

University of Bristol

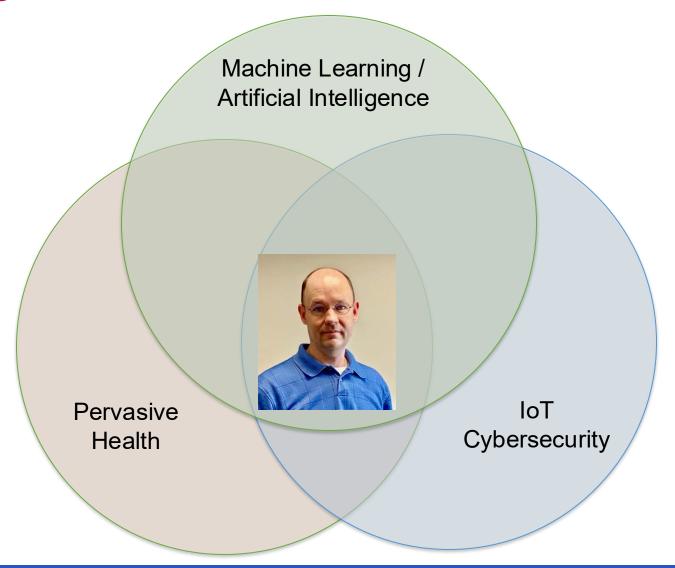


Pervasive Health Monitoring: An Overview

Dr. James Pope
Senior Lecturer in Data Science
School of Engineering Mathematics and Technology
Intelligent Systems Lab – Data Science SEMT
Communication Systems and Networks Group SEEME



About Me



Pervasive Health Monitoring (PHM)

- Pervasive health monitoring refers to the continuous and unobtrusive tracking of an individual's health status using embedded, wearable, or ambient technologies integrated into everyday life.
- Keywords: Smart Home, Wearables, Indoor Localisation, Human Activity Recognition

 Key aspect: Monitoring fades into background, individuals forget that it's there (avoid Hawthorne effects).

PHM Key Characteristics

- Continuous: Health parameters are monitored in real-time or at frequent intervals, not just during clinical visits.
- Unobtrusive: Devices are designed to be minimally invasive—
 often wearable or embedded in the environment—to avoid
 disrupting daily life.
- Context-aware: Monitoring systems can interpret health data in relation to context (e.g., activity, location, time).
- Remote accessibility: Data can be transmitted to healthcare providers or caregivers, enabling remote care and early intervention.

PHM Technologies Involved

- Wearables: Smartwatches, fitness trackers, ECG patches.
- Ambient sensors: Sensors embedded in home environments.
- Mobile health (mHealth): Smartphone-based apps and tools.
- IoT and cloud computing: For integration, storage, analysis.
- AI/ML: anomalies, predicting conditions, and personalizing.

PHM Benefits

- Enables preventive healthcare, personalised, early diagnosis.
- Reduces hospital visits and costs through remote patient management.
- Improves quality of life, especially for elderly and chronically ill patients.
- Shifts focus from reactive, clinic-based care to proactive, patient-centered wellness.

PHM and Al Challenge

- Supervised performs well, better understood -> requires annotations/labels
- PHM often lack annotations/labels

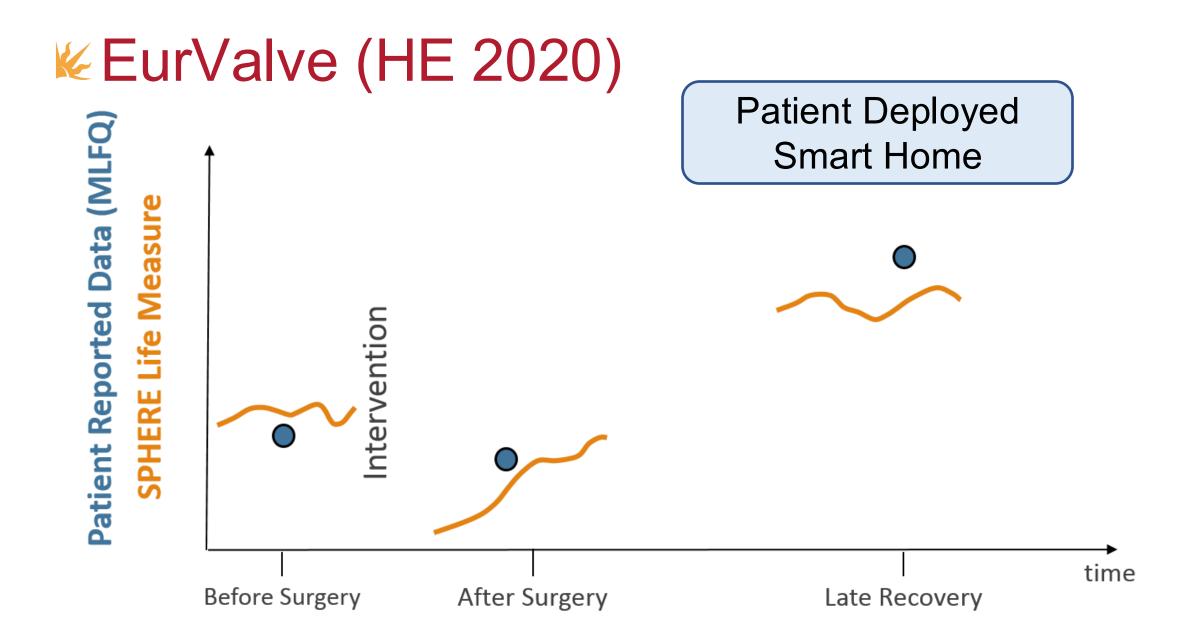
Who "owns" the data? Who "stores/controls" the data?

