Classification of atrial ectopic origins into spatial segments based on the 12-lead ECG

Master's Thesis Final Presentation

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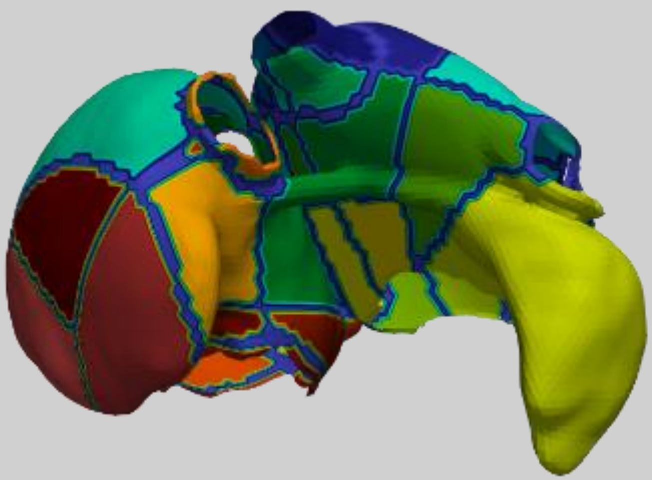
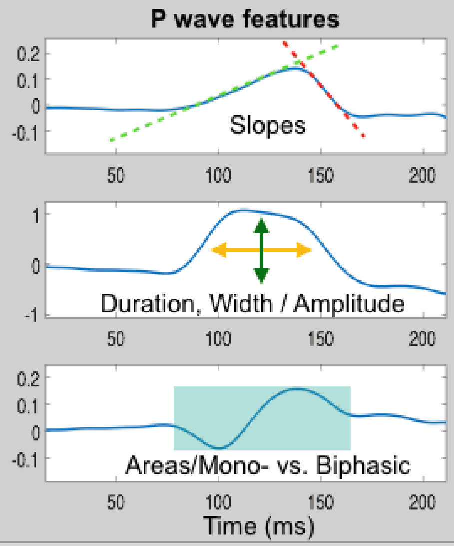
INSTITUTE OF BIOMEDICAL ENGINEERING





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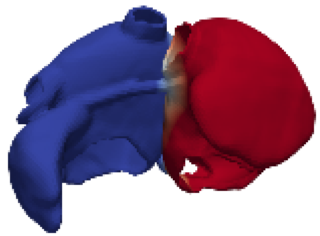
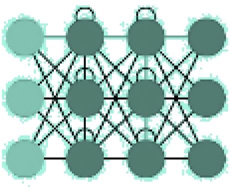
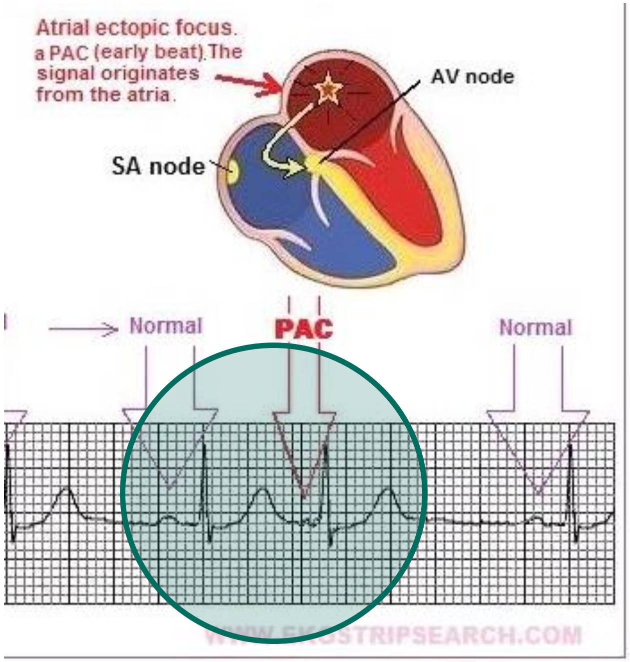




