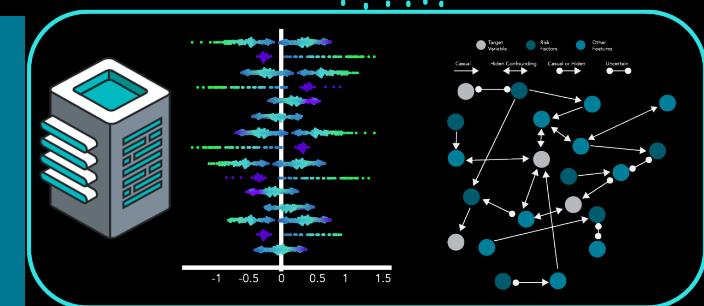
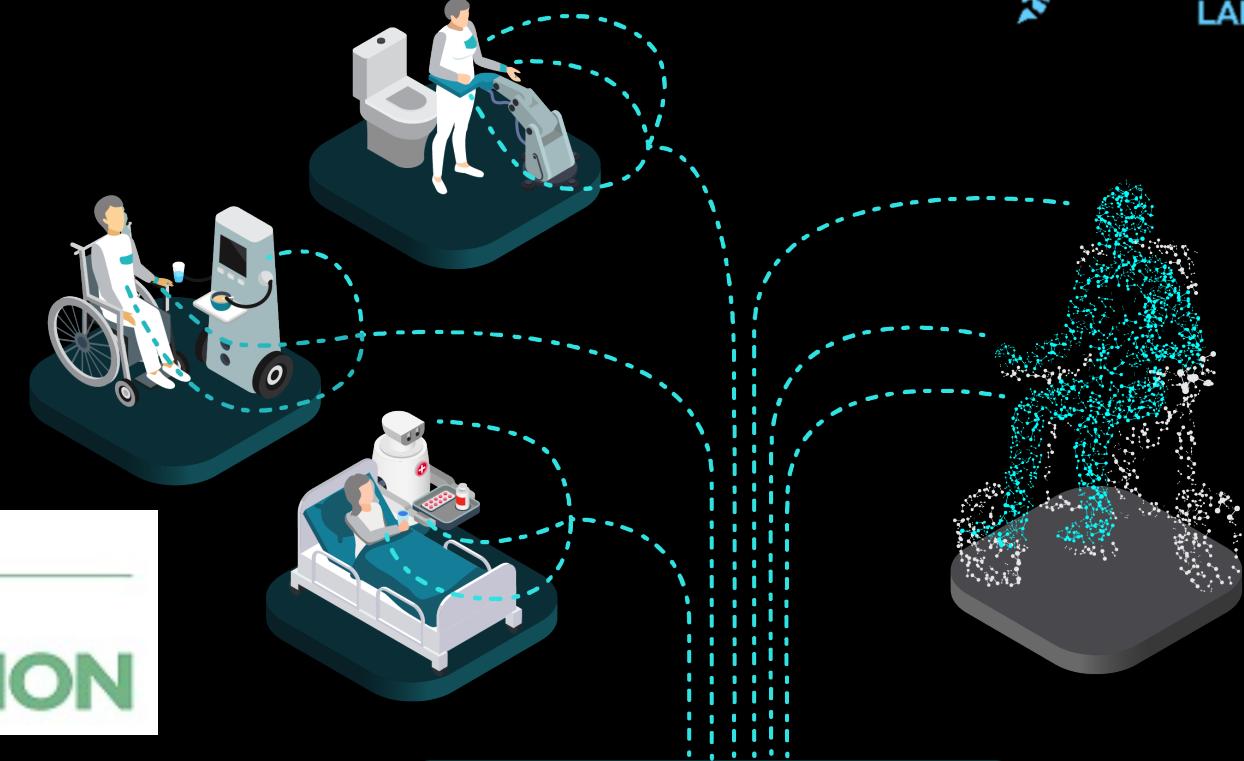




2024
SUMMER SCHOOL ON
SSNR NEUROREHABILITATION

Workshop:
Machine Learning Processing
for Wearable Data in Healthcare



Workshop: Machine Learning Processing for Wearable Data in Healthcare

Classification and Regression Cases in Rehabilitation Event Detection

**Dr Diego Paez
Mehdi Ejtehadi, Yanke Li, Bertram Fuchs**

WS Day 1: Feature Extraction in Healthcare Data for ML Modelling

Content and Learning Outcomes:

1. Healthcare monitoring and data in the rehabilitation process.
2. Introduction to learning from patient data.
 1. Classification algorithms: Basics of boundaries and similarity metrics in latent spaces (reduced dimensions)
3. Time series data preprocessing and classification methods
 1. Preprocessing steps: Imputation, Labelling check,
4. Tutorial with multimodal time-series data in activities of daily living.
 1. Introduction to the dataset – scai-sensei
 2. Pre-processing steps: .
 3. Toolbox for feature extraction
 4. Decisions in pre-processing (windowing, normalization, quality)

WS Day 2:

Evaluation Metrics for Acceptable Machine Learning

Content and Learning Outcomes:

1. Data-driven model principles: Bias variance trade-off, model training, and generalization. Yanke Li
2. An introduction to data quality assessment and model evaluation metrics with a focus on explainability, robustness and generalization. Diego Paez
3. Tutorial for model training and feature selection methods in time-series
 1. Feature Selection Methods
 2. Building Classification Models

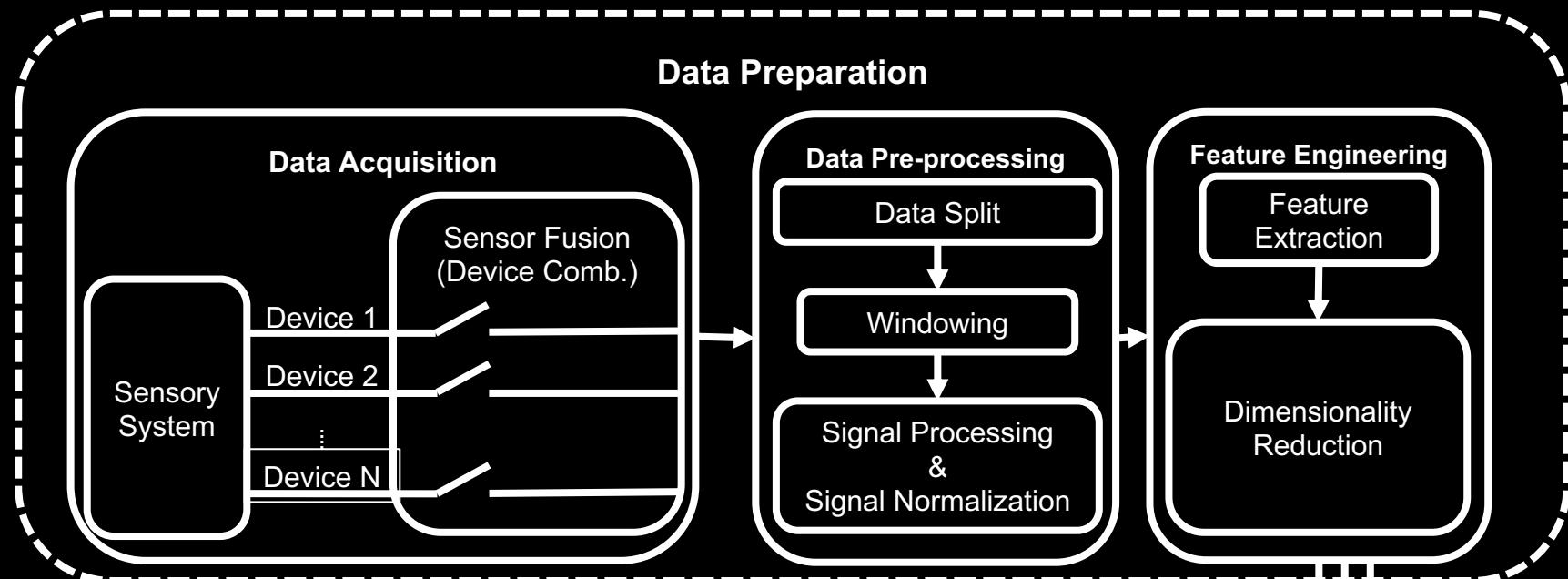
WS Day 3:

Learning Interpretability and Explainability Metrics

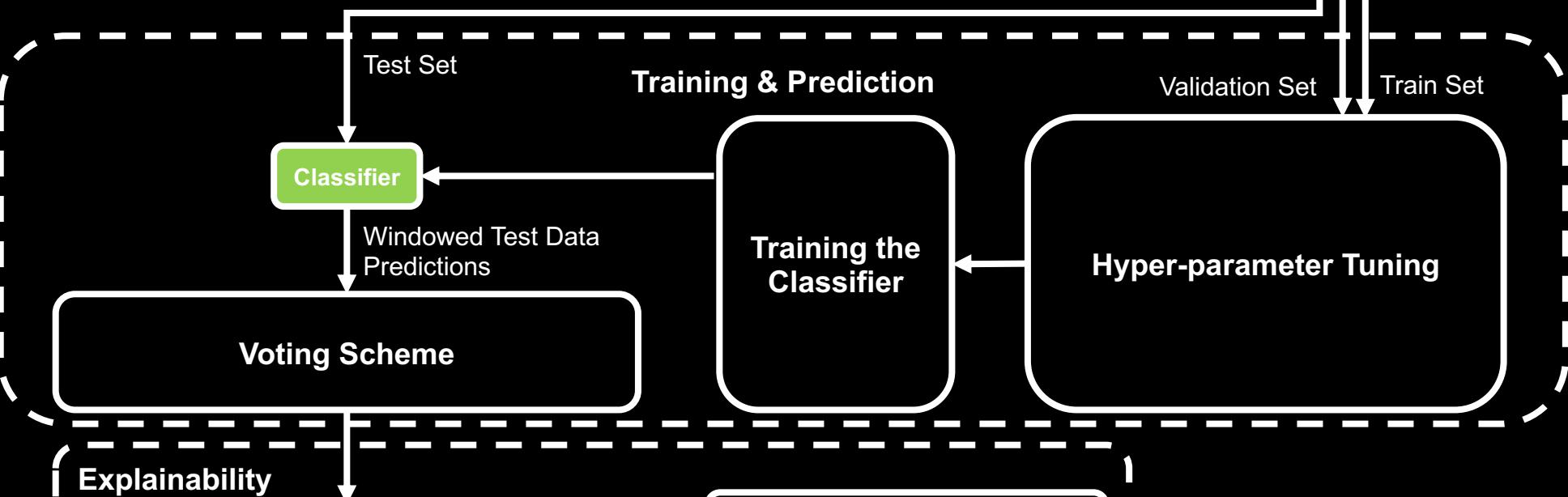
Content and Learning Outcomes:

1. Transparency and Explainability in AI for Healthcare
2. Causal feature selection in time series (Markov Blanket) as an explainability method for Robust transferability across datasets. Yanke Li
3. Tutorial for explainable methods in classification:
 1. LIME
 2. SHAP Values
4. Presentations by groups:
 1. Model results, explainability and generalization

WS Day 1



WS Day 2



WS Day 3

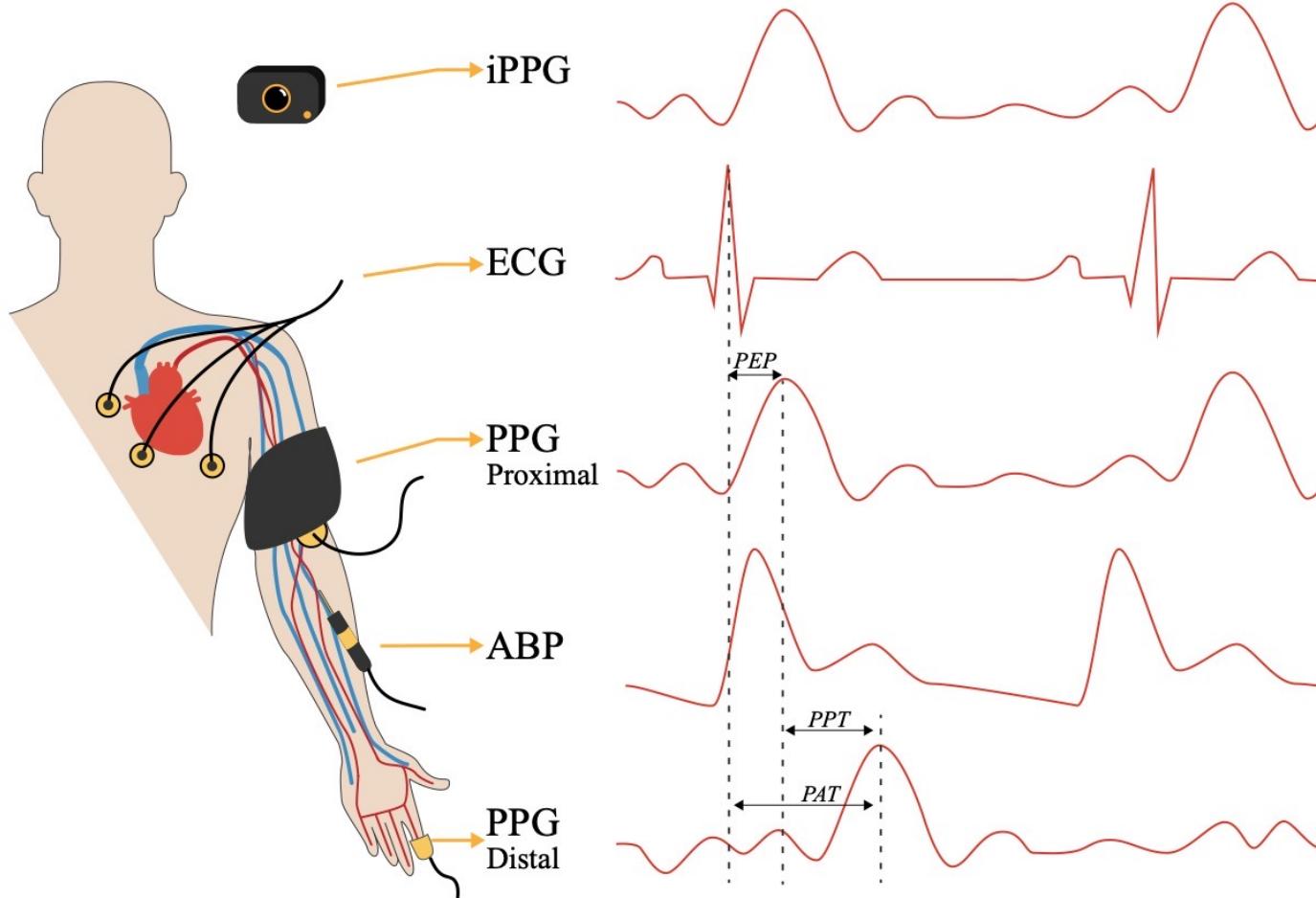


Self Introduction

Group Building



Periodic Time Series

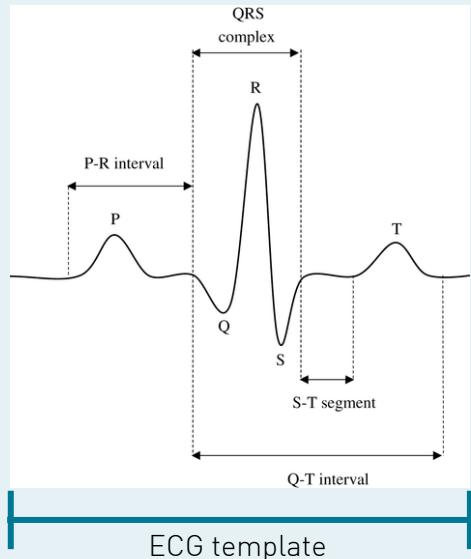


A. Cisnal, I. Podder, L. Grossman, K. Dherman, and D. Paez-Granados. "Standardizing Cuffless Blood Pressure Research: A Systematic Review of Methods and Reporting Frameworks". Under Review. 2024.

