Advanced pulse wave analysis using image-based representations and machine learning

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https://www.qumphy.ptb.de/home

Aim of the project

The aim of this project is to extract more useful clinical information from pulse waves, in particular from the Blood Pressure and PPG signal, in away that is intuitive, clinically employable, robust and easy to use.

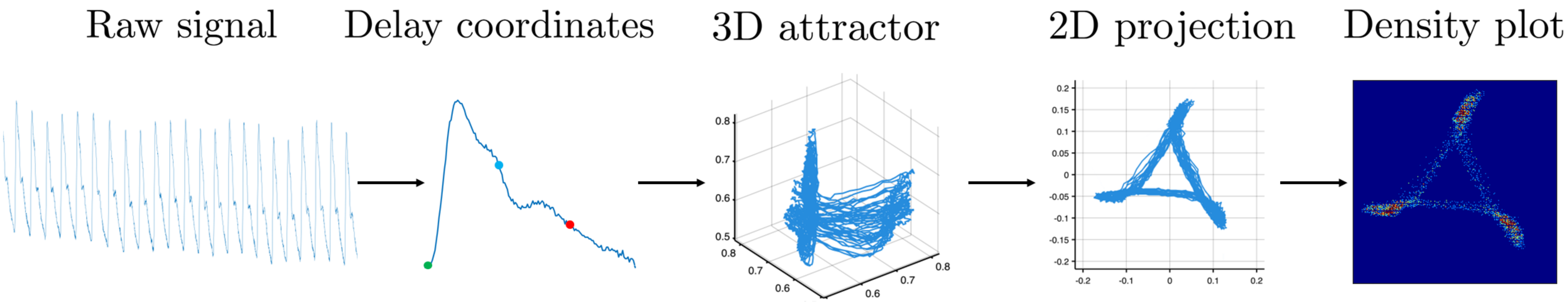
Objectives

The three main objectives are:

1. curation of in vivo datasets
2. creation of a database of in silico pulse waves to model and understand cardiovascular pulse wave changes
3. application of an advanced waveform analysis (SPAR images) to classification and regression problems

The SPAR method

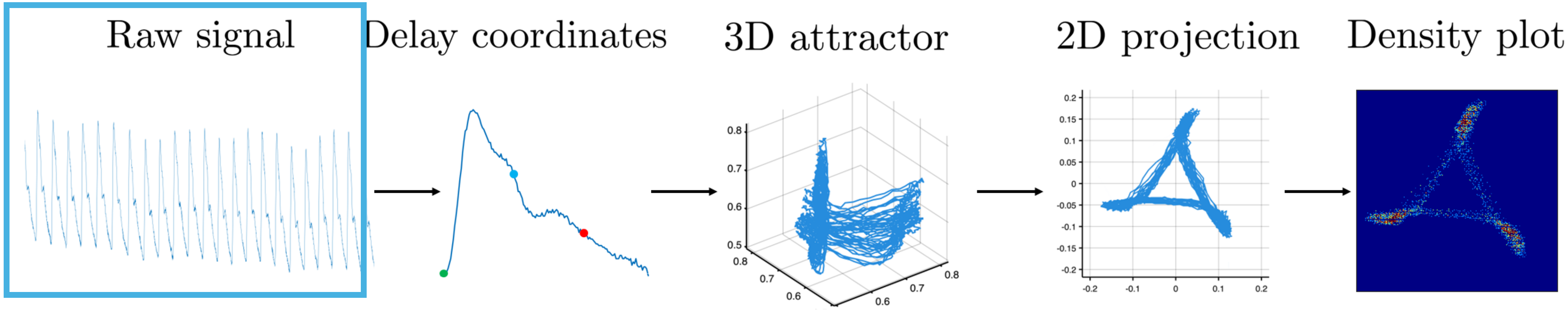
Non-fiducial points-based method that combines mathematics and cardiovascular physiology to quantify morphological features and waveform variability



The SPAR method

4 fundamental steps :

- average cycle length computation
- attractor reconstruction using delay coordinates (τ):
  - x(t): signal
  - y(t): x(t - τ)
  - z(t): x(t - 2τ)
- projection of 3D attractor onto 2D plane
- density construction



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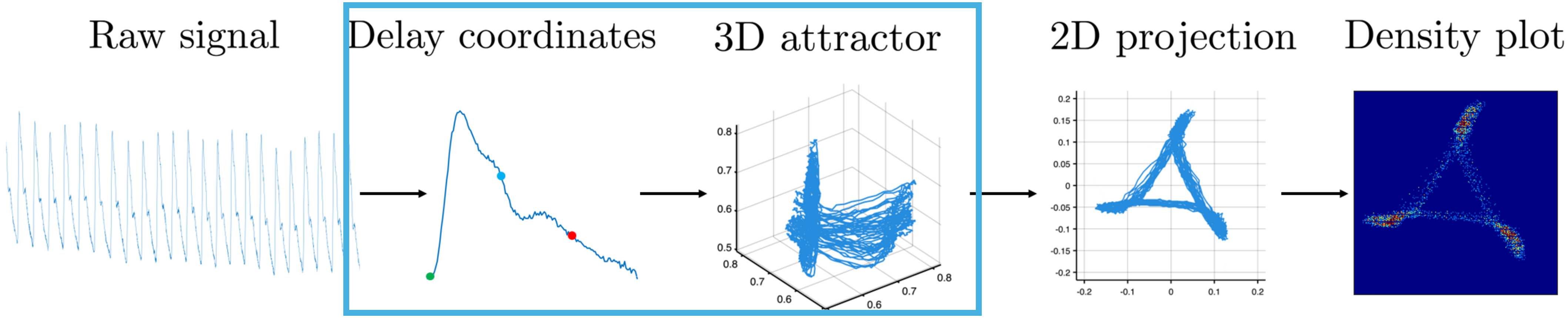