Motivation & Overview

- **Ectopic activity** is associated with multiple **cardiac disorders**
- **Identifying** the presence and **origin of ectopic activity** may be vital in **improving diagnosis** and treatment of disorders such as atrial fibrillation (AFib)



http://www.rbain.org.uk/Ectopics.html

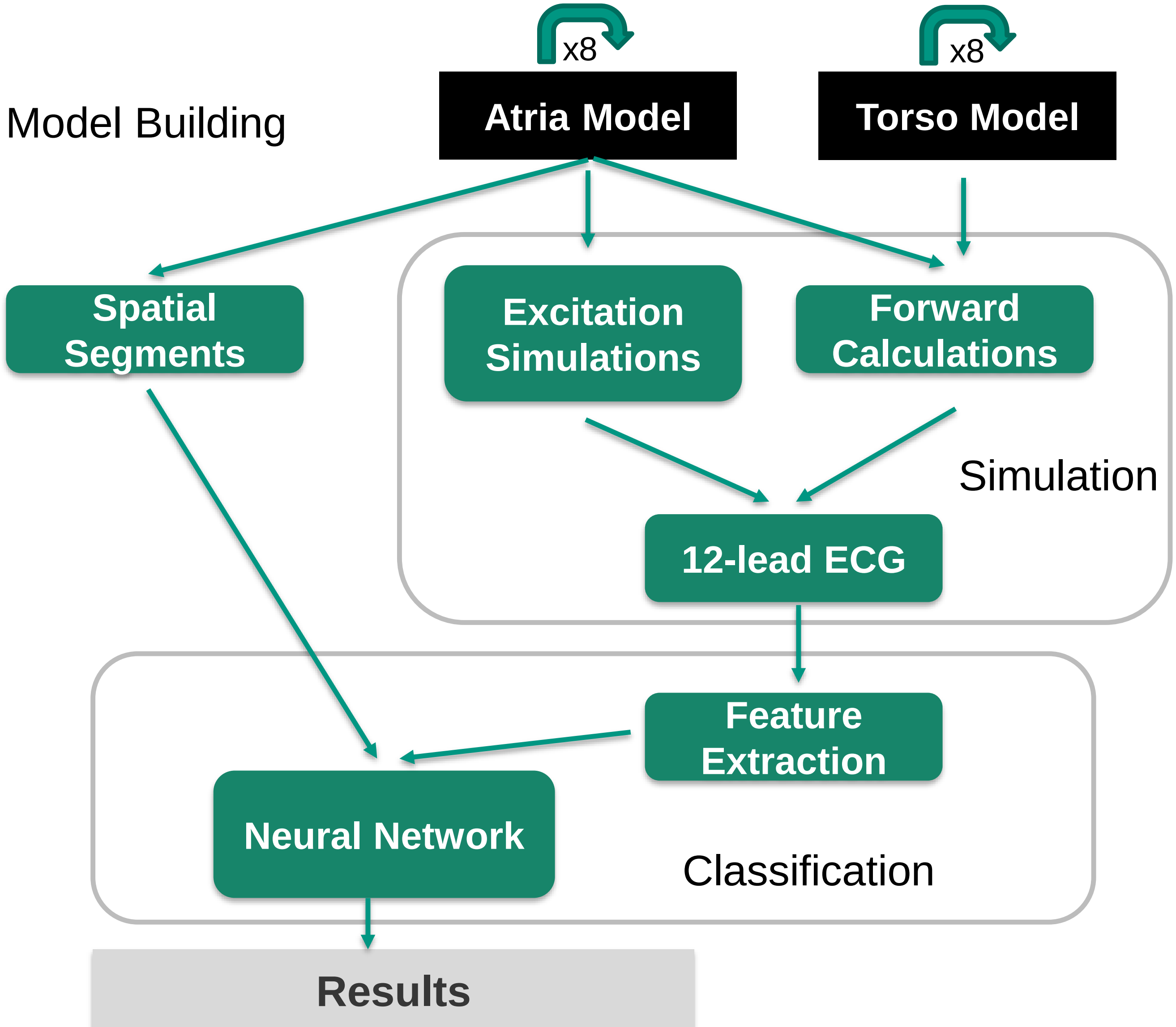
Motivation & Overview | Challenge

- The **non-invasive localization of atrial ectopic foci** during atrial tachycardia is **complex**