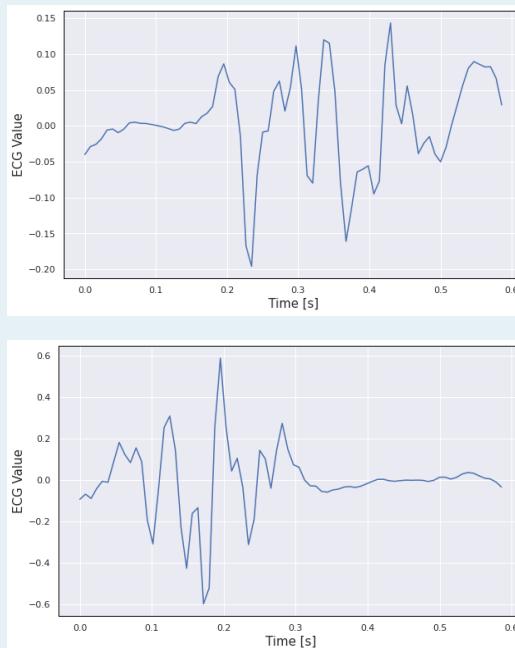
Time Series Data Problem

Electrocardiogram (ECG)

Theoretical ECG template



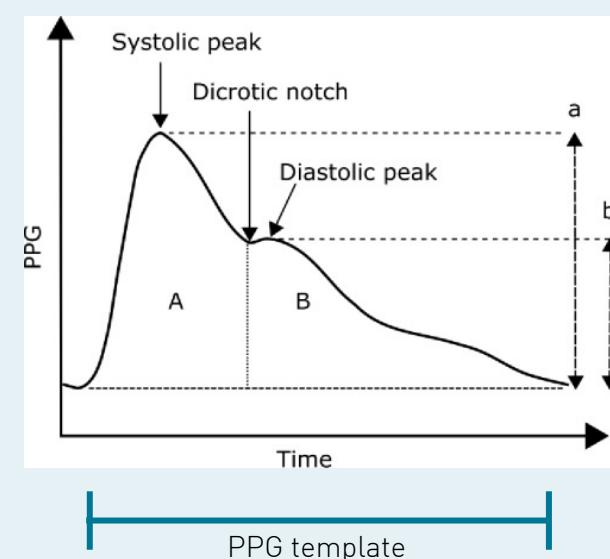
Actual ECG template



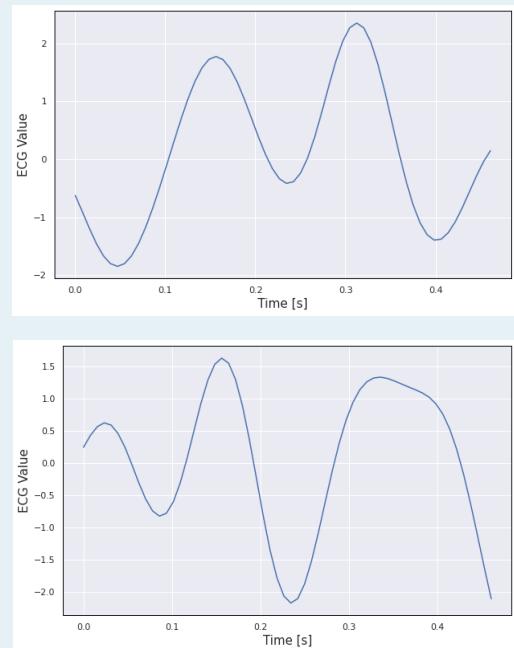
→ Noisy, unreliable

Photoplethysmogram (PPG)

Theoretical PPG template

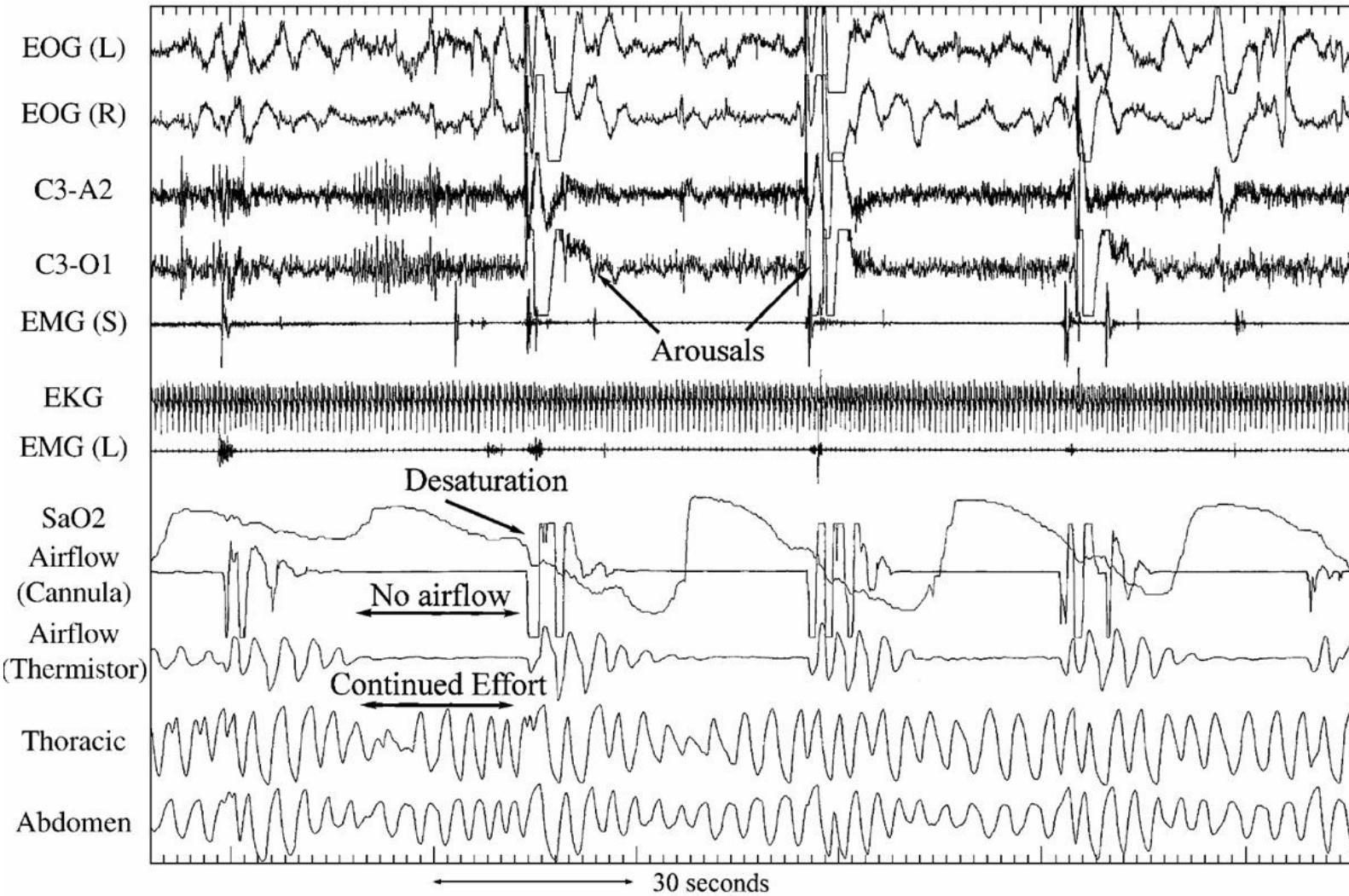


Actual PPG template



→ Noisy, unreliable

Non-periodic Time Series



Brain-Machine Interface

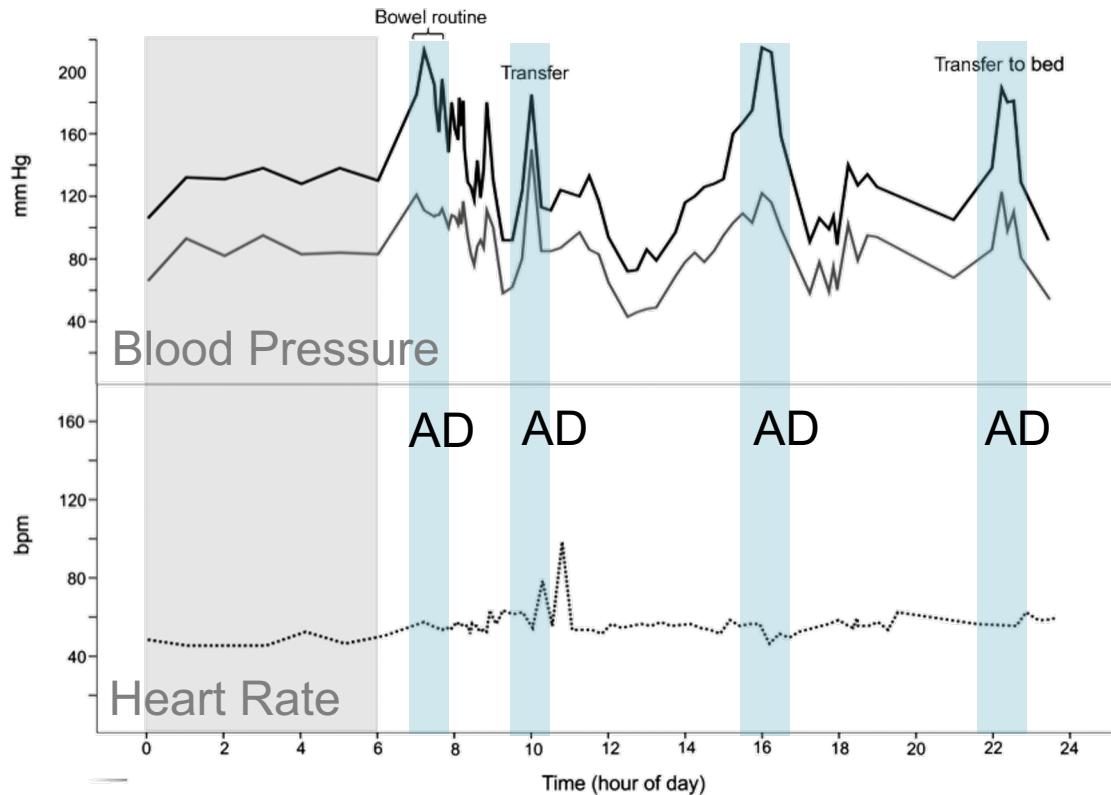
Not ready yet!