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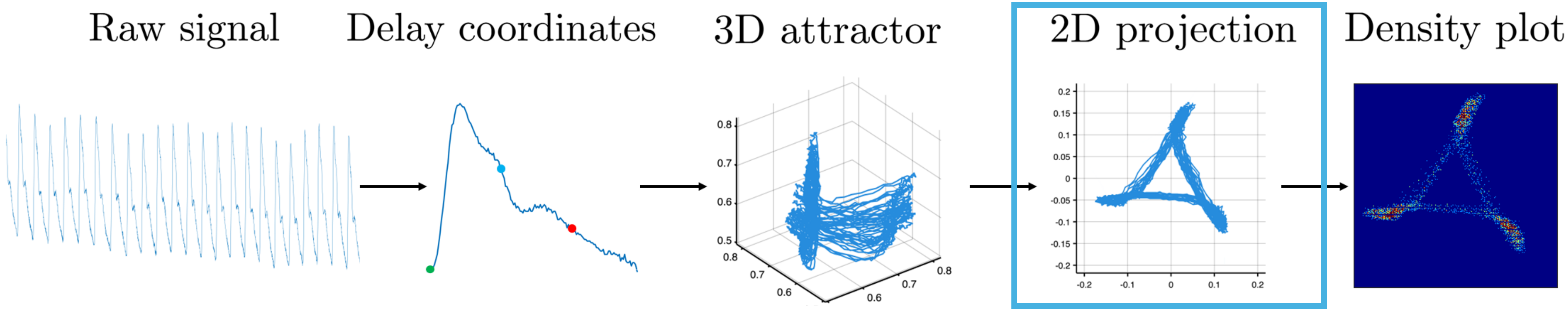

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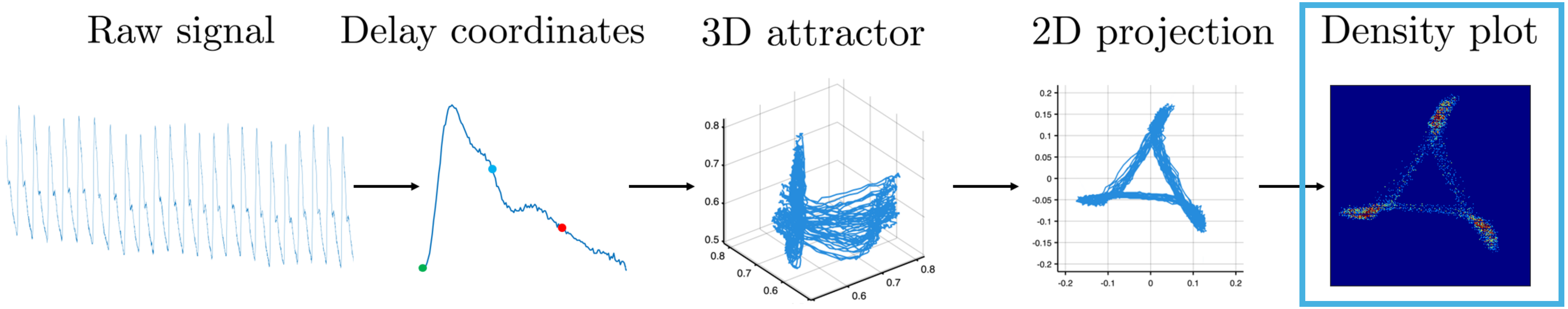
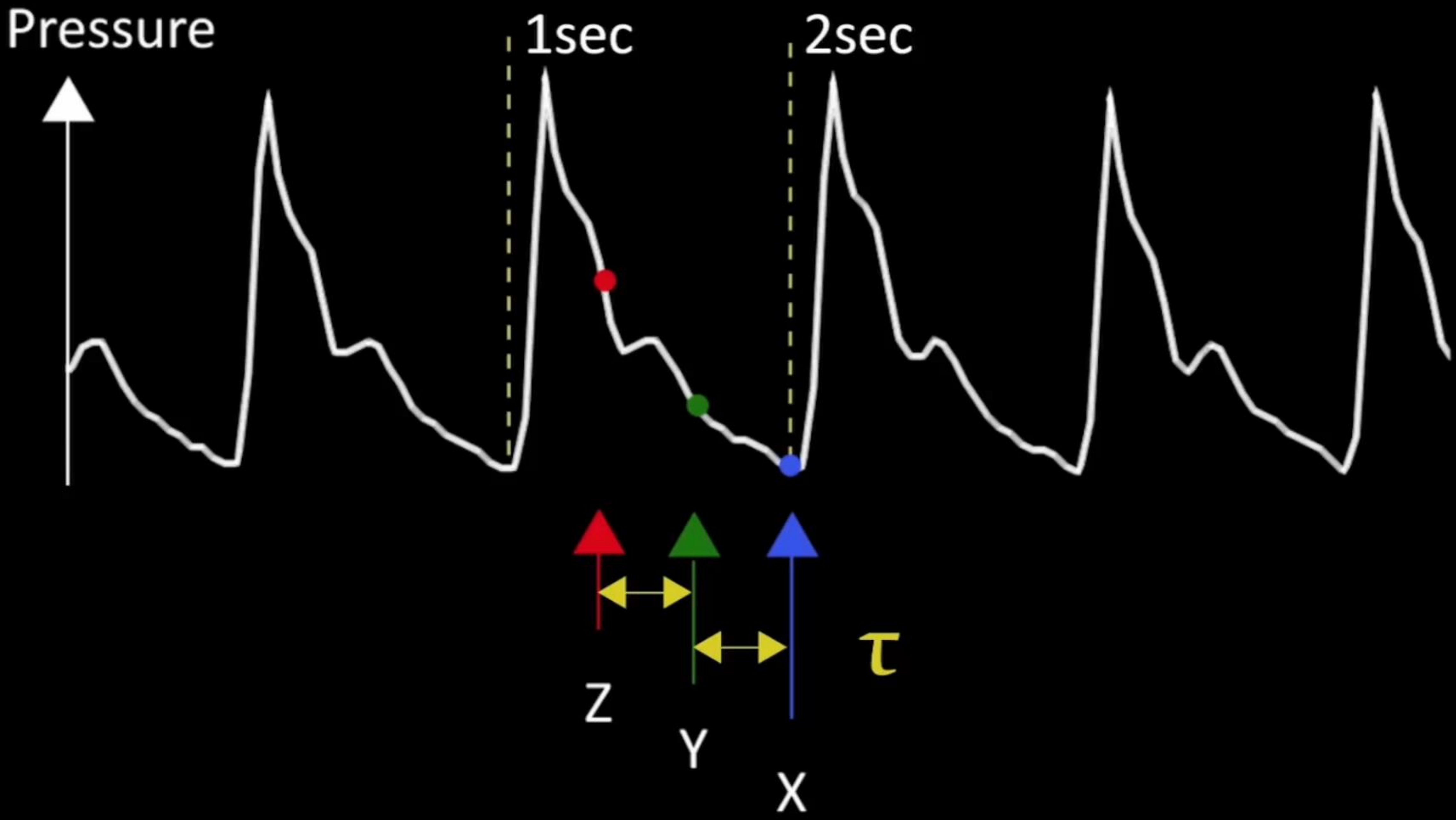
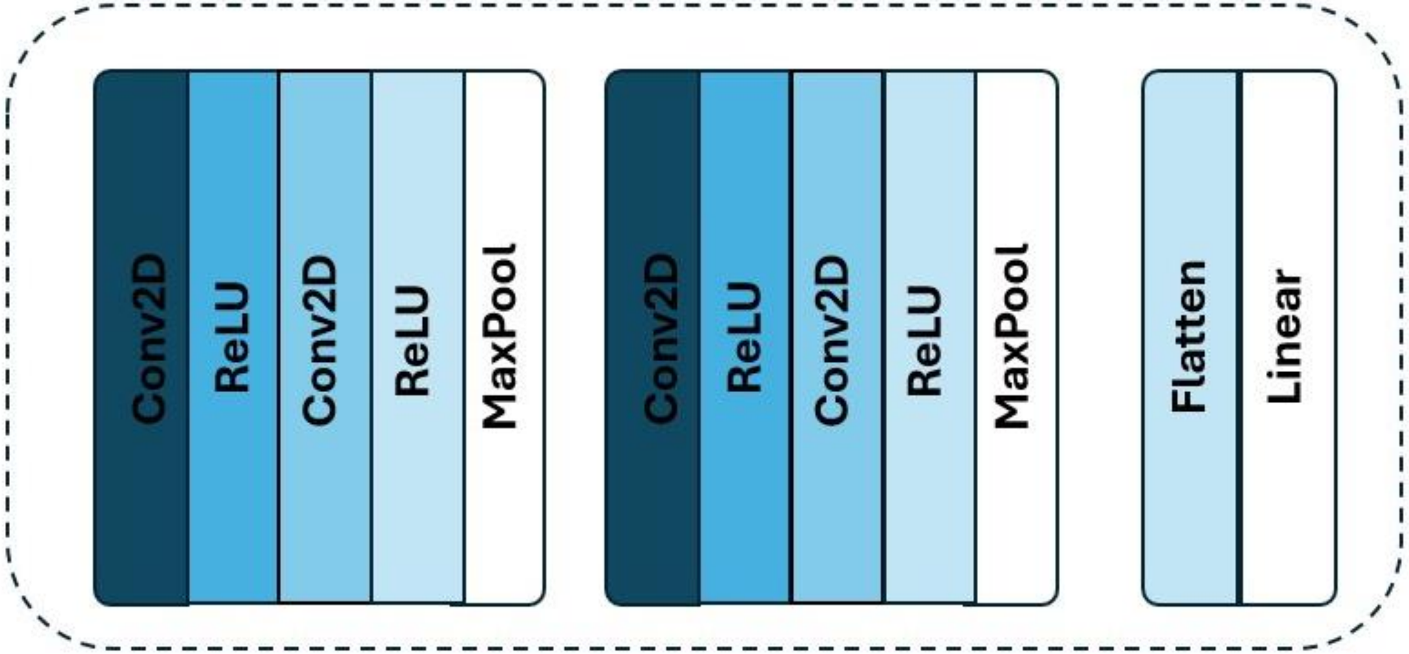