- Most existing algorithms are only based on **P-wave polarity**

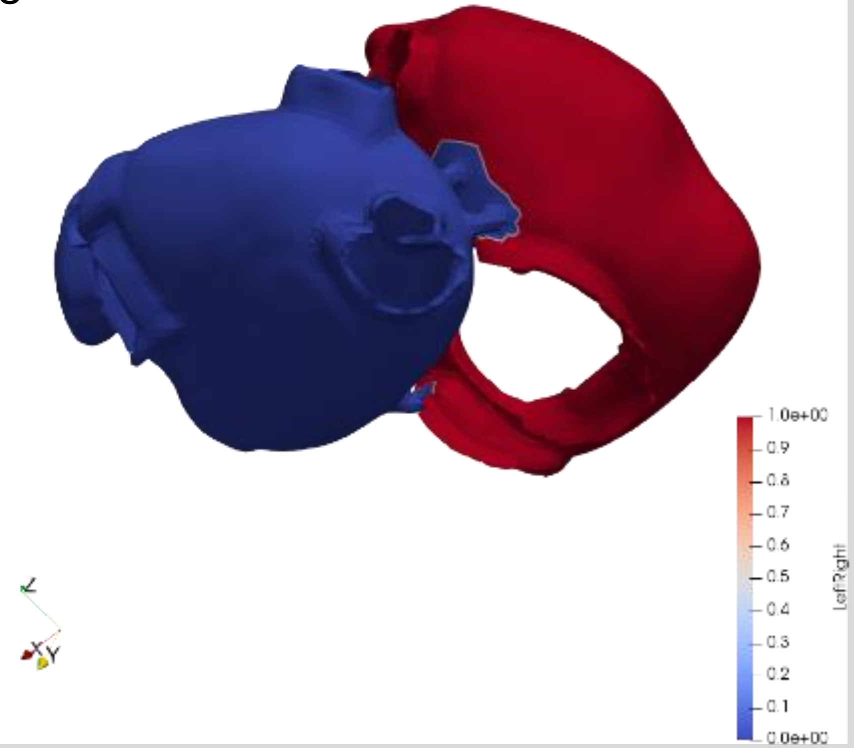
- **Goal**: to create a **classifier** by building a database of simulated 12-lead ECG combined with machine learning techniques **to predict the localization of atrial ectopic triggers**

Motivation & Overview | Thesis Workflow



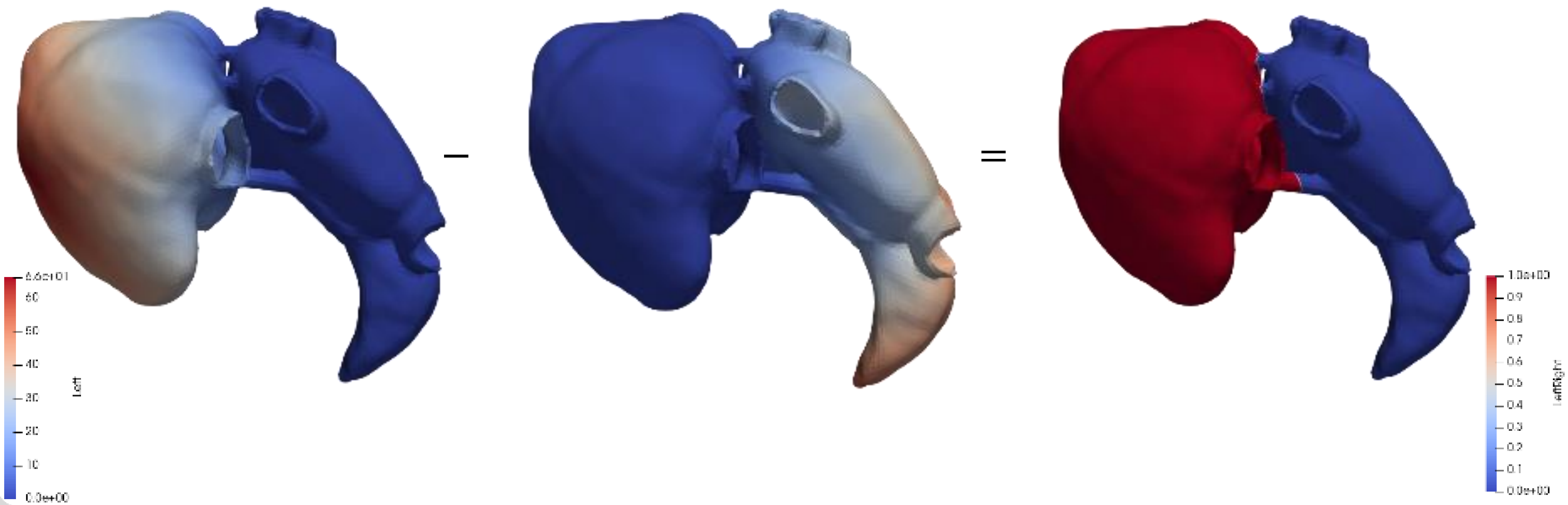
Atria Model | LA & RA separation

- Discovery of errors in the separation
- Separating epicardium and endocardium, we know which points of the endocardium belong to LA and RA.
- Selecting one point in the endocardium, we found the nearest point in the epicardium using the nearest neighbour algorithm