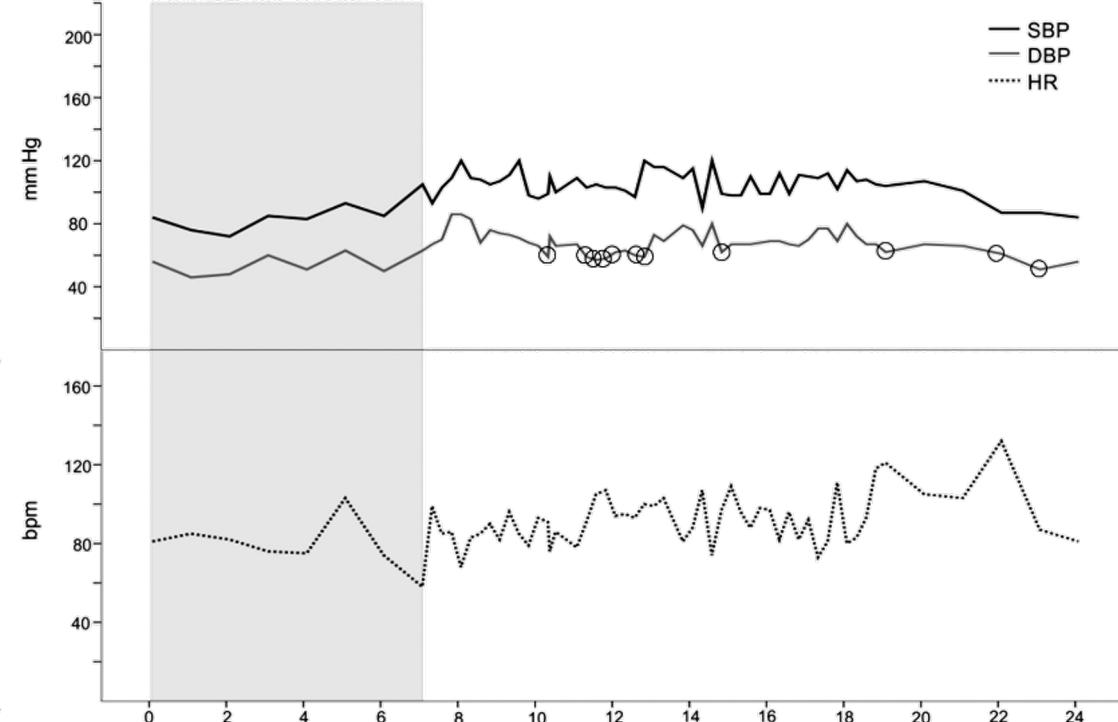
SOURCE: <https://www.smart-stats.org/content/biosignals>

Non-Periodic Time Series

Lesson level: C5



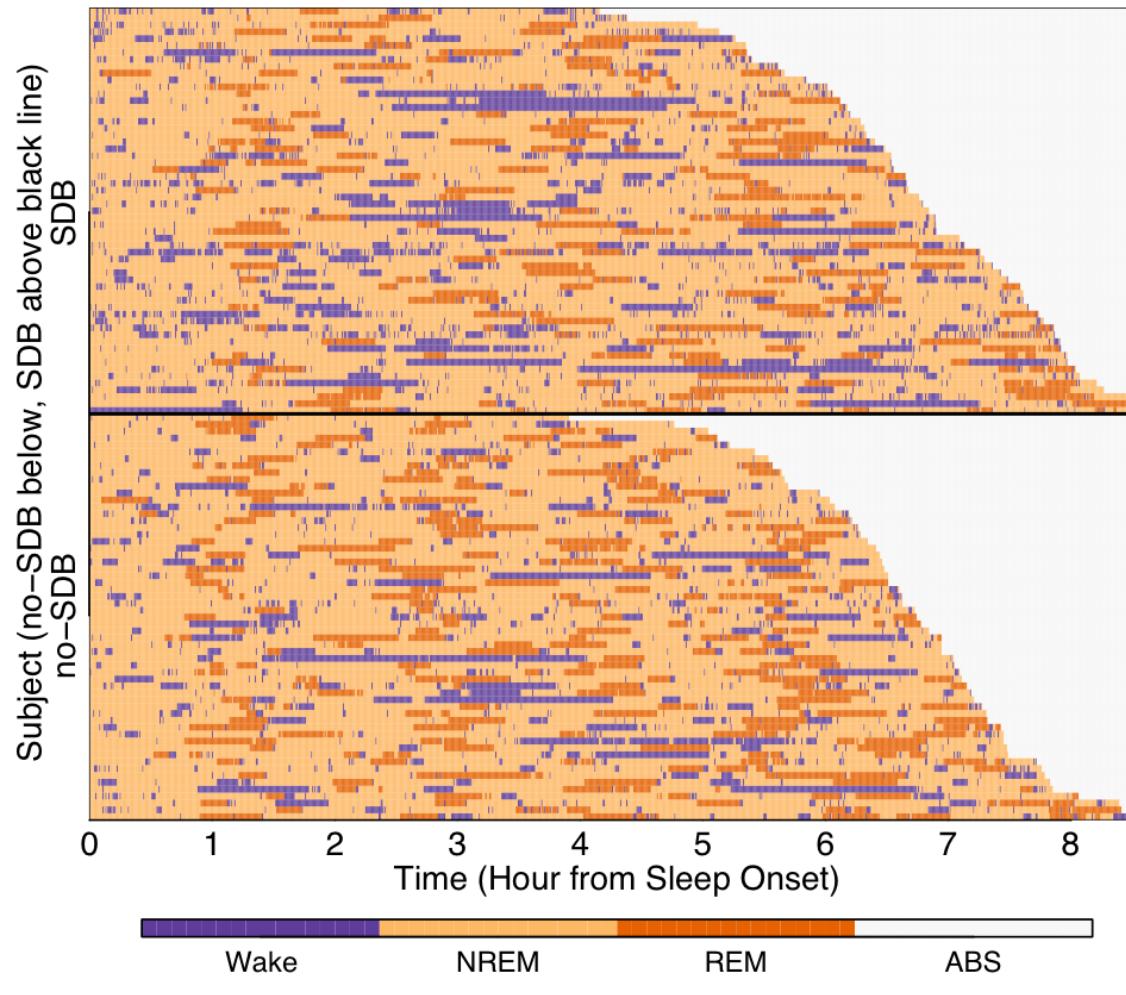
Lesson level: T4



Hubli, M., Gee, C. M., & Krassioukov, A. v. (2015). Refined assessment of blood pressure instability after spinal cord injury. *American Journal of Hypertension*, 28(2), 173–181. <https://doi.org/10.1093/ajh/hpu122>

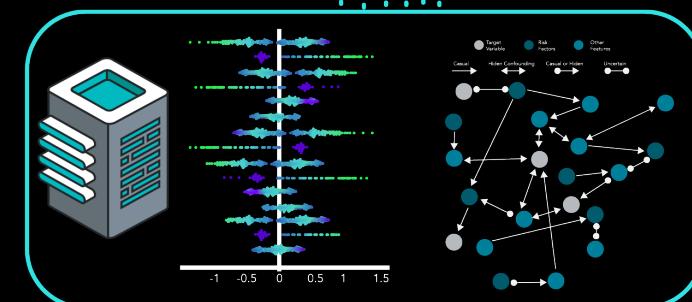
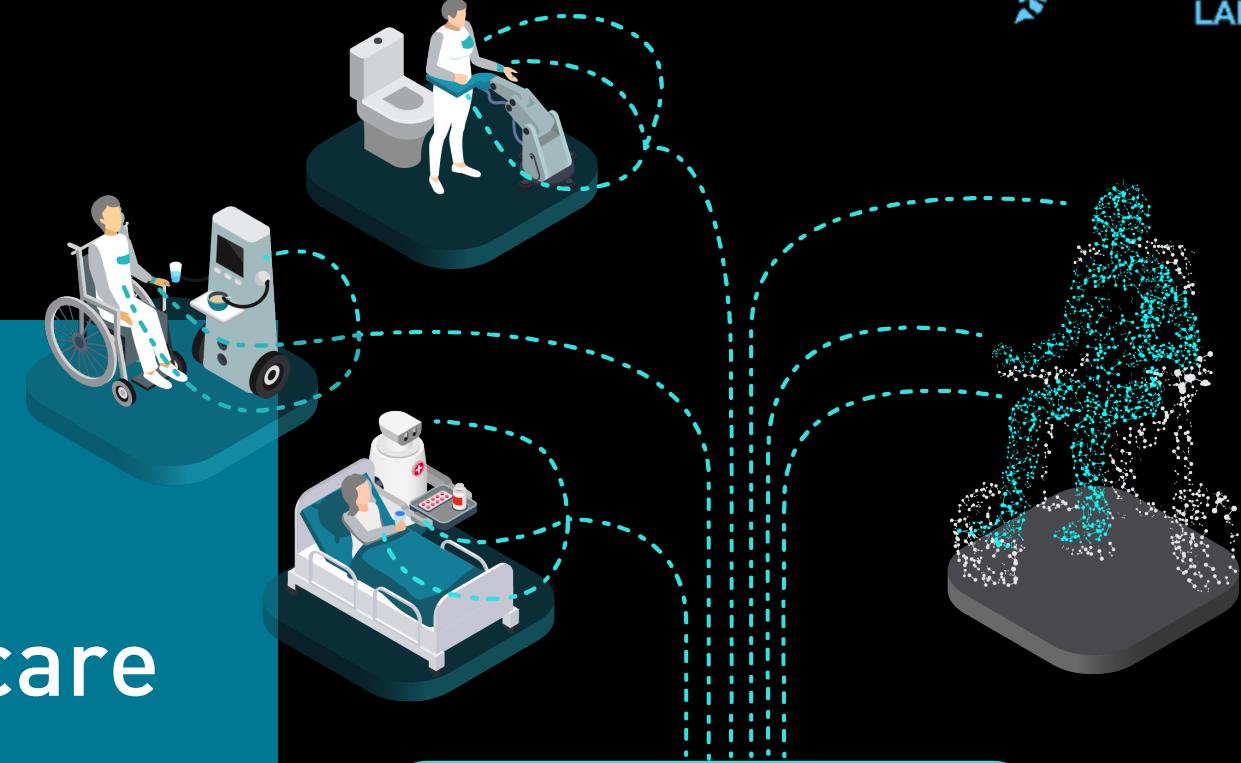
Non-Periodic Time Series

Lasagna Plot of Sleep States: Entire-row Sorted

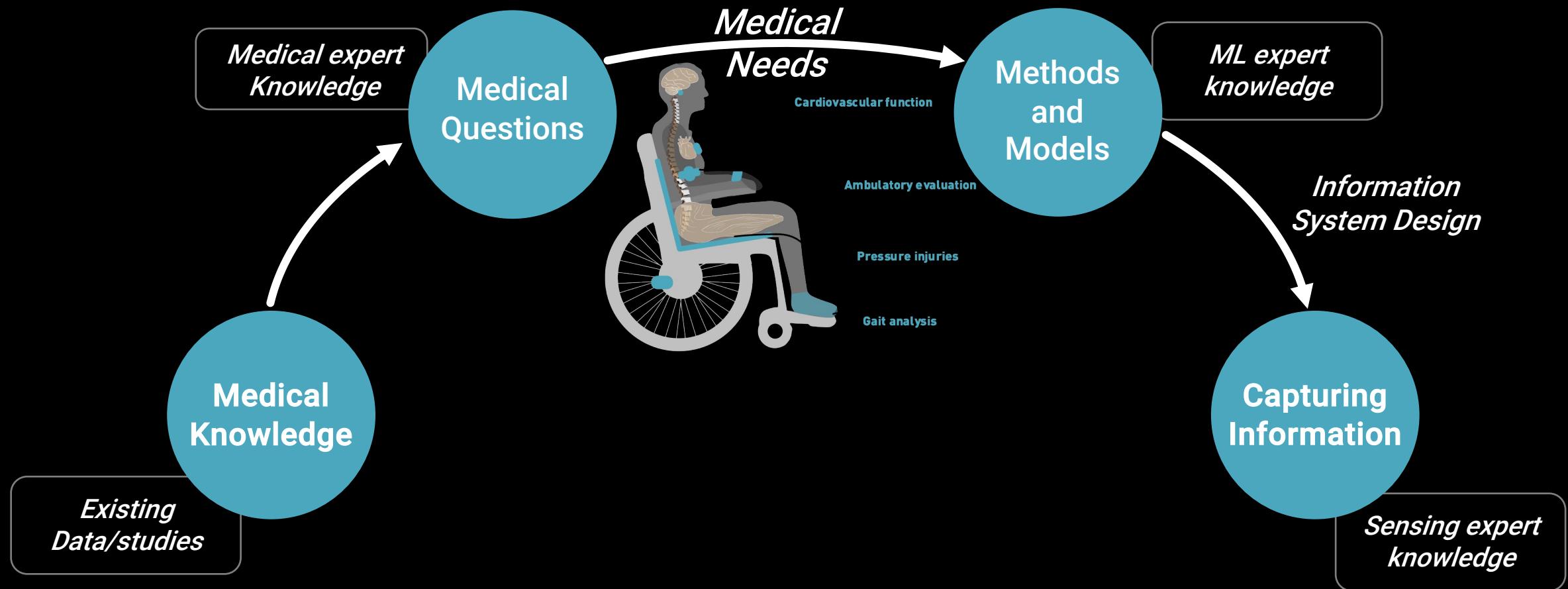


SOURCE: <https://www.smart-stats.org/content/biosignals>

AI in Life-long Rehabilitation and Monitoring in Healthcare

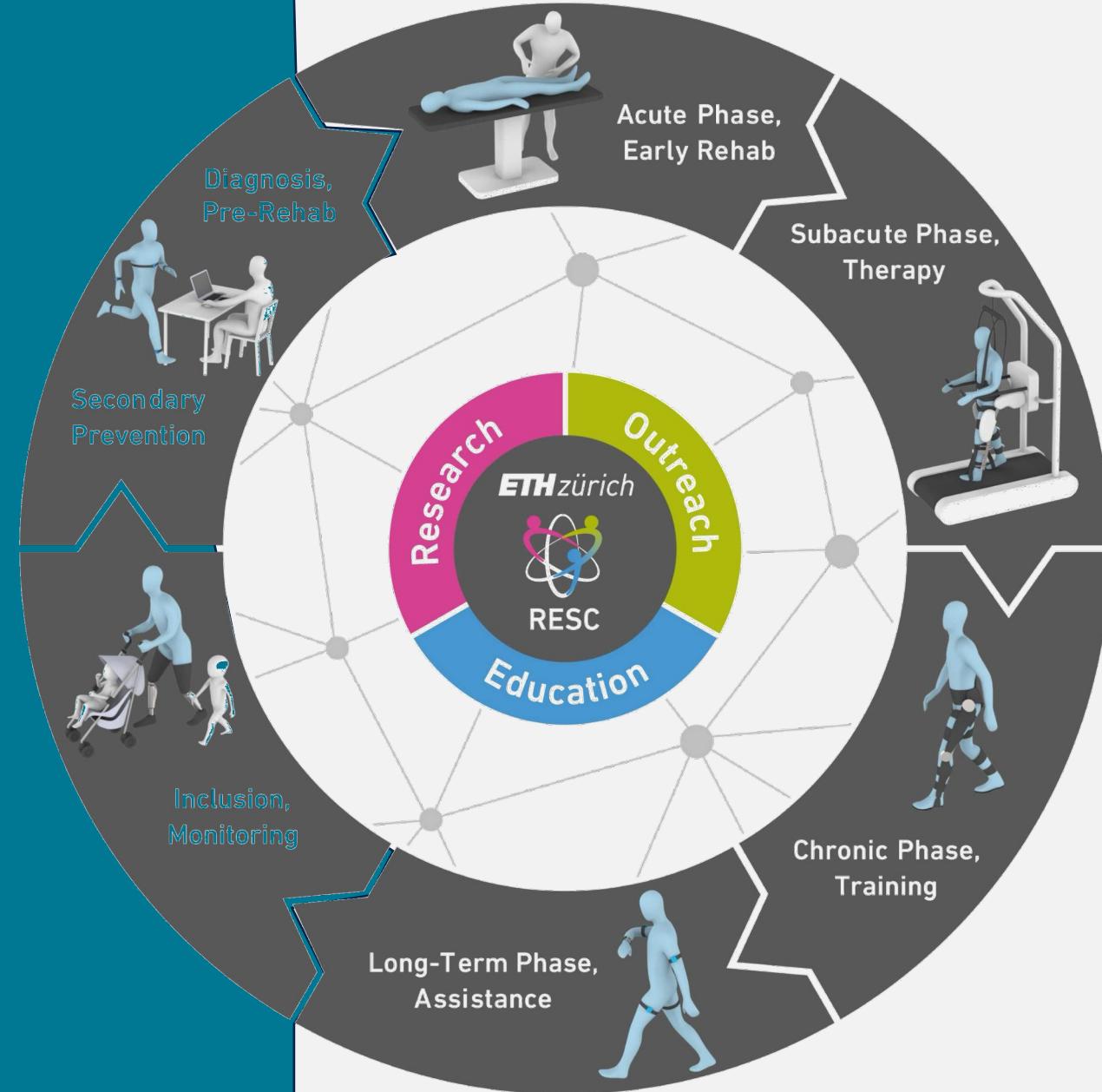


Dr. Diego Paez-Granados
Head of SCAI Lab, ETH Zürich
Digital Health Care & Rehabilitation
Group Leader, SPF