Pressure
1sec
2sec
τ
Z
Y
X

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a type of artificial intelligence that is very good at recognizing patterns in images by learning different features in images through layers of processing.

A CNN was developed and used for multiple classification tasks, using image-based representations of the PPG signal as input data

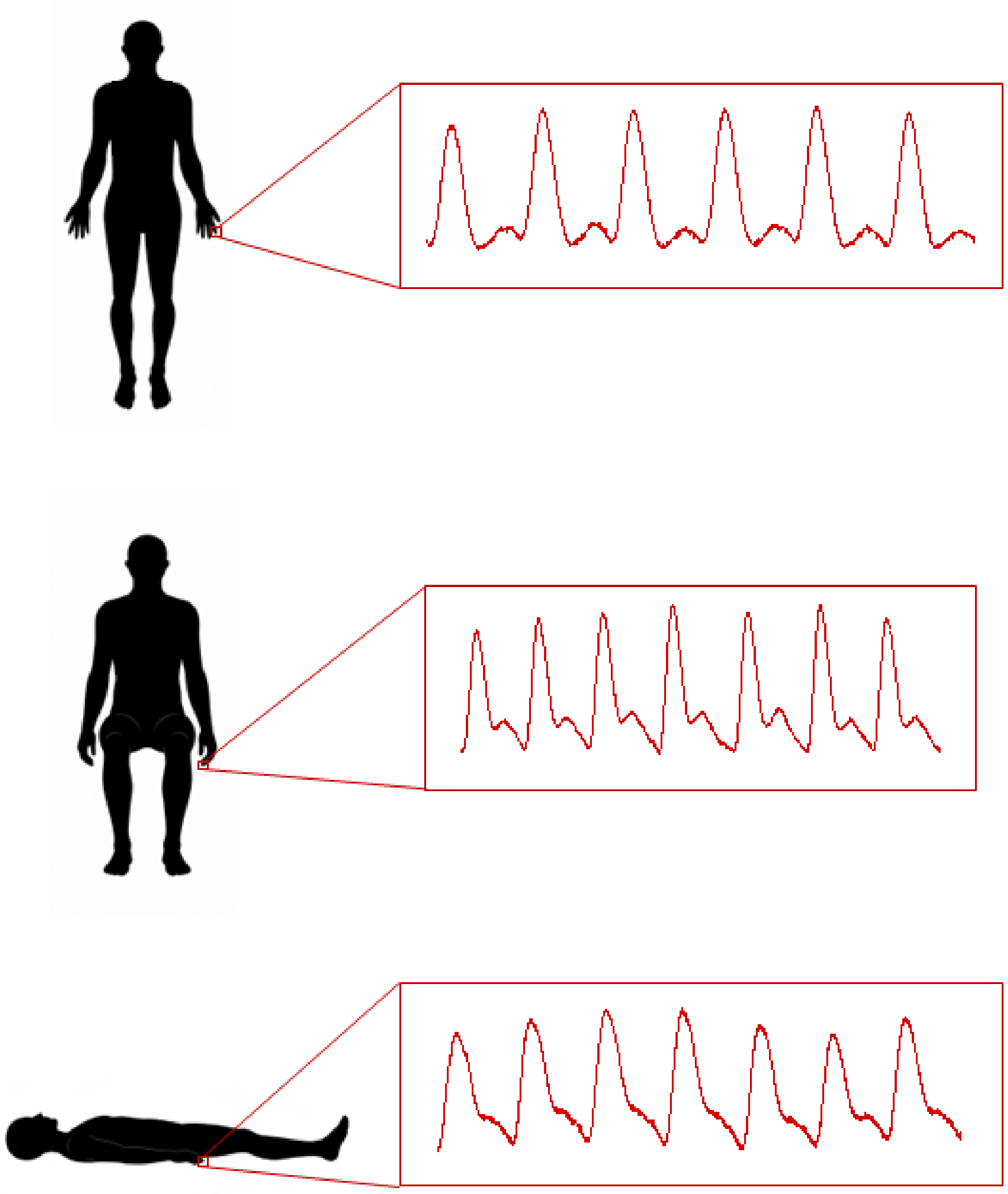


Selection and evaluation of external datasets

Problem: researchers from different backgrounds approach data in different ways, often overlooking or underestimating crucial aspects of the selected data