Atria Model | LA & RA separation

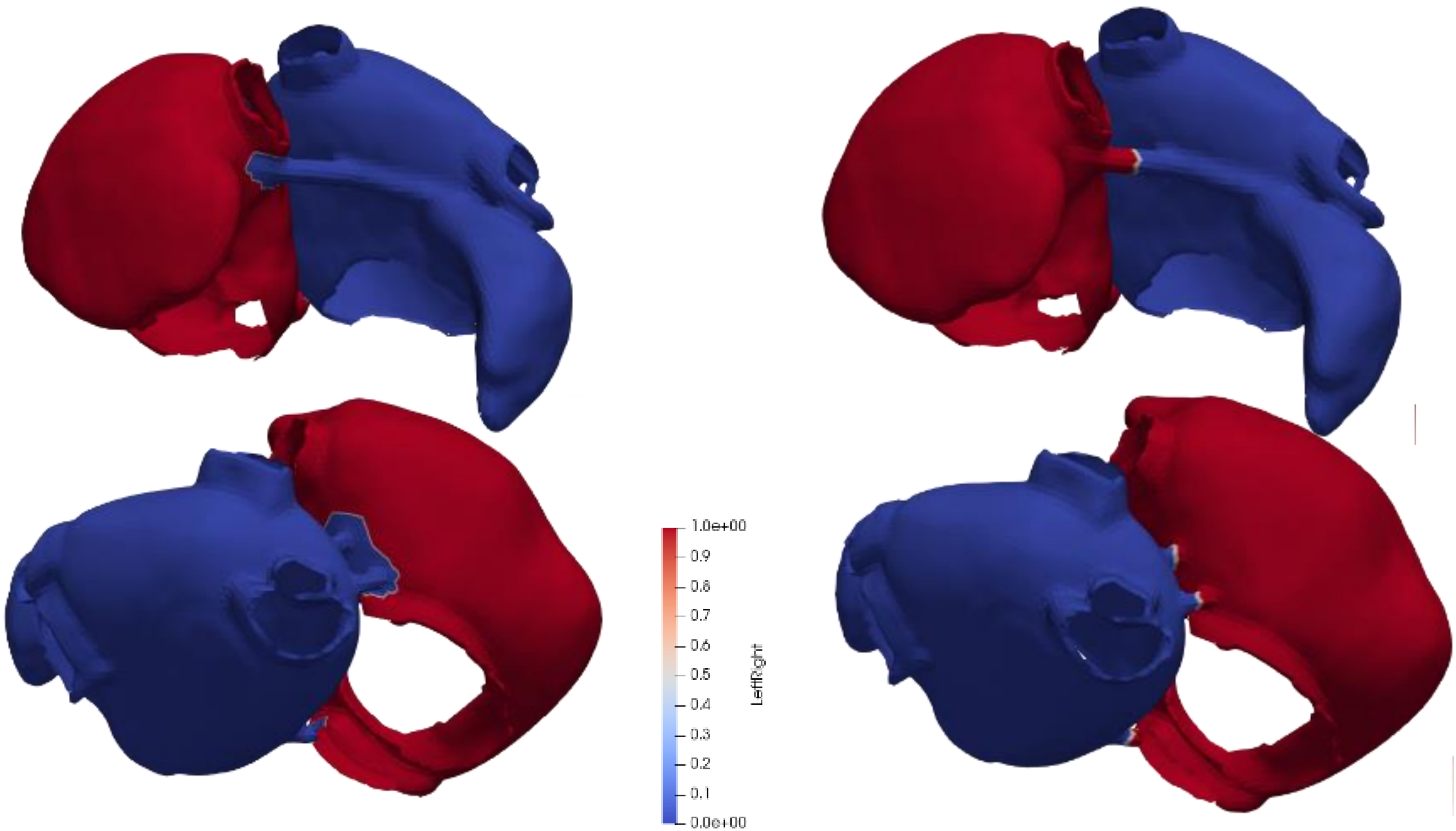
- Run Fast Marching on **tetrahedral mesh**
- Start on the **Endocardium** points belong to LA and RA
- $T_{leftright} = T_{left} - T_{right}$
- Apply a threshold, $thr = 0$