Long Term Rehabilitation and Healthcare

Needs during
Outpatient
Long-term living
with Chronic
Conditions

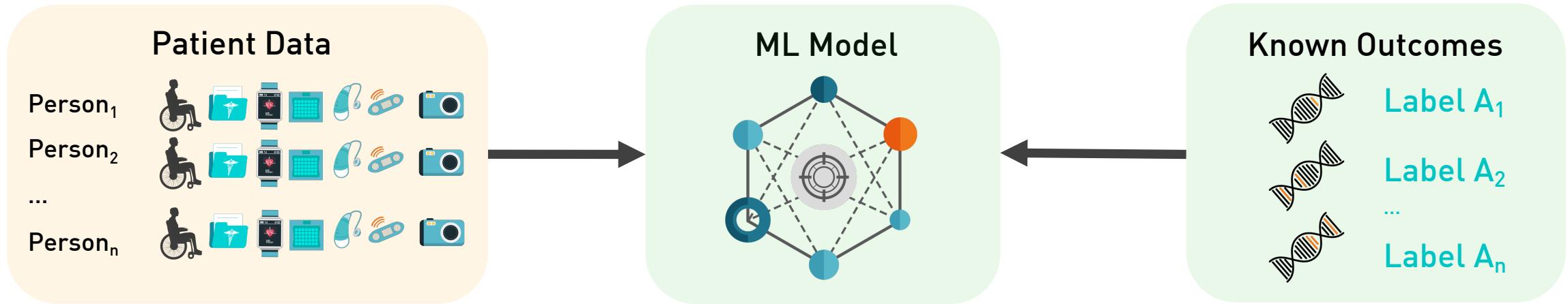


Needs during
Inpatient
Phase

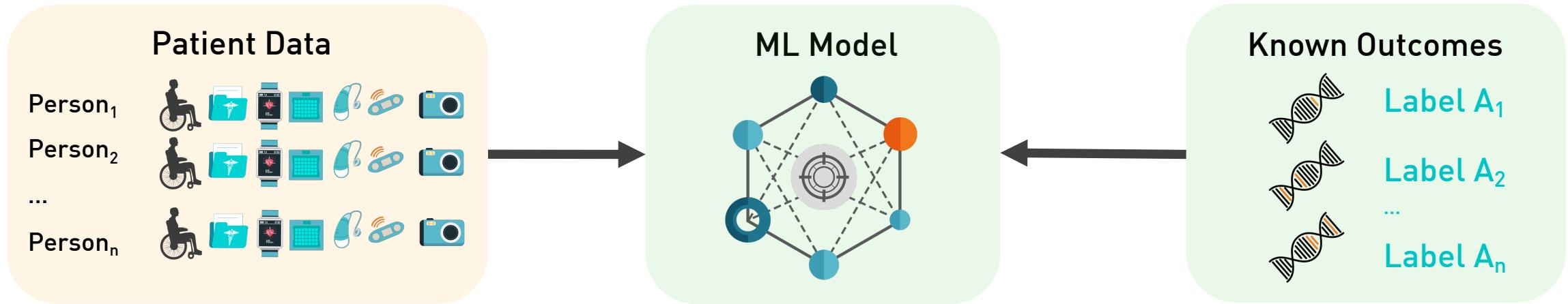
Needs during
Outpatient
Rehabilitation
and re-integration
phases