PHM Use Cases

- Smart-home Systems
 - EurValve (Cardiac)
 - Parkinsons' Disease (PD) SENSORS / TORUS
 - Stroke Rehabilitation
- Mobile Systems
 - REST, using sleep and activity to measure mood (Hanna Kristiina Isotalus)
 - Skin Tone Bias (JGI, Mingmar Sherpa)
- Vital signs (PHM?)
 - Peri-operative Mortality Prediction (INSPIRE Dataset, Surgeon at UHBW)
- Population health
 - Health Camps in Nepal (PhD Candidate Cornell, Mingmar Sherpa)



Wearables, Smart Home, Localisation, Human Activity Recognition



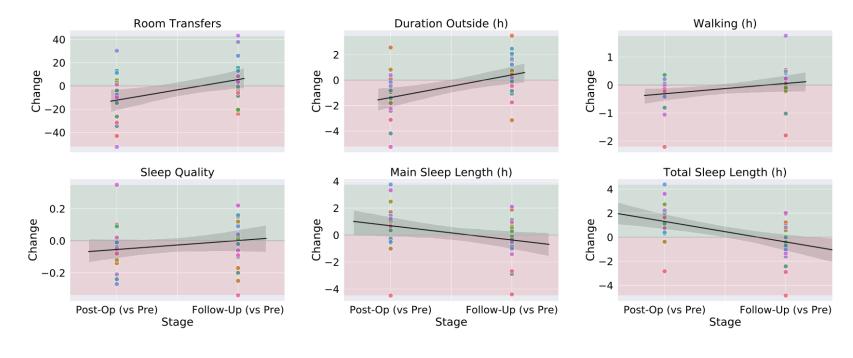
⊯ EurValve: Kit

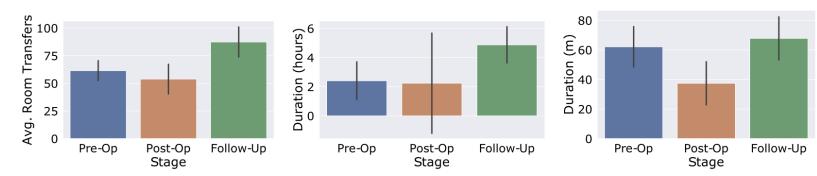


3-axis Accelerometer 4 RSSI for each Anchor

Seminar

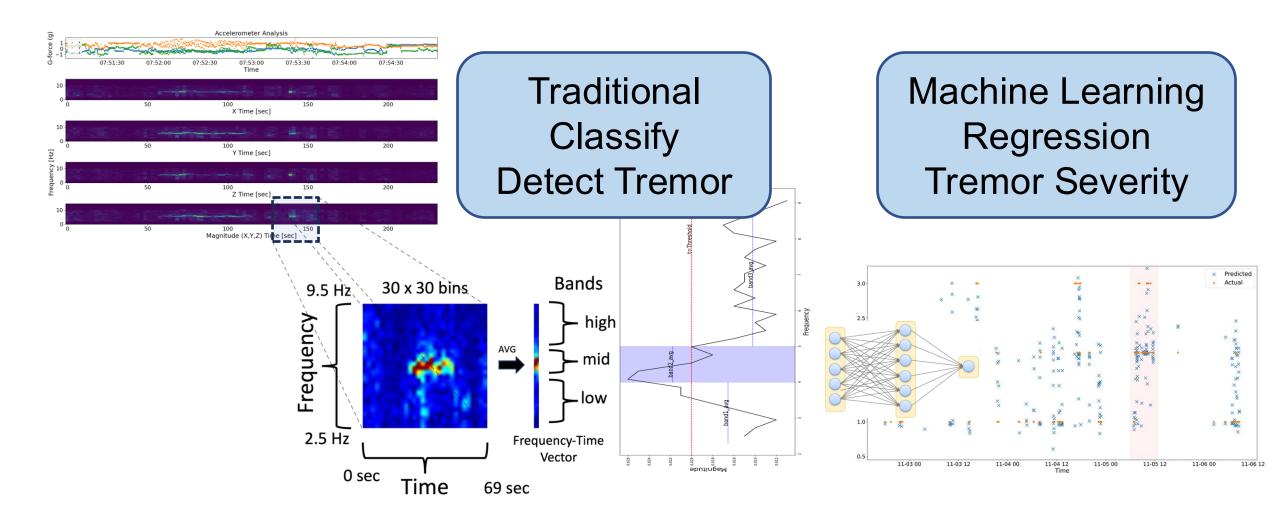
 Successful Intervention





- transfers (with standard de- side (with standard devia- (with standard deviation) viation) for patient A.
 - tion) for patient A.
- Average daily room (b) Average daily hours out- (c) Average daily walking for patient A.

PD SENSORS: Parkinson's Disease



Seminar

PD SENSORS: Human Activity Recognition

- Lying Down
- Sitting
- Standing
- Walking
- Sit-to-Stand duration
- Turning duration



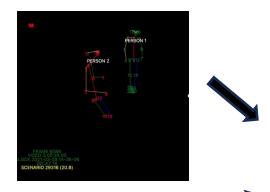
PD SENSORS: Wearables, Cameras

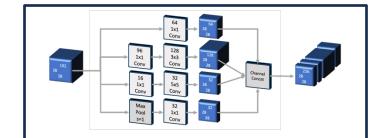
PhD Student Dina Molnar

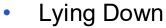
<u>Input</u>

Al Model