Solution: data approach and selection guidelines, generated from the collaboration between interdisciplinary researchers

Selection and evaluation of external datasets



Datasets

- **Aurora-BP**: PPG, arterial tonometry and actigraphy data, 1121participants aged 21 to 85
- **Vortal**: PPG and ECG, 56 subjects aged 18-35 (40 subjects) or 70+(16 subjects)
- (**Asklepios**: arterial tonometry data, 2324 participants aged 30 to 59)

Vascular age assessment

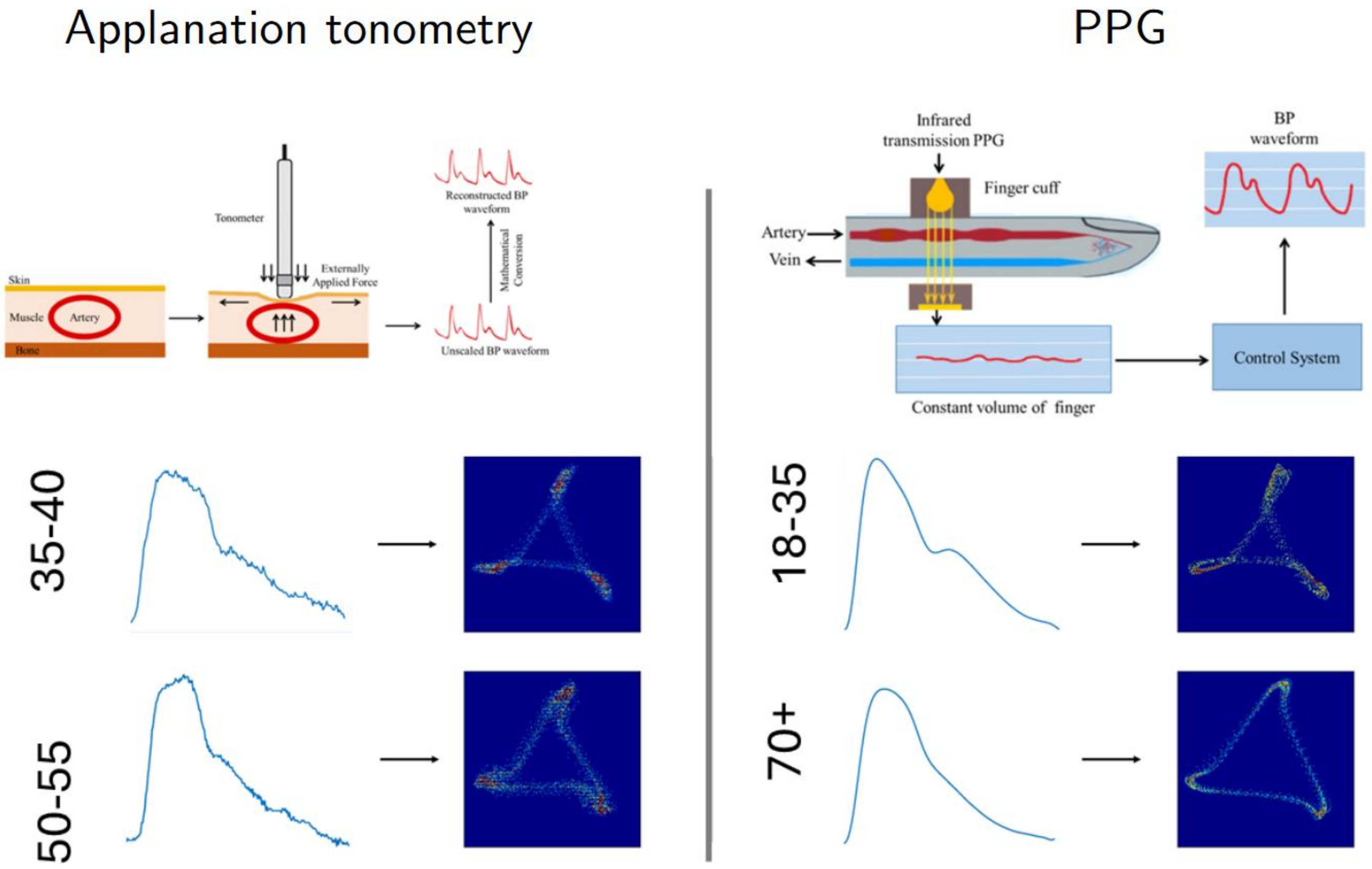
Clinical background and motivation

- **What**: Vascular ageing (VA) is a complex process that involves the gradual deterioration of arterial structure and function over time. Early VA(EVA) can increase the risk of cardiovascular disease

- **Why**: Timely detection of EVA is critical for the timely identification and treatment of cardiovascular disease (CVD)

- **How**: Using CNNs and image-based representations to look at morphological changes in the pulse wave, comparing signal-based estimates of vascular age to a person's chronological age

Data



Applanation tonometry
PPG
Tonometer
Externally Applied Force
Skin
Muscle
Artery
Bone
Reconstructed BP waveform
Mathematical Conversion
Unscaled BP waveform
Infrared transmission PPG
Finger cuff
Artery
Vein
BP waveform
Control System
Constant volume of finger
35-40
50-55
18-35
70+