Learning from Patient Data

Machine Learning Pipeline for Medical Care

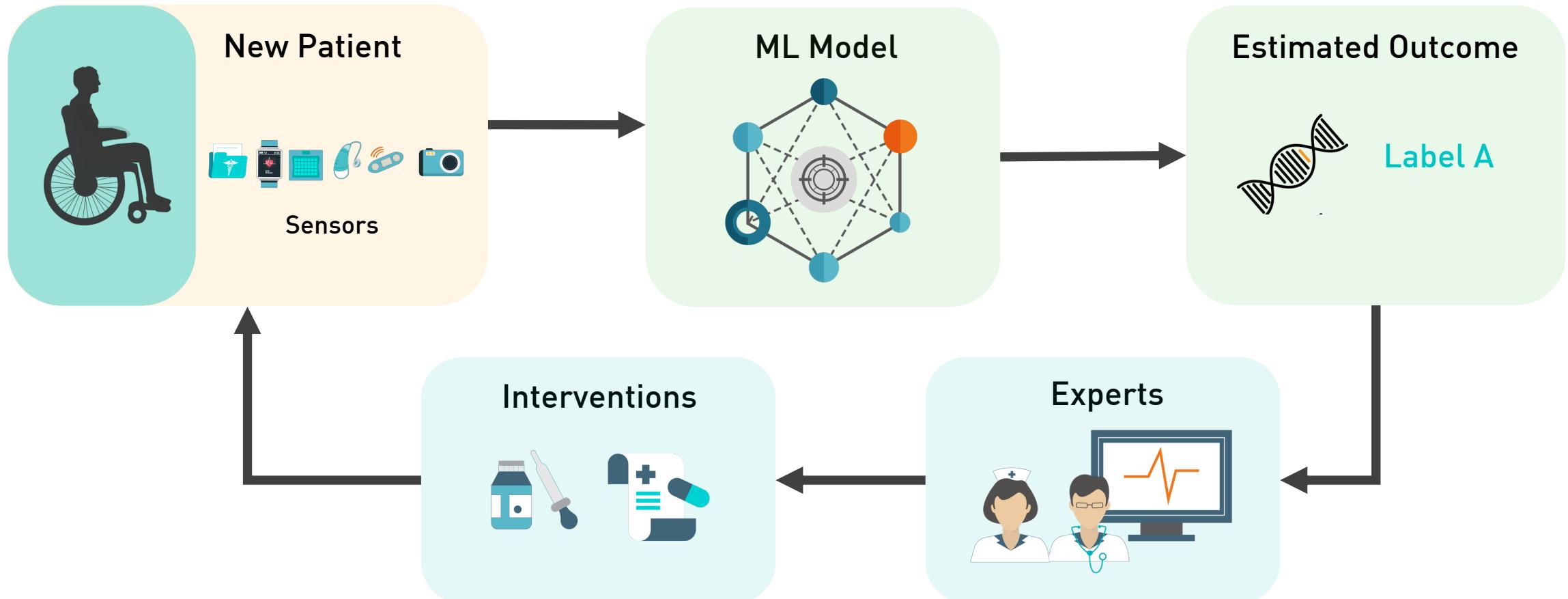


Machine Learning Pipeline for Medical Care

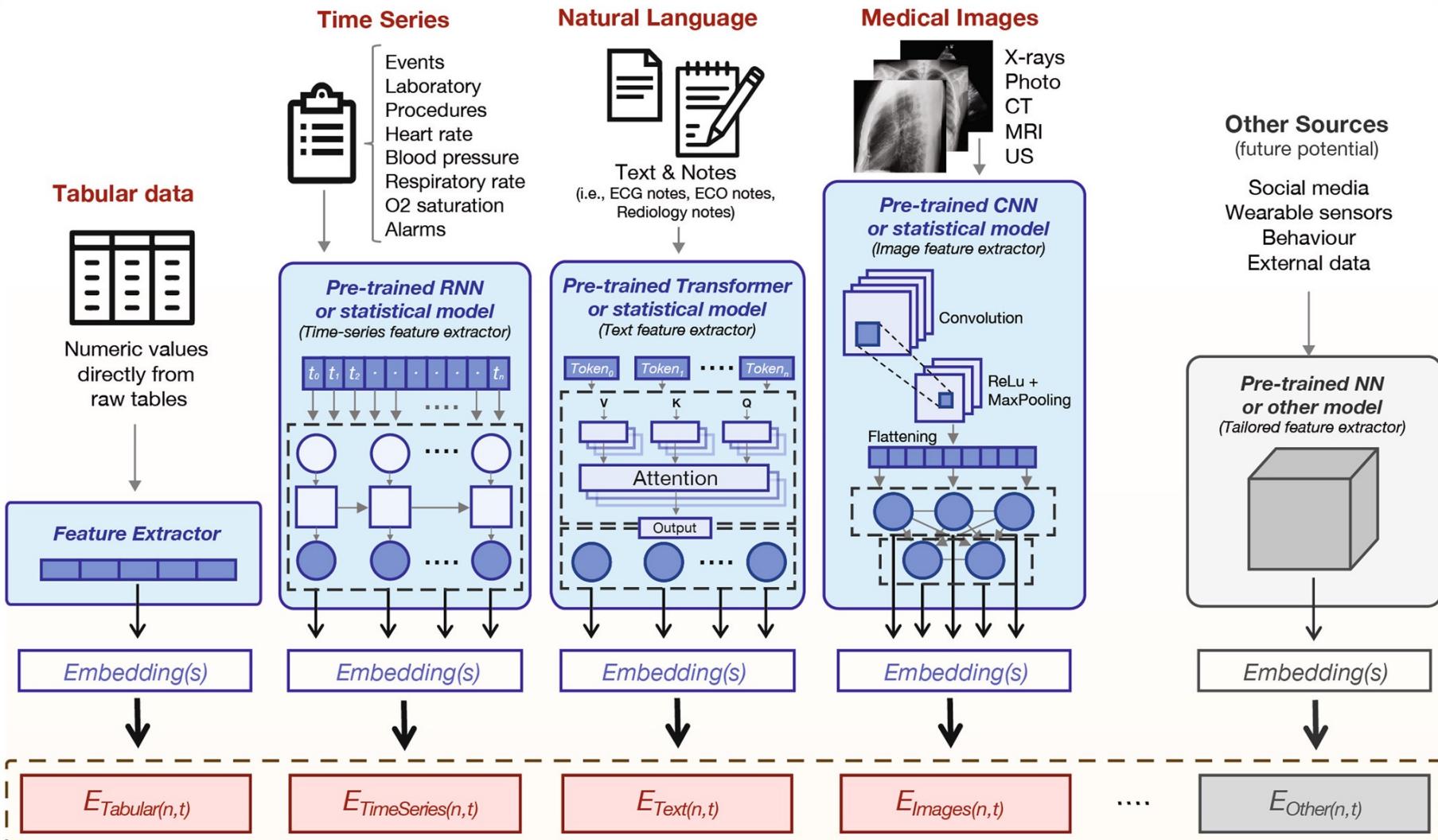


Machine Learning Pipeline for Medical Care

Ideal Case

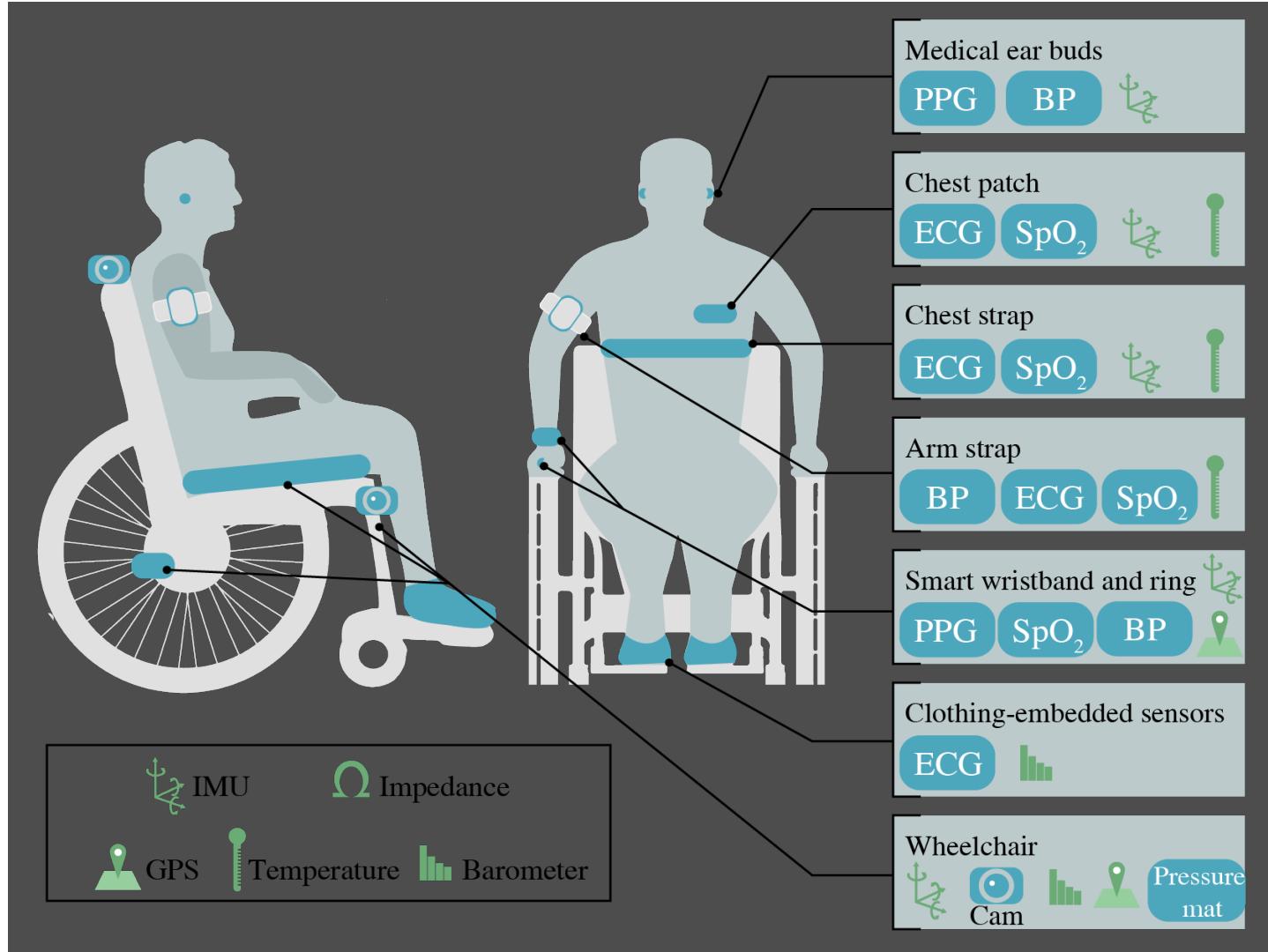


The reality of Healthcare and Rehabilitation Data



Soenksen, L.R., Ma, Y., Zeng, C. et al. Integrated multimodal artificial intelligence framework for healthcare applications. *npj Digit. Med.* 5, 149 (2022). <https://doi.org/10.1038/s41746-022-00689-4>

Learning ADLs for Monitoring Disease Progress in Outpatient Life



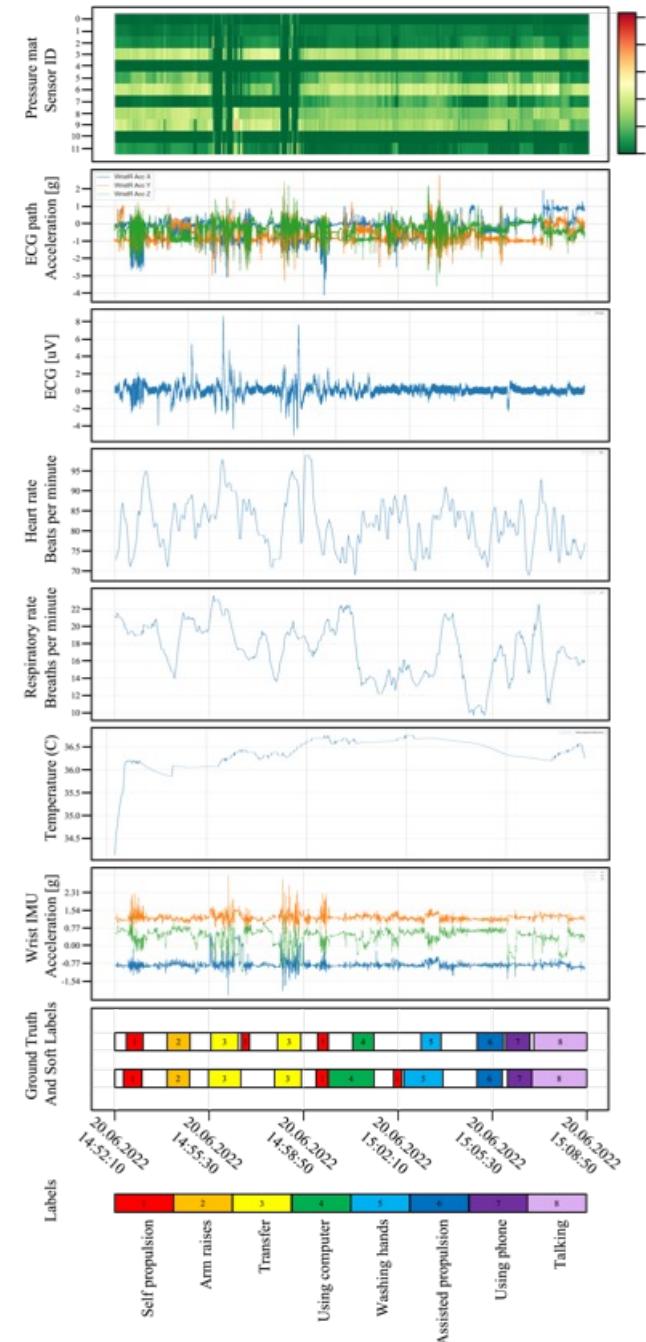
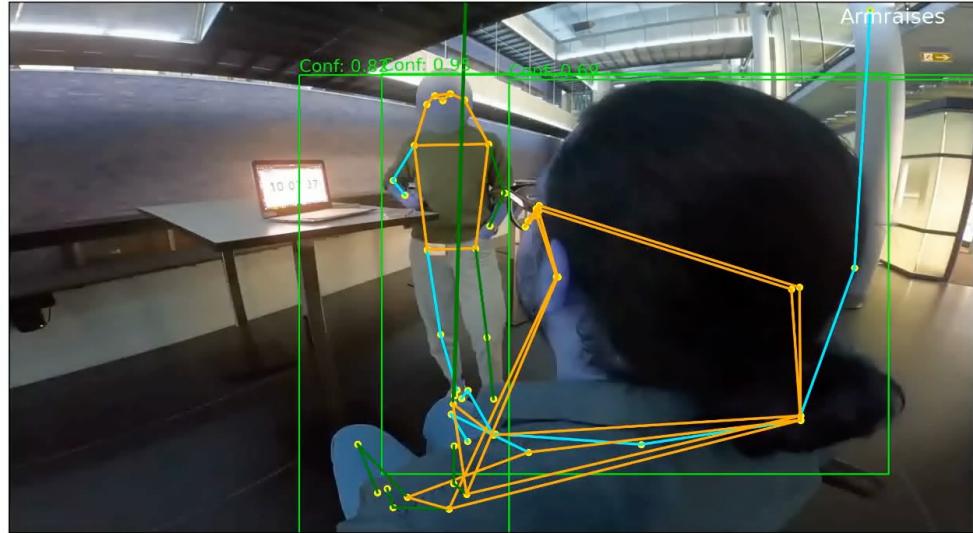
Methods

Centralized, compressed sensing of the body and the environment.
Long-term data collection for studying SCI morbidities.

Big Data Analysis for Precision Medicine and Rehabilitation on SCI

1. Functioning in daily life
2. Cardiovascular function
3. Neurology & Autonomic Dysreflexia
4. Pressure Injuries
5. Urinary system function

Time Series Data



S. Bensland, A. Paul, L. Grossmann, I. Eriks-Hogland, R. Riener, and D. Paez-Granados.
"Healthcare Monitoring for SCI individuals: Learning Activities of Daily Living through a SlowFast Network". In: IEEE International Conference on System Integration. Jan. 2023.
<https://doi.org/10.1109/SII55687.2023.10039043>

Learning ADLs for Monitoring Disease Progress in Outpatients

Arm Raises



Pressure Relief



Exercise

Using Phone



Using Computer



Talking



Eating



Social

Assisted Propulsion



Self Propulsion



Mobility

Transfer[◊]



Transfer

Washing Hands



Changing Clothes



Self Care

Resting

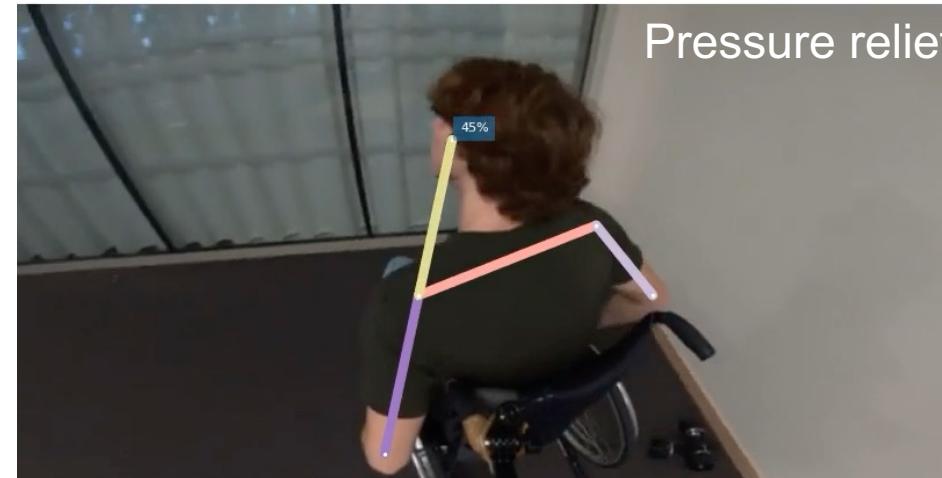


Learning ADLs for Monitoring Disease Progress in Outpatients

Excercising



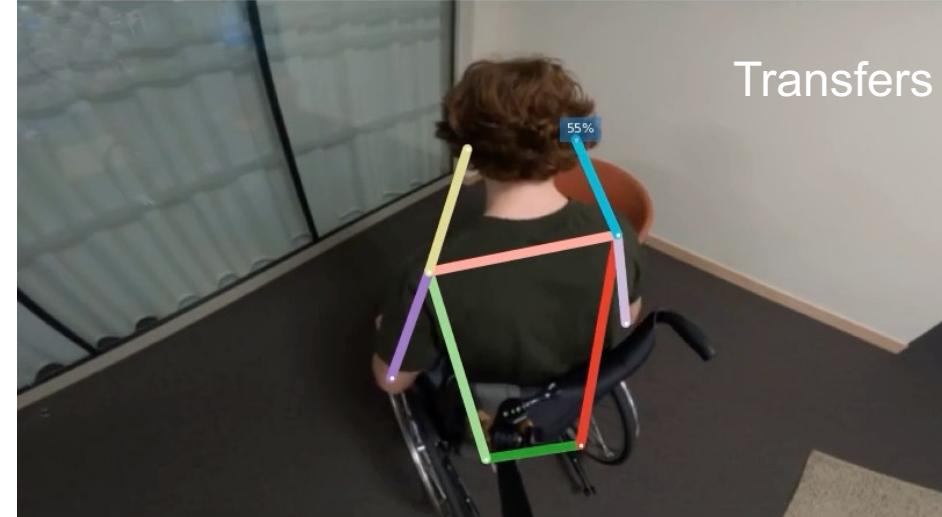
Pressure relief



Wheeling



Transfers

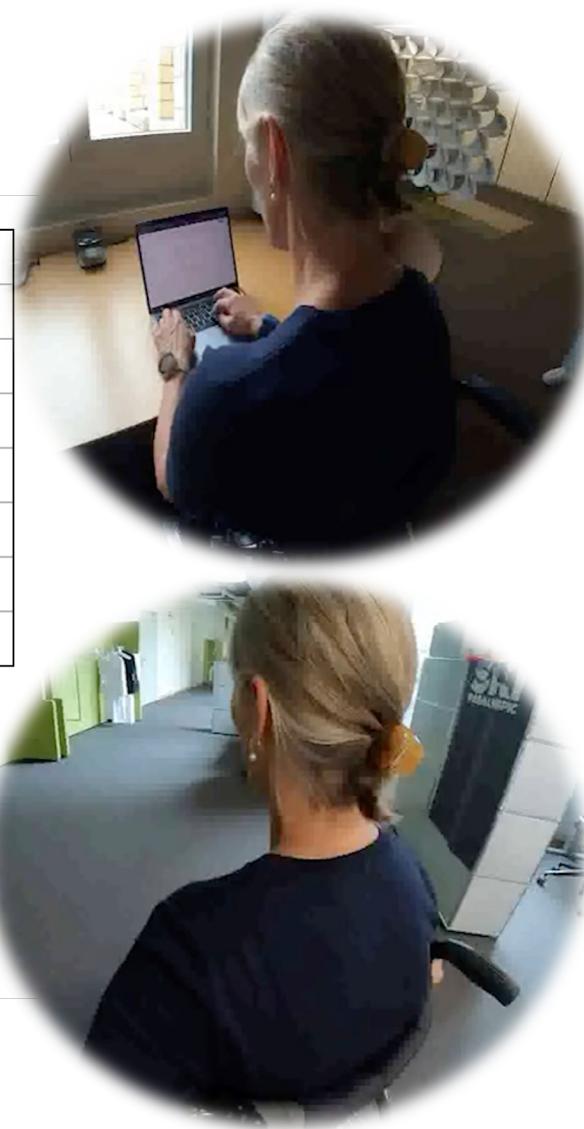
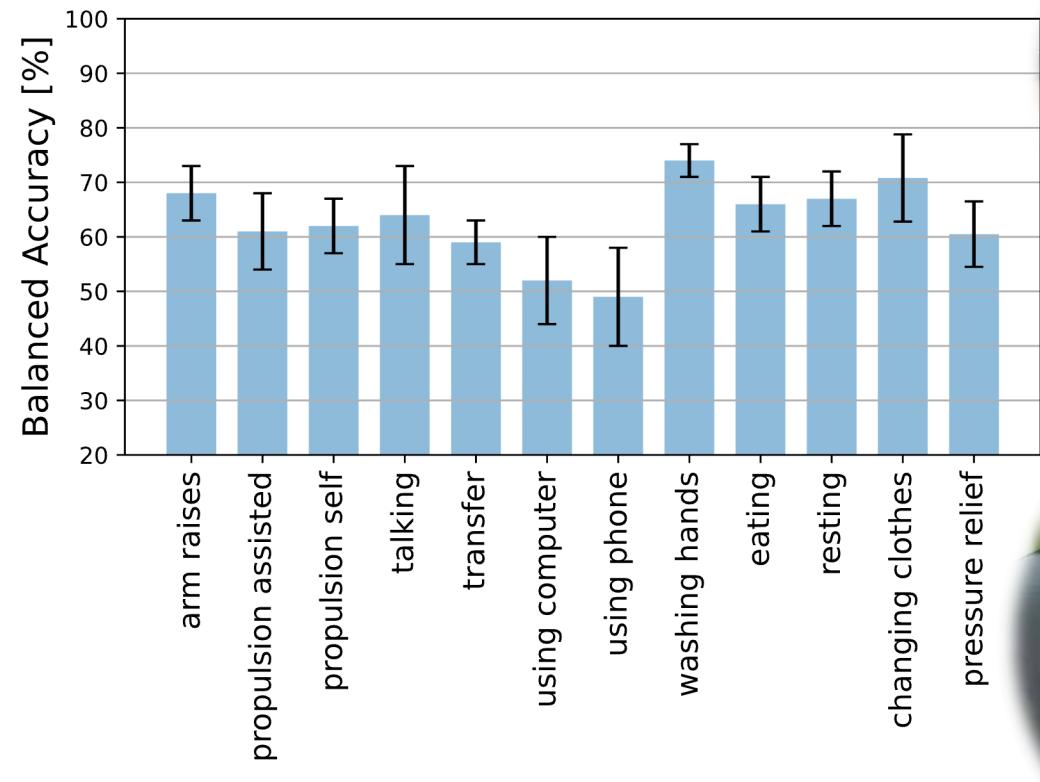


