic curve) of 0.9.
Model | AUPRC score | AUROC score
Model 1 (BRNN) | 0.432 | 0.893
Model 2 (BRNN) | 0.429 | 0.893
Model 3 (BRNN) | 0.428 | 0.891
Model 4 (BRNN) | 0.430 | 0.893
Model 5 (BRNN) | 0.428 | 0.895
Ensemble model | 0.452 | 0.901
Discussions
Automatic detection of arousals is an important task but not a trivial one. The main challenges include imbalanced and poorly labelled data and variance between patients. Despite the challenges, our method for automatically classifying target arousal regions, shows encouraging results.
Methods
For each subject a variety of biometric signals, relevant to sleep studies, were recorded. The signals were then preprocessed and meaningful features extracted. The data was prepared for classification and finally deep learning applied to predict arousals.
Feature Extraction
Features were extracted over a 10 second moving window, with a 5 second stride.
• EEG features: Each EEG channel was decomposed into frequency sub-bands, and various time and frequency domain features calculated e.g. Hjorth parameters, Sub-band energy, standard deviation and skewness [3,4].
• Respiratory features: Features indicating respiratory disturbance, were extracted from the respiratory signals. These included correlation of abdomen and chest EMG and statistical features
• ECG features: The heart beats were located using an R-peak finder and the R-R interval was calculated. Frequency domain features and statistical features were calculated from the interpolated R-R interval [5].
Classification
We implemented a three-layer neural network with the following layers:
• BRNN-LSTM layer with 50 LSTM hidden blocks.
• Dense layer with 50 nodes, using Relu activation function.
• Dense-output layer with 2 nodes, using Softmax activation function
⇒ The predictions of 5 neural networks were averaged per subject.
Before training a classifier, the input data was normalized and reshaped for the recurrent layer. A more balanced training dataset was further created.
Recording
Slice
EEG signals
Respiratory signals
ECG signals
Bandpass filter, R-peak, Interpolate
-Hjorth
-Statistical
-RMS
-Abd./chest correlation
-Statistical
EEG features
Resp. features
ECG features
Features
Normalize
Reshape
Average
Classifiers (5x RNN)
Ensemble classifier
Predictions
Preprocess
Feature extraction
Data preparation
Classification
Acknowledgement
References

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