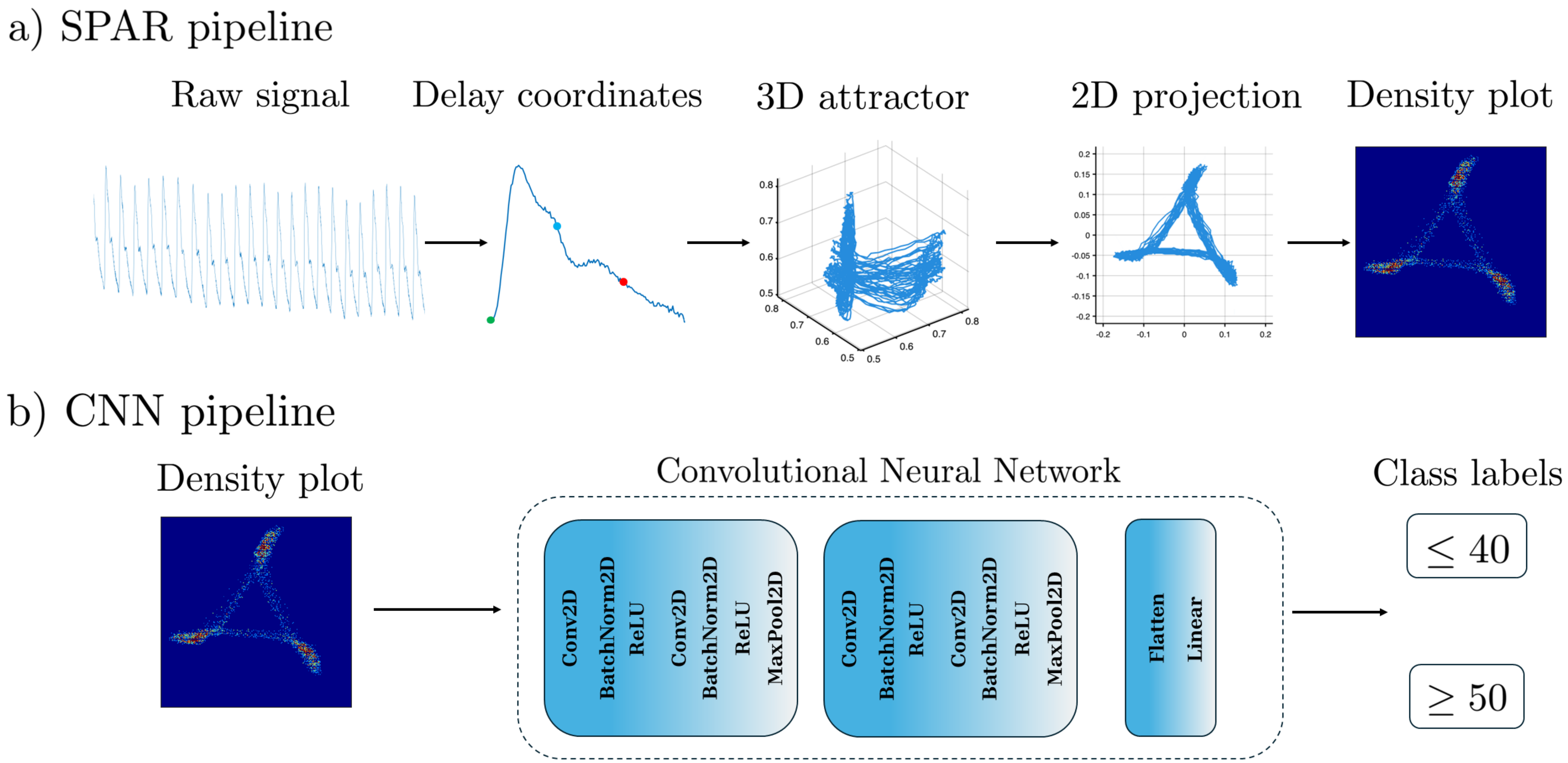
Data

Data

	Asklepios	**Vortal**
Number of participants	Total: 2,324 361 aged 35-40 398 aged 50-55	Total: 56 40 young (18-35) 16 elderly (50+)
Signal type	Tonometry	PPG
Raw signal length	20s	10 min
Analysed signal length	20s	20 s

Free from diagnosed CVD at study initiation, data collected in supine position

Methods


a) SPAR pipeline
Raw signal
Delay coordinates
3D attractor
2D projection
Density plot
b) CNN pipeline
Density plot
Convolutional Neural Network
Conv2D
BatchNorm2D
ReLU
Conv2D
BatchNorm2D
ReLU
MaxPool2D
Conv2D
BatchNorm2D
ReLU
Conv2D
BatchNorm2D
ReLU
MaxPool2D
Flatten
Linear
Class labels
≤ 40
≥ 50

Training and testing

Train set: 80% of Asklepios AG 35-40 and 50-55

Validation set: 10% of Asklepios AG 35-40 and 50-55

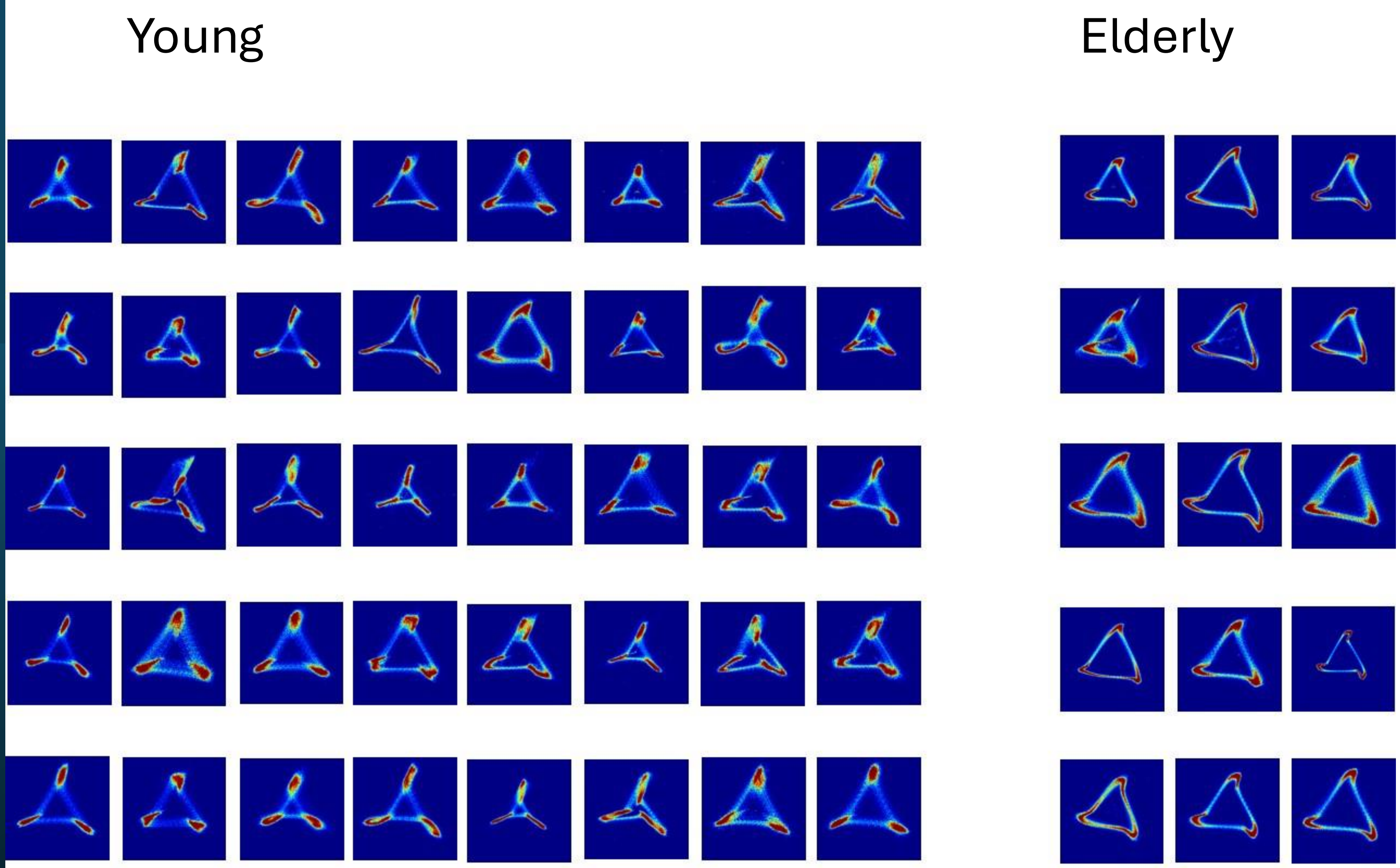
Test set: 3 scenarios
- test on Asklepios 35-40 and 50-55
- test on Asklepios 30-40 and 50-59
- test on Vortal