ADL Detection - N2N-video-based

Fine-tuned Slow-fast Network

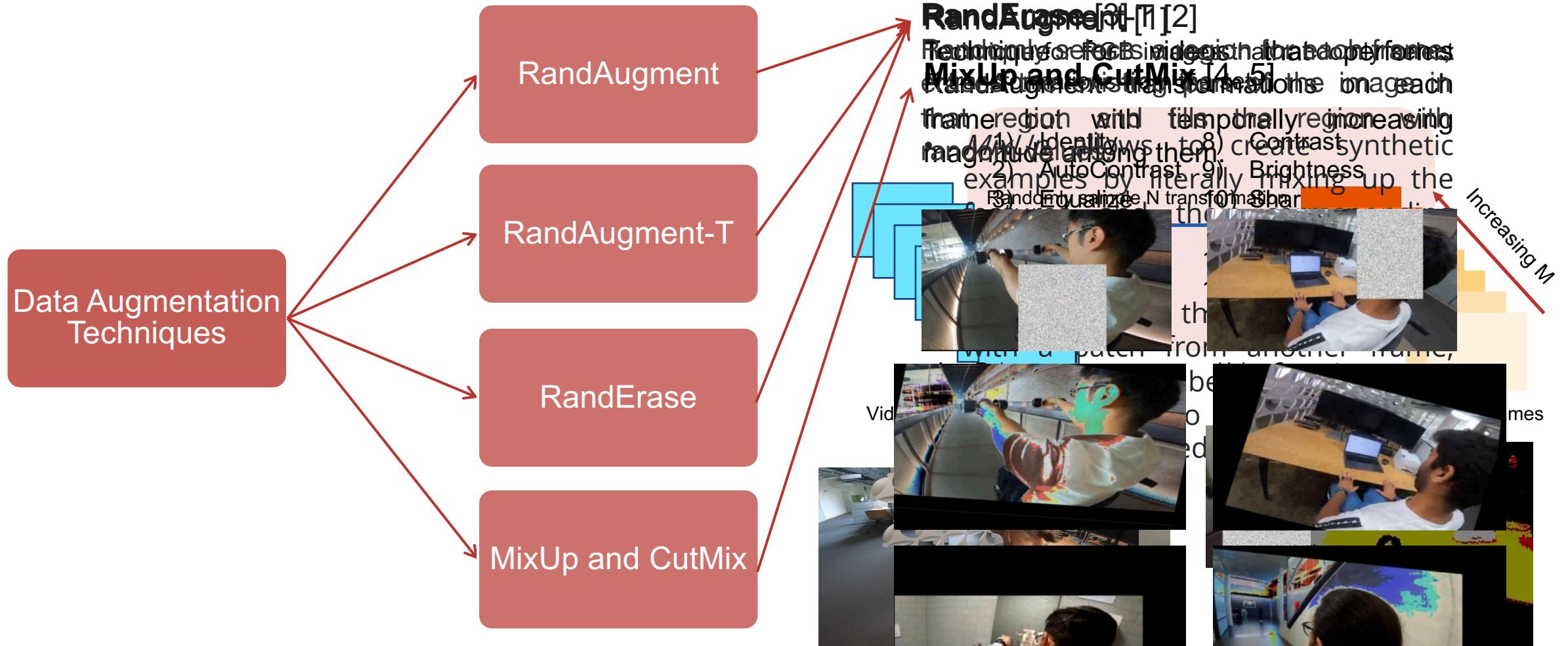
Dataset

Classes	12
Participants	3 wheelchair + 21 healthy
Total Videos	485
Videos per Class	
Self Propulsion	46
Assisted Propulsion	54
Transfer	36
Using Phone	74
Talking	85
Washing Hands	30
Arm Raises	30
Using Computer	45
Eating	38
Resting	34
Changing Clothes	16
Pressure Relief	31



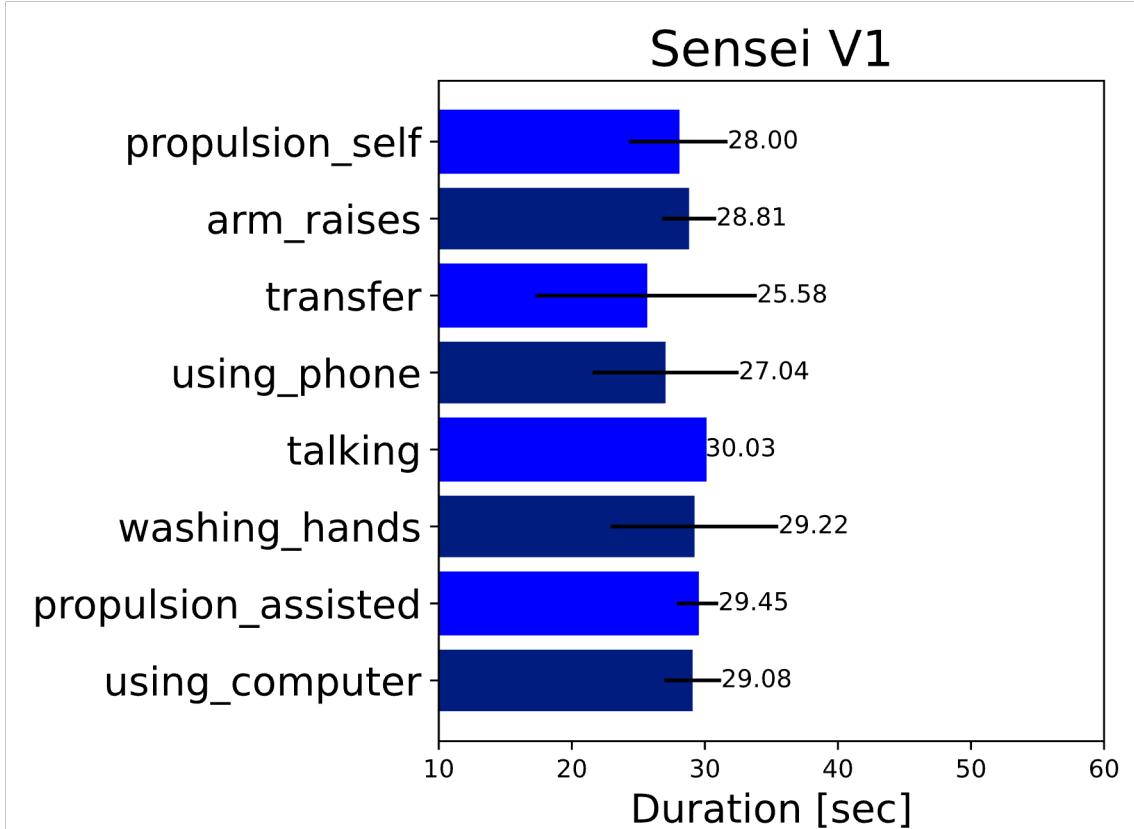
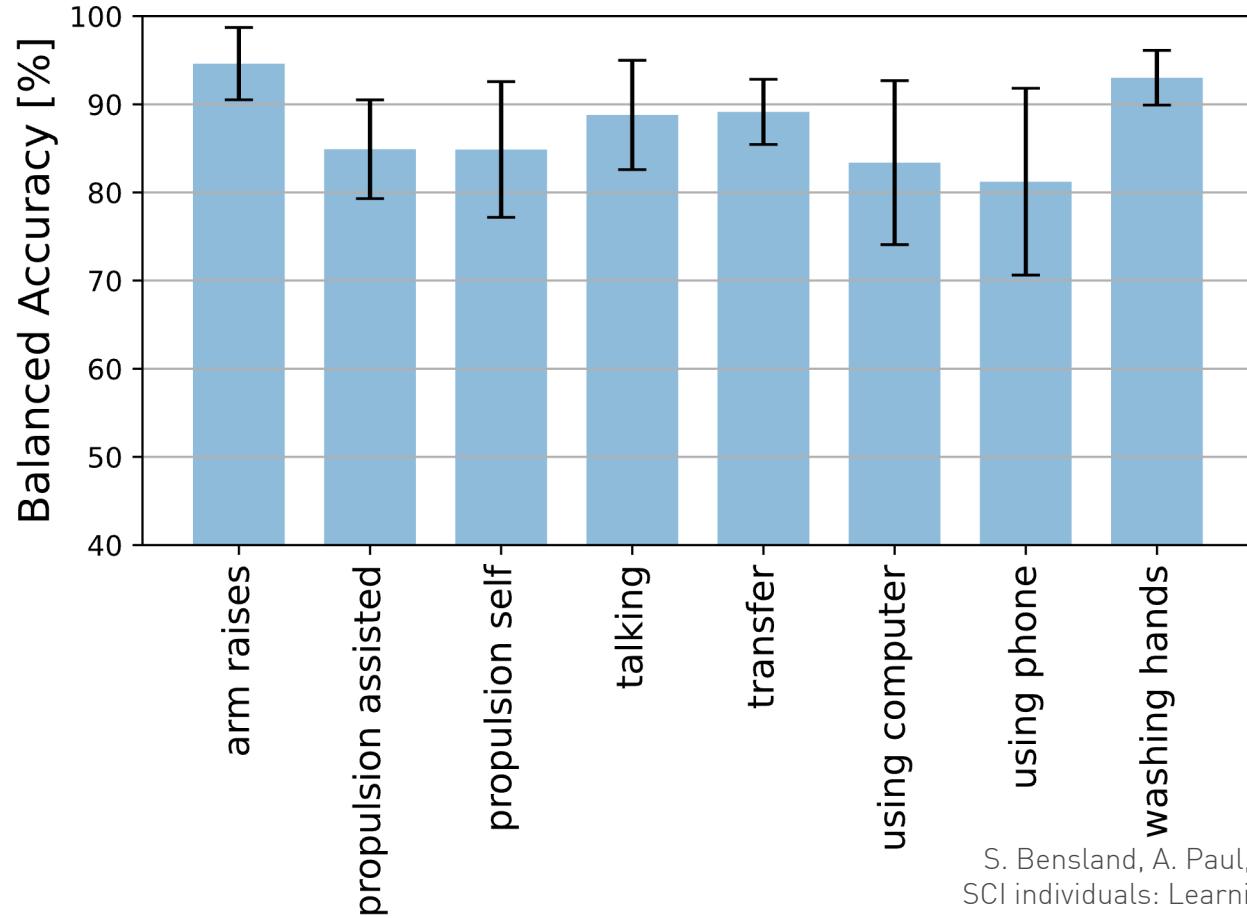
S. Bensland, A. Paul, L. Grossmann, I. Eriks-Hogland, R. Riener, and D. Paez-Granados. "Healthcare Monitoring for SCI individuals: Learning Activities of Daily Living through a SlowFast Network". In: IEEE International Conference on System Integration. Jan. 2023. <https://doi.org/10.1109/SII55687.2023.10039043>