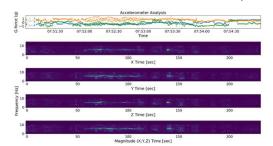
<u>Output</u>







- Sitting
- Standing
- Walking
- Sit-to-Stand duration
- Turning duration



Combine with camera/pose, multi-modal HAR TORUS Project





Stroke Rehab: Exercise Program

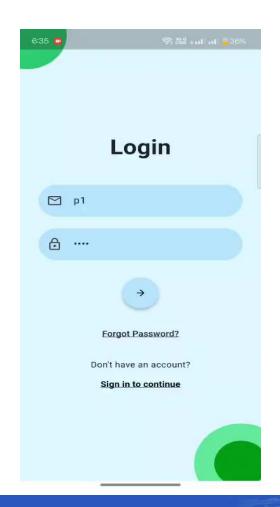
MSc Student Thrisha Rajkumar, "Codesign of Artificial Intelligence Algorithm for Personalised Exercise Videos to Enhance Community-Based Rehabilitation for People with Stroke"

App Overview

- Built using Flutter (Android, iOS, Web)
- Co-designed with clinicians, PwS, and digital health experts
- Goal: Deliver personalised home rehab support for people with stroke

Personalised Routines

Based on individual goals, stroke type, and recovery stage







Stroke Rehab: Exercise Program

Input Features

Al Model

Output

Session/ Exercises

Demographics

Stroke diagnosis

Clinical Reasoning

Natural Language Processing (NLP)

Random Forest / Decision Trees

est /

 Personalised exercise routine recommendation

Adaptive routine level (Easy / Moderate / Challenging)

 Based on progress and feedback

supervised learning and clinical reasoning embeddings

Seminar

16

Tone Bias: Skin Lesion Images

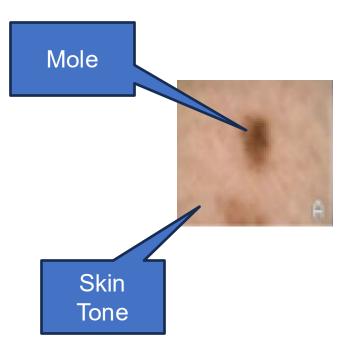


Huw Day, Will Chapman

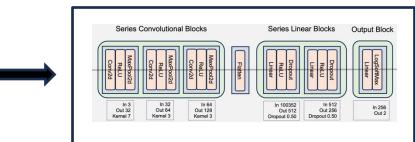
<u>Input</u>

Al Model

Output



How to map Fitzpatrick Skin Type -> Skin Tone?