10-fold cross validation was performed, due to the small size of the datasets

Results

	F1 score (%)	Sensitivity (%)	Specificity (%)
Test Asklepios 35-40 and 50-55	70.9 ± 8.6	67.0 ± 12.3	85.0 ± 8.3
Test Asklepios 30-40 and 50-59	79.3 ± 2.0	70.5 ± 3.1	84.3 ± 4.8
Test Vortal	72.8 ± 2.5	86.9 ± 5.9	79.0 ± 2.0

Results – Vortal population attractors



Discussion

Simple **SPAR-based CNN model** that **classifies individuals** into two **closely spaced age groups** within a **CVD-free population**

Both pulse wave types contained **enough information** in their shape to **distinguish** between the **two age groups**

Our findings support **further research** into the use of **SPAR** with **community-worn PPG devices** for the **detection** and **stratification** of **cardiovascular risk**

Related publication – CinC25

Attractor Image-Based Deep Learning of Arterial Pulse Waves for Age Classification

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[6]School of Cancer and Pharmaceutical Sciences, King's College London, London, UK

Hypertension assessment

Clinical background and motivation

- **What: Hypertension** is a leading risk factor for premature death worldwide

- **Why**: Early detection, especially in community settings, could expedite treatment and improve overall health outcomes

- **How**: Using **CNNs** and **image-based representations** to look at **morphological changes** in the pulse wave

Data - Asklepios

2,524 subjects included for analysis in the Asklepios cohort

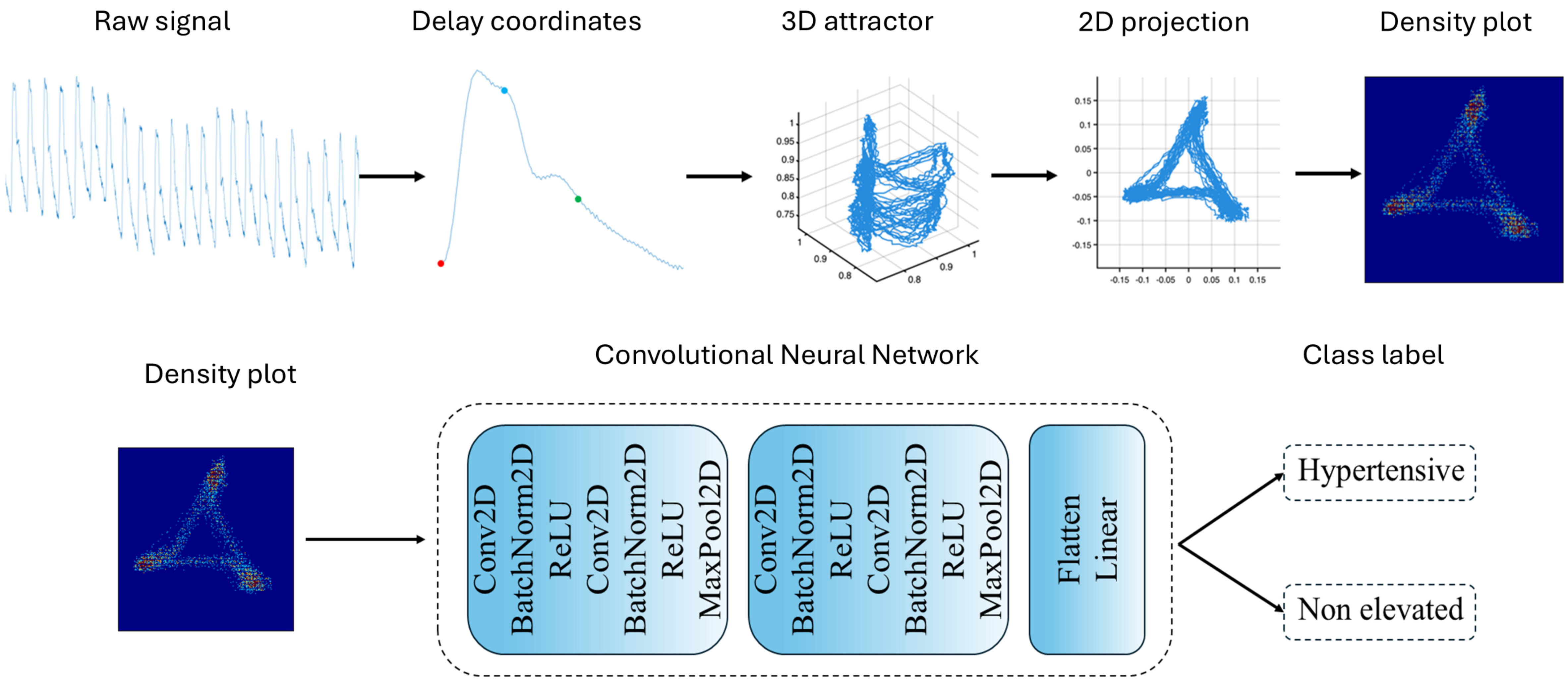
Filter for:

- hypertensive status: **non-elevated BP** (SBP<120 mmHg and DBP<70 mmHg) or **untreated hypertension** (SBP>140 mmHg or DBP>90 mmHg, **not** taking anti-hypertension **drugs**)
- no associated cardiovascular disease

Resulting in:

- **294** subjects with **non-elevated BP**
- **442** subjects with **untreated hypertension**

Methods



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Conv2D
BatchNorm2D
ReLU
Conv2D
BatchNorm2D
ReLU
MaxPool2D
Flatten
Linear
Hypertensive
Non elevated