Data Augmentation Techniques



Performance after Data Augmentation

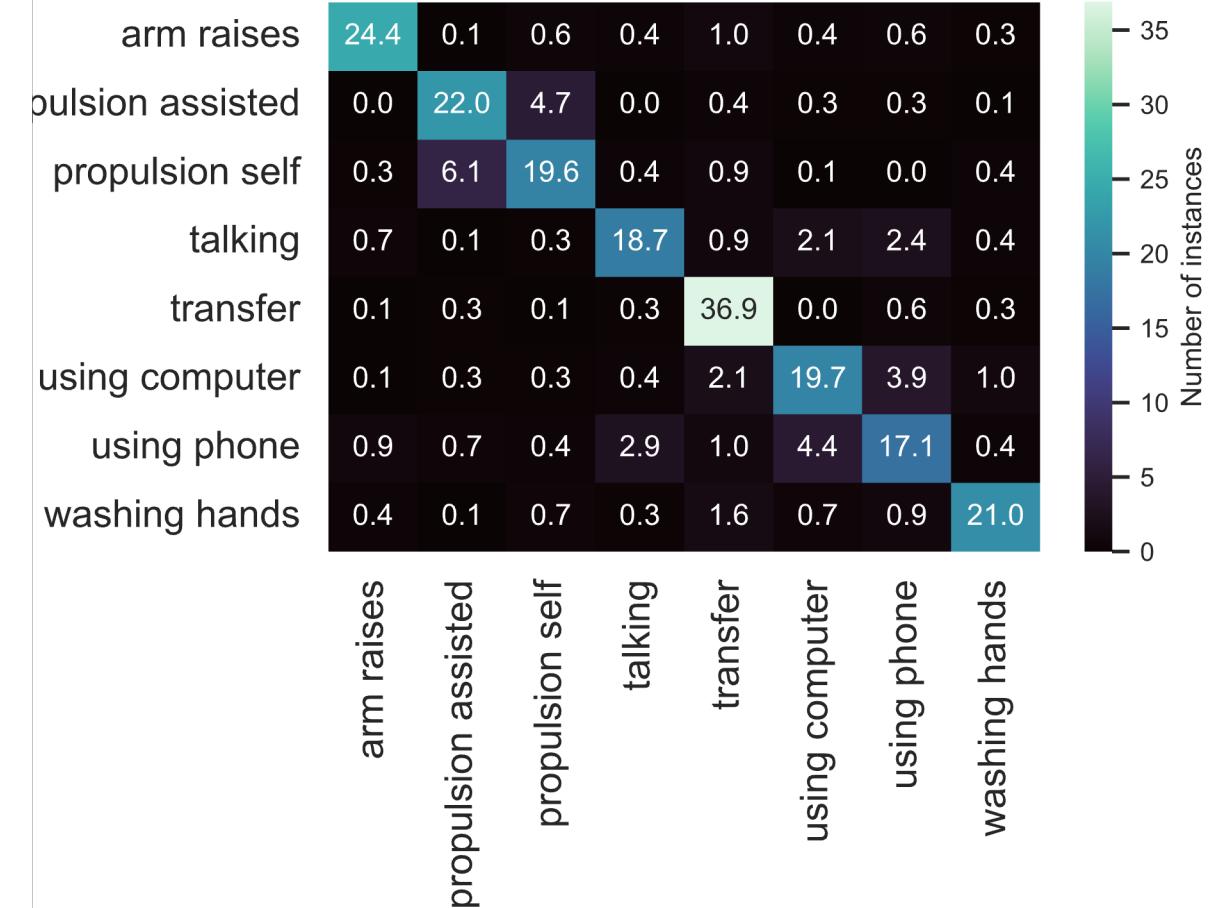
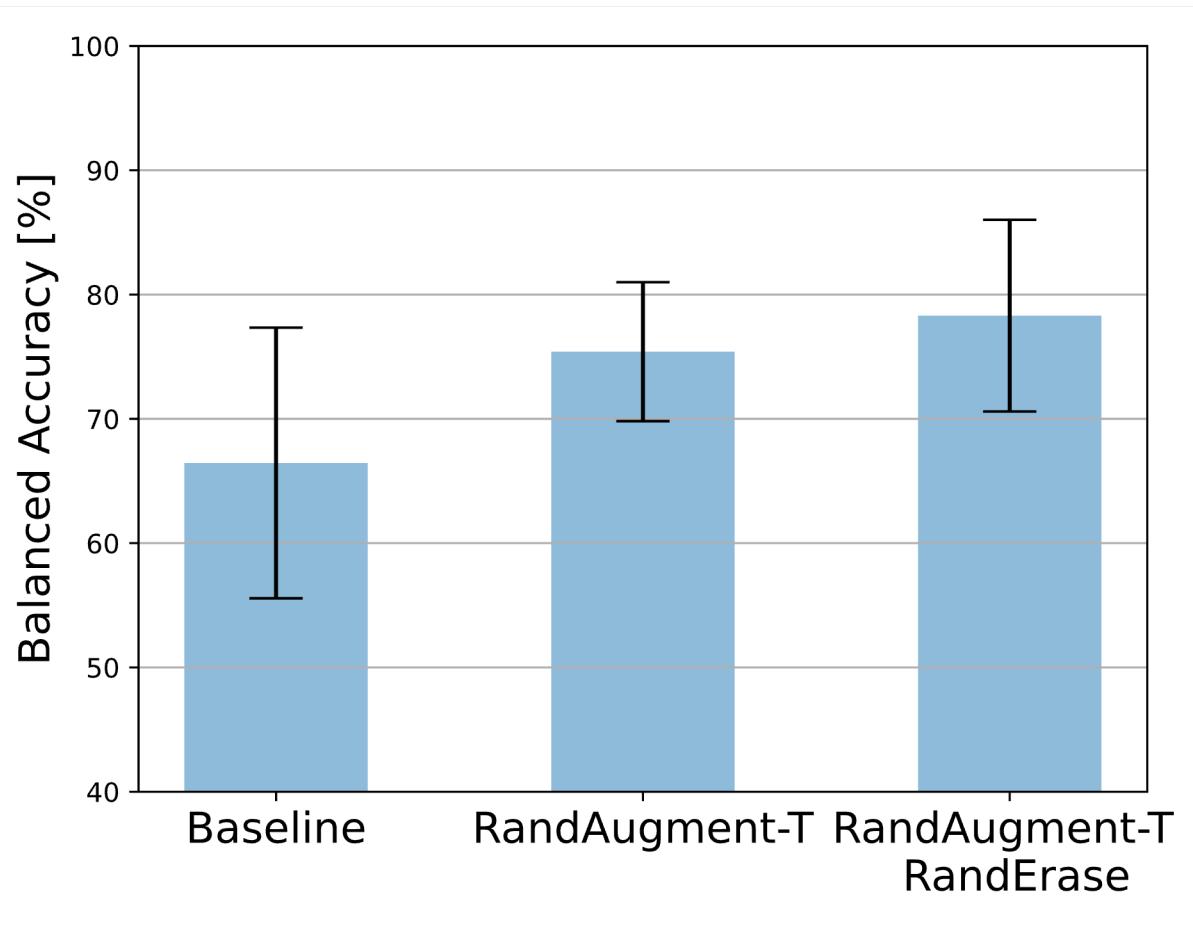
- Per class balanced accuracy is computed for the best model with RandAugment-T and Random Erasing



S. Bensland, A. Paul, L. Grossmann, I. Eriks-Hogland, R. Riener, and D. Paez-Granados. "Healthcare Monitoring for SCI individuals: Learning Activities of Daily Living through a SlowFast Network". In: IEEE International Conference on System Integration. Jan. 2023. <https://doi.org/10.1109/SII55687.2023.10039043>

Performance after Data Augmentation

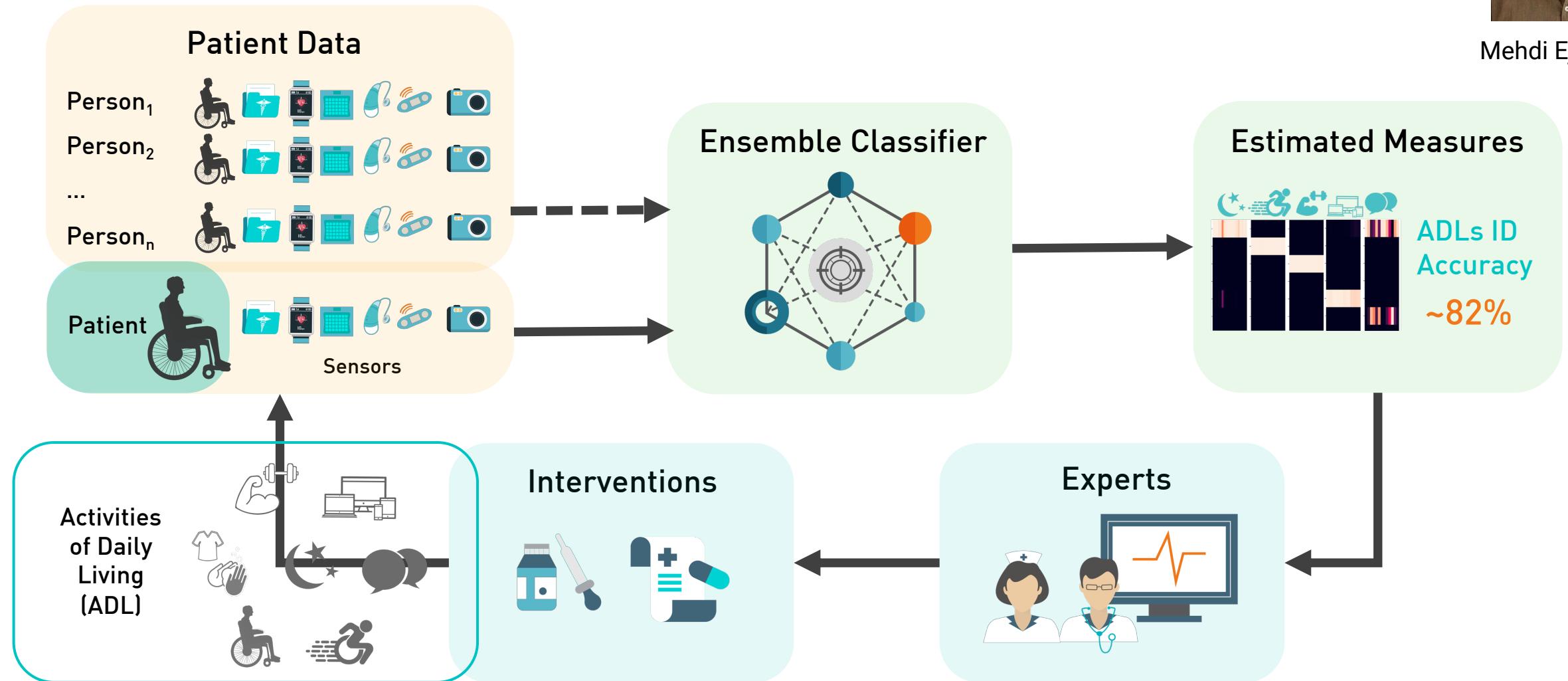
- Per class balanced accuracy is computed for the best model with RandAugment-T and Random Erasing





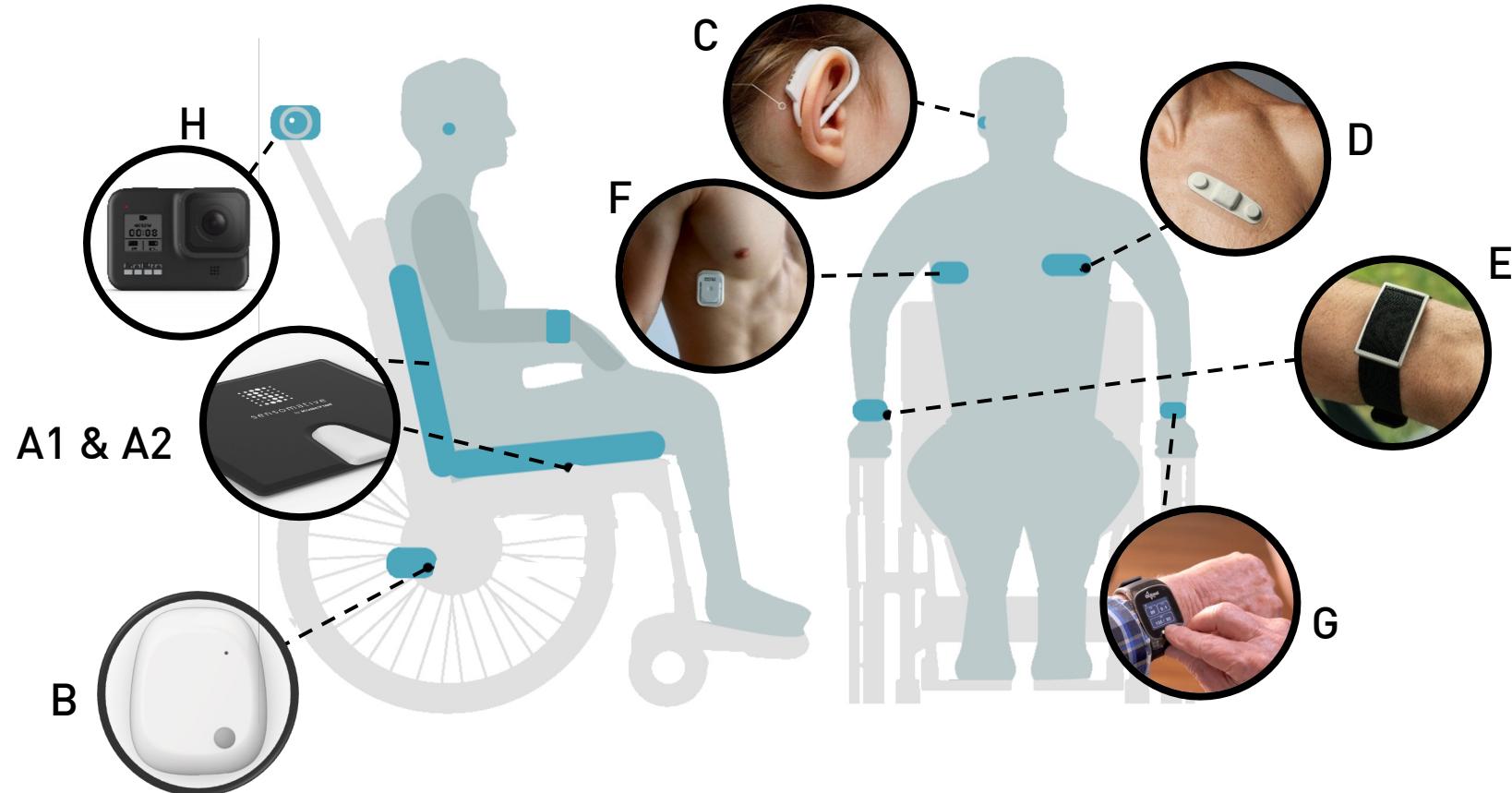
Day 1: Time Series for Monitoring in Daily Life

Mehdi Ejtehadi



M. Ejtehadi, S. Amrein, I. Eriks-Hogland, R. Riener, and D. Paez-Granados. "Learning Activities of Daily Living from Unobtrusive Multi-modal Wearable Sensors: Towards Monitoring Outpatient Rehabilitation". In: IEEE International Conference on Robotics and Rehabilitation. Sept. 2023. DOI: 10.3929/ethz-b-000619499.