Atria Model | LA & RA separation

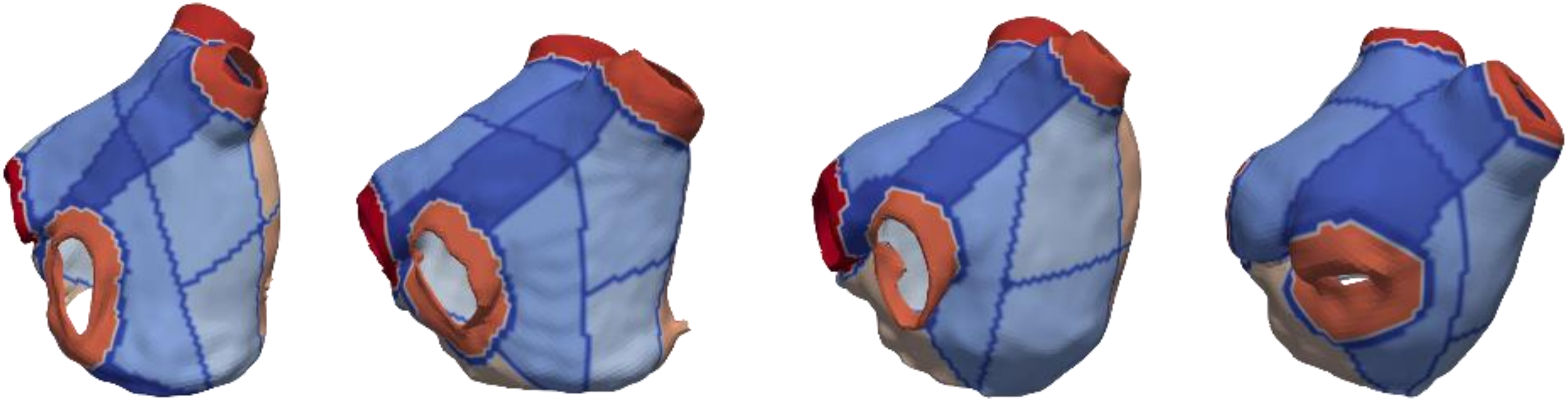
Old separation

New separation

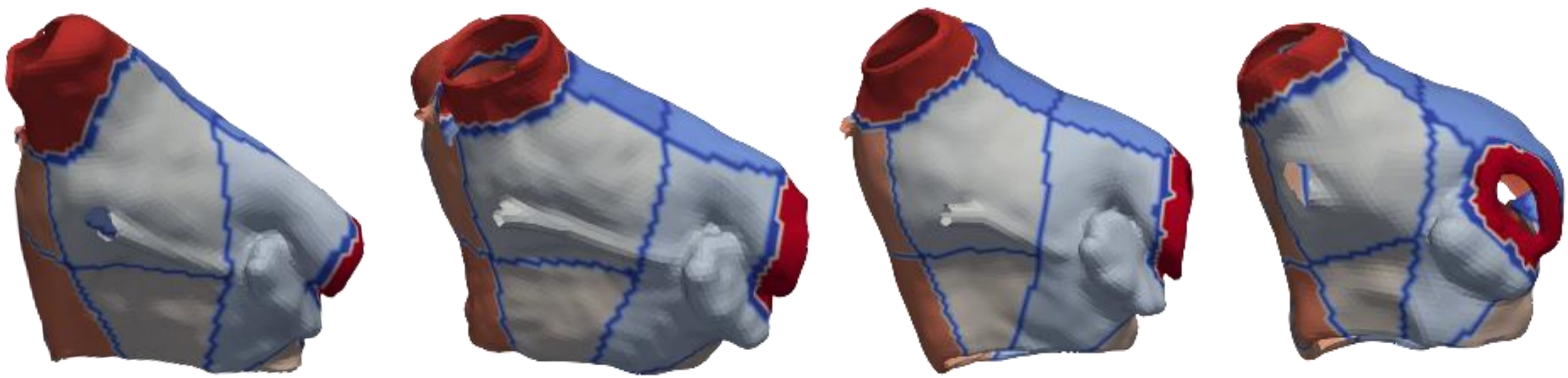