Training and testing

Train set: 70% of each class

Validation set: 20% of each class

Test set: 10% of each class

10-fold cross validation was performed, due to the small size of the dataset

Results

Mean metrics after 10-fold cross validation were:

- F1 score: 85.0%
- Accuracy: 88.0%
- ROC-AUC score: 87.4%
- Sensitivity: 87.6%
- Specificity: 87.3%

Discussion

Simple **SPAR-based CNN model** that **classifies individuals** according to hypertensive status

Novel approach to studying pulse waves using **image-based representations** of the tonometry signal and CNNs for hypertension classification

These preliminary findings will be **further investigated** by conducting **longitudinal studies** and studies in **larger populations**

Biological sex assessment

Clinical background and motivation

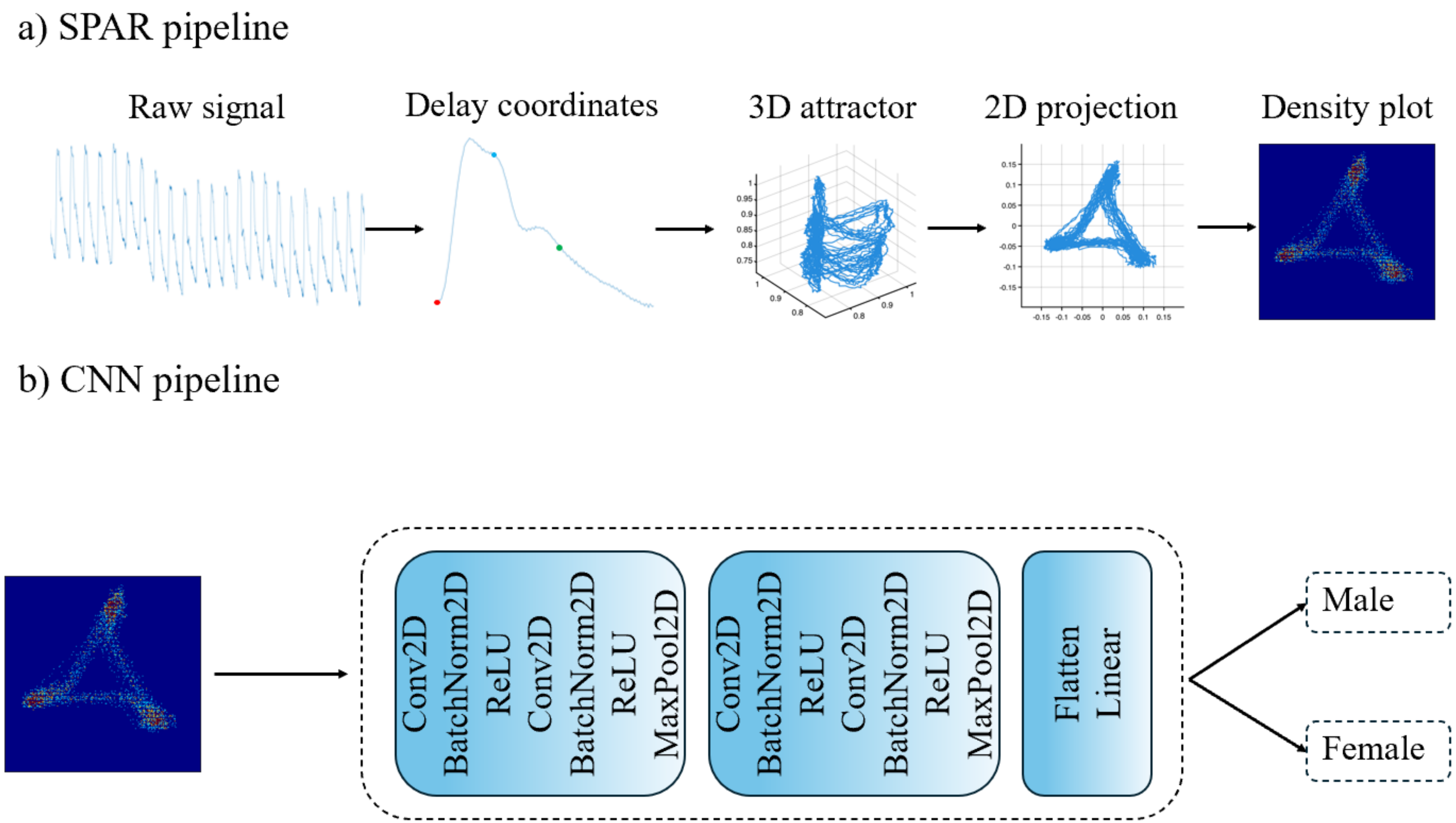
Potential sex-related bias in algorithms developed on predominantly male populations

Progression towards personalised medicine

Data

Aurora-BP data, all segments of ”optical quality” above 0.65.