1=Cancer



0=Benign

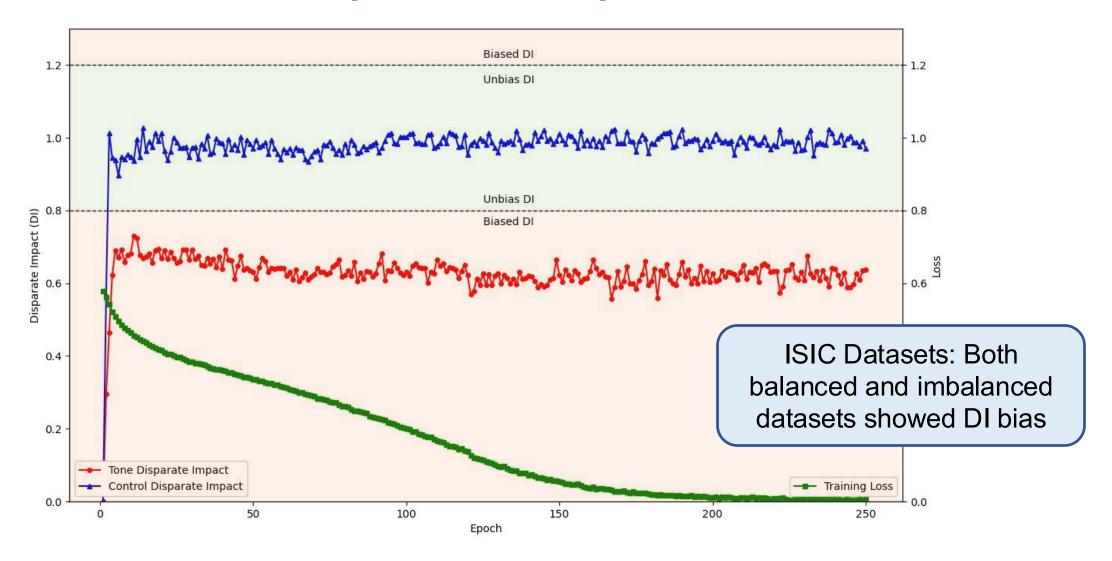
What did the model "learn"?

- Mole colour/shape
- Skin tone colour
- Mole/Skin Contrast

"Mind the Gap" Darker Skin



Tone Bias: Disparate Impact



Seminar Seminar

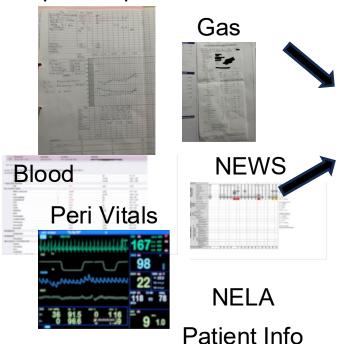
INSPIRE: https://physionet.org/content/inspire/1.3/

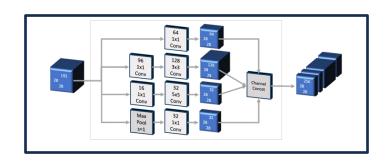
<u>Input</u>

Al Model

Output

Preop/Postop Vitals





Dies during (or within 30 days) of operation

Survives

Combine (mostly) time series data Integrate PHM data?

Al (and Health) Near-term Risks

- Fake images, voices and video
- Massive job losses
- Massive surveillance
- Model discrimination/bias
- End of humanity

 "Do not forget that AI will be immensely helpful in areas like healthcare" (why AI development should not be stopped)

Prof. Geoffrey Hinton - "Will digital intelligence replace biological intelligence?" Romanes Lecture YouTube: https://www.youtube.com/watch?v=N1TEjTeQeg0 [last accessed 7 Jul 2025].

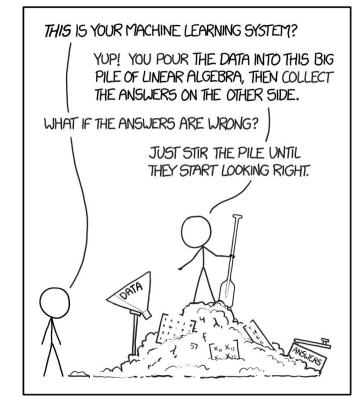
Seminar



University of Bristol



Thank You for Listening!!!



Source: https://xkcd.com/