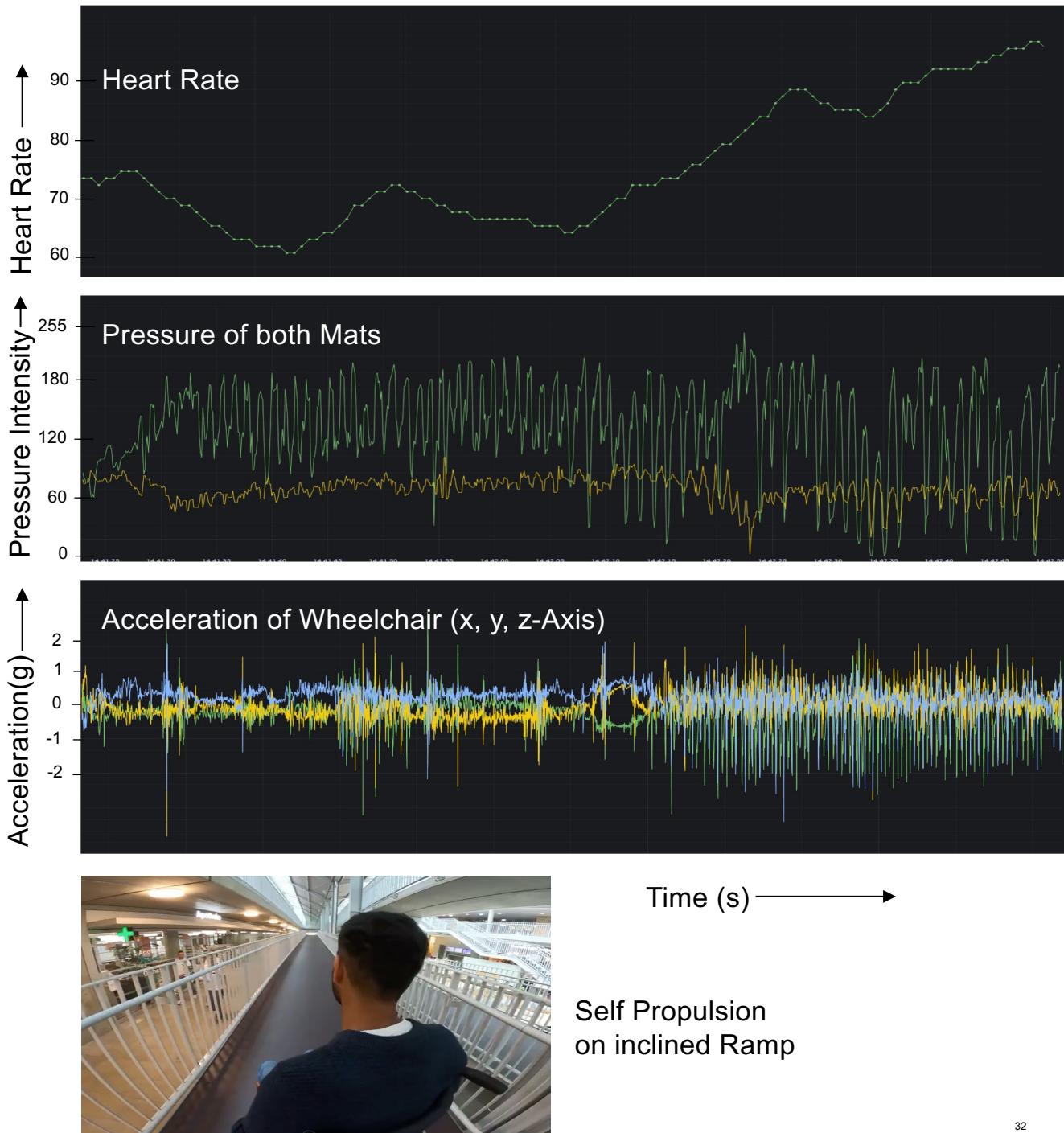
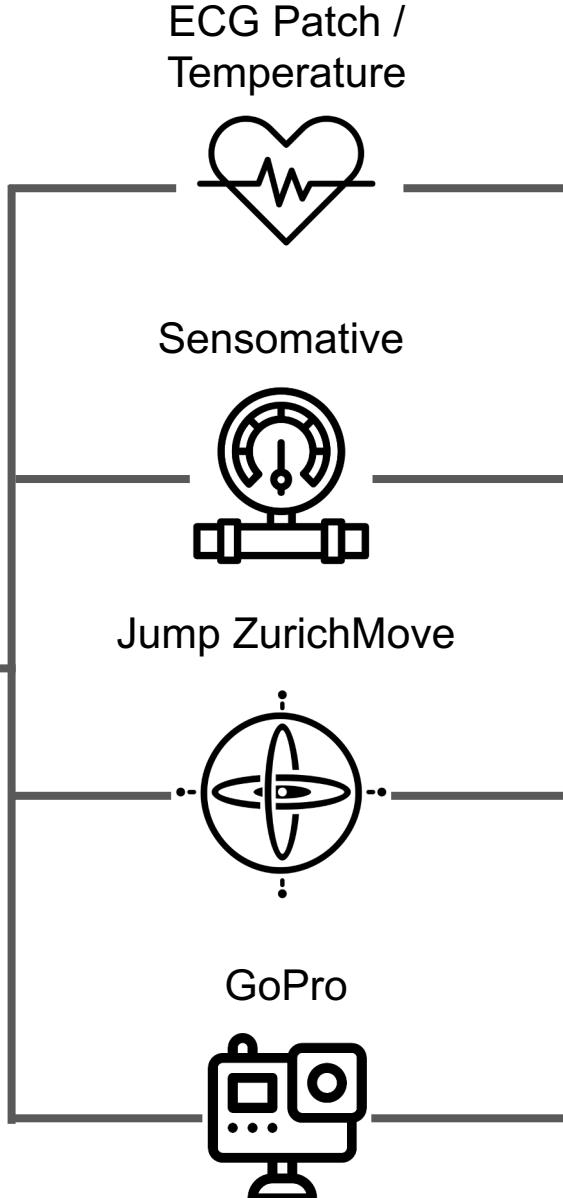
Unobtrusive Sensing for ADLs Monitoring



M. Ejtehadi, S. Amrein, I. Eriks-Hogland, R. Riener, and D. Paez-Granados. "Learning Activities of Daily Living from Unobtrusive Multi-modal Wearable Sensors: Towards Monitoring Outpatient Rehabilitation". In: IEEE International Conference on Robotics and Rehabilitation. Sept. 2023.
<https://doi.org/10.1109/ICORR58425.2023.10304743>



Unobtrusive Sensing

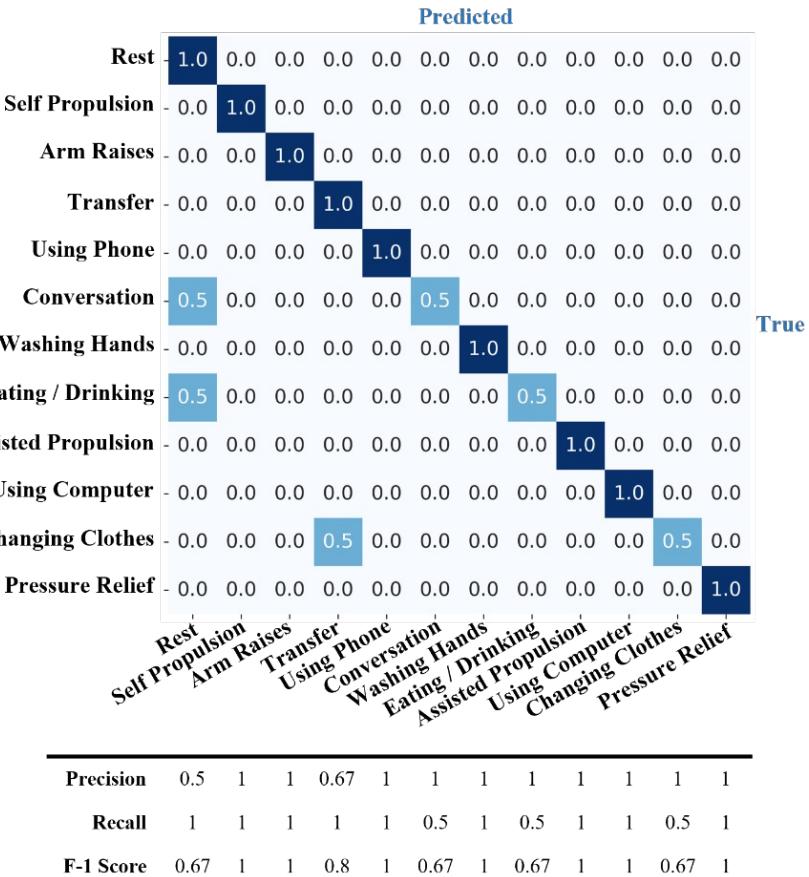


Results

(A)

Devices		Classifiers		Devices		Classifiers		Devices		Classifiers																
E	C	A2	A1	D	B	RF	XB	CB	E	C	A2	A1	D	B	RF	XB	CB	E	C	A2	A1	D	B	RF	XB	CB
✓	✗	✗	✗	✗	✗	0.70	0.64	0.69	1	✓	✓	✓	✗	✗	0.70	0.78	0.79	1	✓	✓	✓	✗	✓	0.72	0.80	0.80
✗	✓	✗	✗	✗	✗	0.37	0.41	0.36		✓	✓	✓	✗	✗	0.67	0.76	0.72		✓	✓	✓	✗	✓	0.68	0.82	0.77
✗	✗	✓	✗	✗	✗	0.40	0.44	0.43		✓	✓	✗	✗	✗	0.76	0.76	0.77		✓	✓	✗	✓	✗	0.70	0.78	0.72
✗	✗	✗	✓	✗	✗	0.25	0.32	0.36		✓	✓	✗	✗	✗	0.72	0.75	0.77		✓	✓	✗	✓	✗	0.66	0.72	0.74
✗	✗	✗	✗	✓	✗	0.49	0.54	0.52		✓	✗	✓	✗	✗	0.66	0.77	0.73		✓	✓	✗	✓	✓	0.74	0.74	0.80
✗	✗	✗	✗	✗	✓	0.53	0.51	0.52		✓	✗	✓	✗	✗	0.71	0.78	0.74		✓	✓	✗	✓	✓	0.72	0.75	0.72
✗	✗	✗	✗	✗	✓	0.53	0.51	0.52		✓	✗	✓	✗	✗	0.71	0.78	0.74		✓	✗	✓	✓	✗	0.72	0.75	0.72
✓	✓	✗	✗	✗	✗	0.73	0.72	0.74		✓	✗	✓	✗	✗	0.65	0.77	0.76		✓	✗	✓	✓	✓	0.68	0.72	0.72
✓	✗	✓	✗	✗	✗	0.65	0.76	0.73		✓	✗	✓	✗	✗	0.69	0.73	0.72		✓	✗	✓	✓	✓	0.69	0.79	0.79
✓	✗	✗	✓	✗	✗	0.63	0.70	0.71		✓	✗	✗	✓	✗	0.68	0.74	0.72		✓	✗	✗	✓	✓	0.72	0.73	0.77
✓	✗	✗	✗	✓	✗	0.78	0.74	0.75		✓	✗	✗	✓	✓	0.72	0.74	0.76		✗	✓	✓	✓	✗	0.55	0.60	0.57
✓	✗	✗	✗	✗	✓	0.70	0.72	0.73		✗	✓	✓	✓	✗	0.41	0.51	0.49		✗	✓	✓	✓	✓	0.46	0.51	0.51
✗	✓	✓	✗	✗	✗	0.43	0.54	0.49		✗	✓	✓	✗	✗	0.56	0.59	0.60		✗	✓	✓	✓	✓	0.60	0.63	0.59
✗	✓	✗	✓	✗	✗	0.30	0.47	0.44		✗	✓	✓	✗	✓	0.52	0.58	0.54		✗	✓	✓	✓	✓	0.58	0.58	0.57
✗	✓	✗	✗	✓	✗	0.54	0.56	0.54		✗	✓	✗	✓	✗	0.45	0.55	0.52		✗	✗	✓	✓	✓	0.55	0.55	0.53
✗	✓	✗	✗	✗	✓	0.58	0.55	0.57		✗	✓	✗	✓	✓	0.49	0.56	0.51		✓	✓	✓	✓	✓	0.72	0.74	0.76
✗	✗	✓	✓	✗	✗	0.35	0.45	0.43		✗	✓	✗	✓	✓	0.58	0.55	0.61		✓	✓	✓	✓	✓	0.69	0.77	0.73
✗	✗	✓	✗	✗	✓	0.53	0.58	0.58		✗	✗	✓	✓	✓	0.49	0.55	0.54		✓	✓	✓	✗	✓	0.69	0.80	0.79
✗	✗	✓	✗	✗	✓	0.49	0.55	0.54		✗	✗	✓	✓	✓	0.47	0.51	0.51		✓	✓	✗	✓	✓	0.72	0.73	0.78
✗	✗	✗	✓	✓	✗	0.44	0.50	0.52		✗	✗	✓	✗	✓	0.59	0.56	0.58		✓	✗	✓	✓	✓	0.71	0.74	0.76
✗	✗	✗	✓	✗	✓	0.46	0.50	0.50		✗	✗	✗	✓	✓	0.53	0.58	0.52		✗	✓	✓	✓	✓	0.58	0.58	0.57
✗	✗	✗	✗	✓	✓	0.55	0.51	0.57	0	✓	✓	✓	✓	✗	0.70	0.77	0.77	0	✓	✓	✓	✓	✓	0.72	0.77	0.79

(B)



M. Ejtehadi, S. Amrein, I. Eriks-Hogland, R. Riener, and D. Paez-Granados. "Learning Activities of Daily Living from Unobtrusive Multi-modal Wearable Sensors: Towards Monitoring Outpatient Rehabilitation". In: IEEE International Conference on Robotics and Rehabilitation. Sept. 2023. <https://doi.org/10.1109/ICORR58425.2023.10304743>

Tutorial: Wearable Data in ADL Classification