Methods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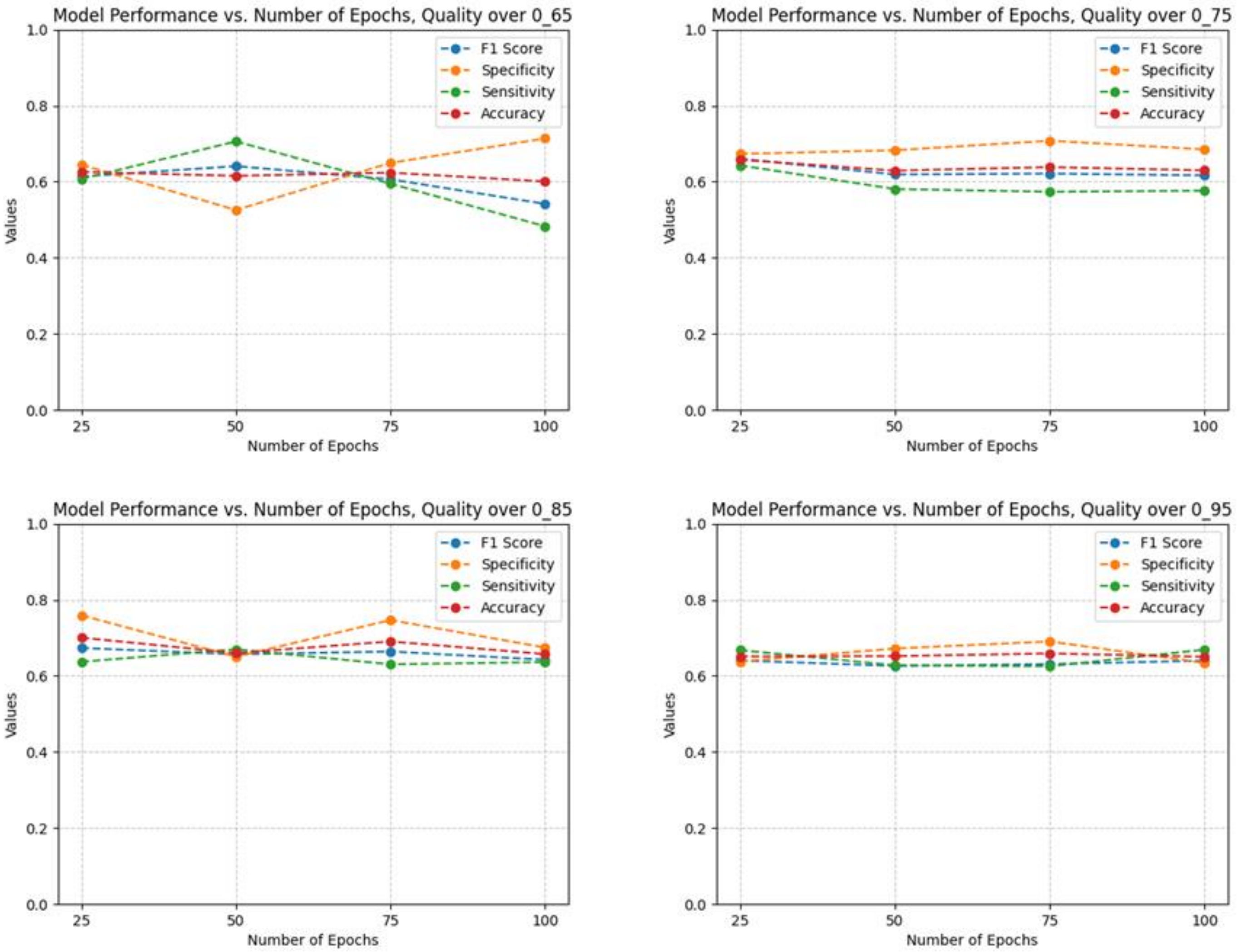
ReLU
Conv2D
BatchNorm2D
ReLU
MaxPool2D
Flatten
Linear
Male
Female

Methods

Thresholds of 0.65, 0.75, 0.85 and 0.95 were considered separately for four different training scenarios, which were then combined with a varying number of training epochs (namely 25, 50, 75 and 100 epochs of training).

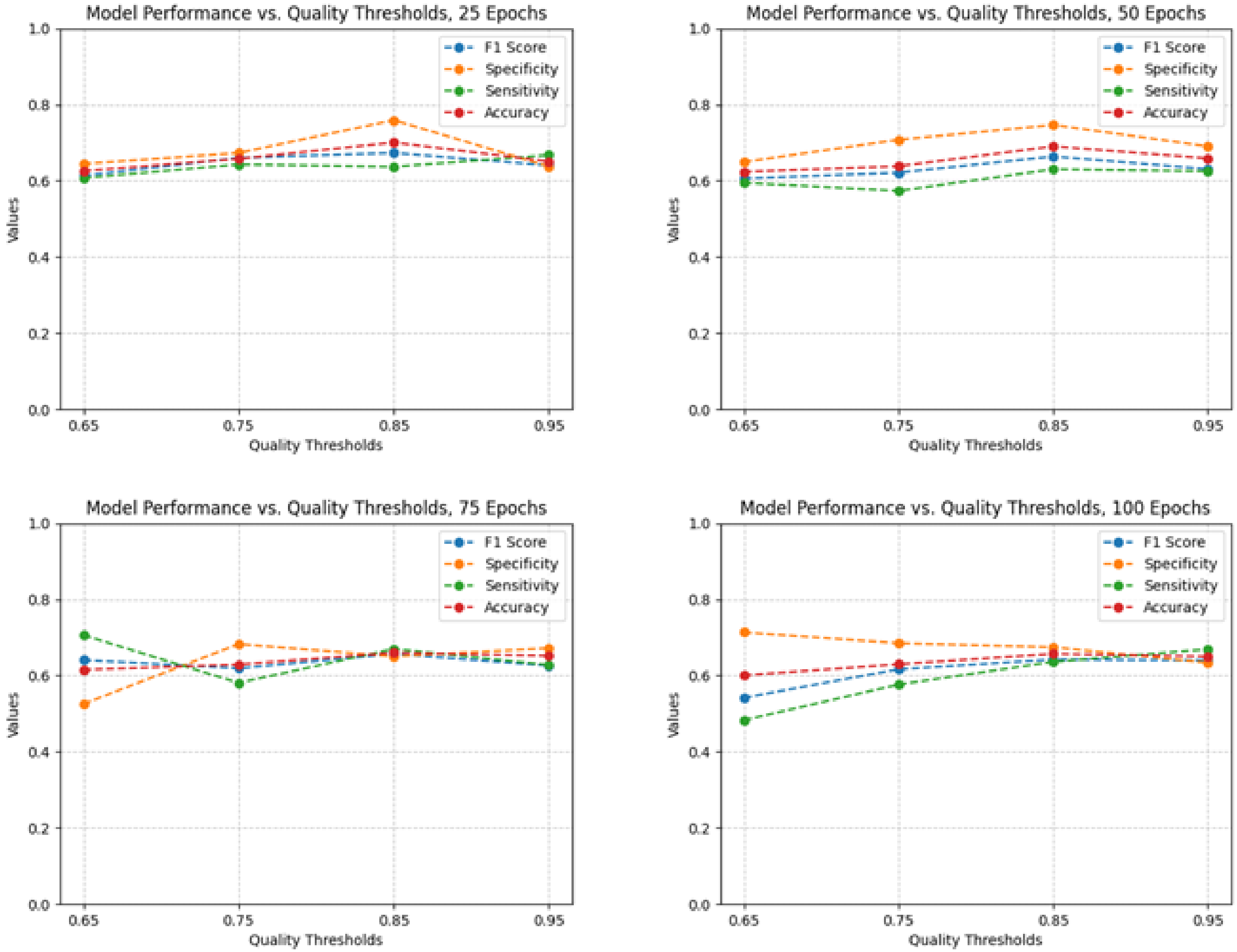
The aim of these different settings was to assess model performance in relation to data quality and training time

Results – increasing quality



Model performance for different training times, increasing quality thresholds. Top to bottom, left to right: optical quality over 0.65, optical quality over 0.75, optical quality over 0.85 and optical quality over 0.95.

Results – increasing training time



Model performance for different quality thresholds, increasing training time. Top to bottom, left to right: 25 epochs, 50 epochs, 75 epochs and 100 epochs.

Thank you for your attention