Atria Model | Segments creation

- LA segmentation

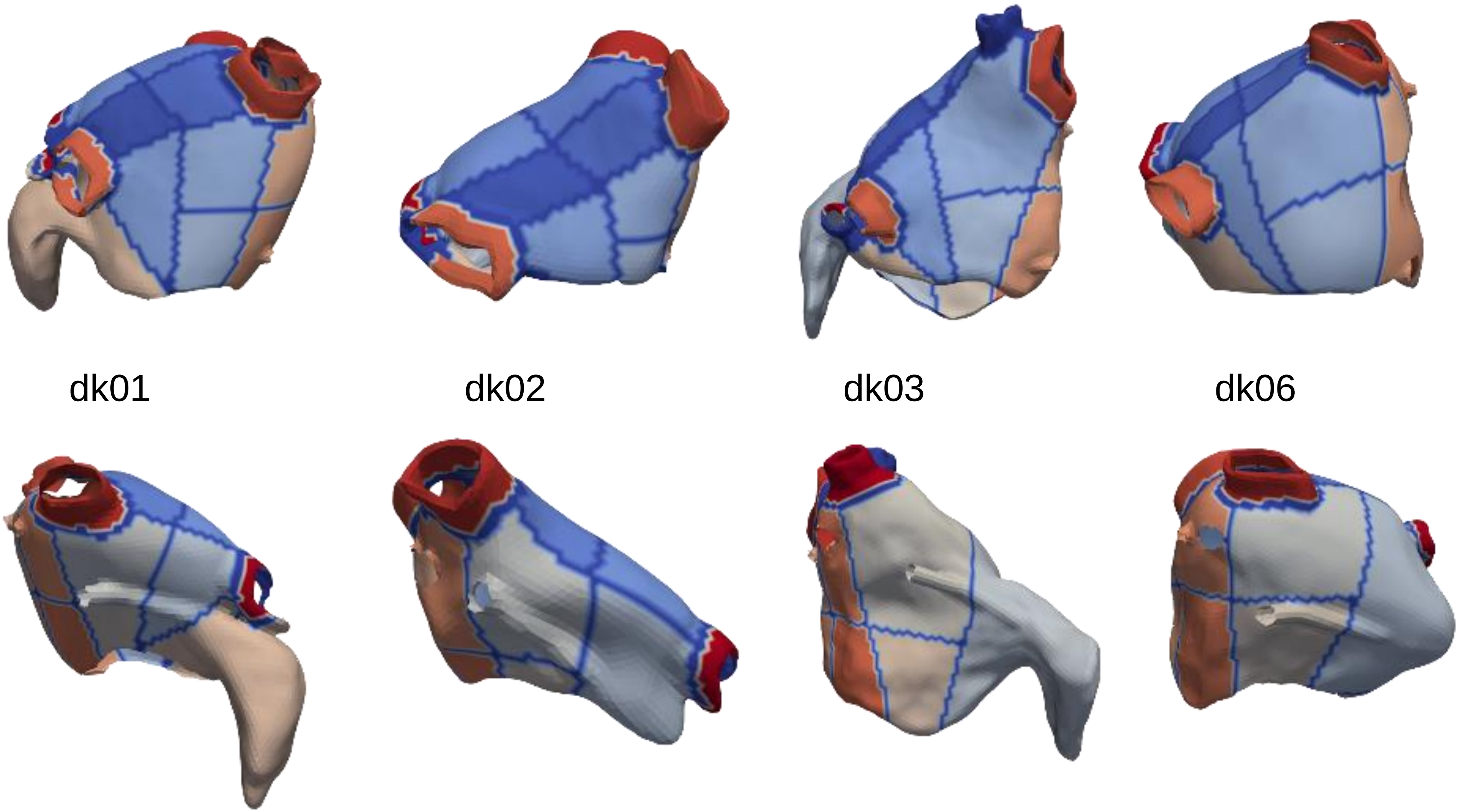


mwk09 mwk07 mwk05 mwk03



Atria Model | Segments creation

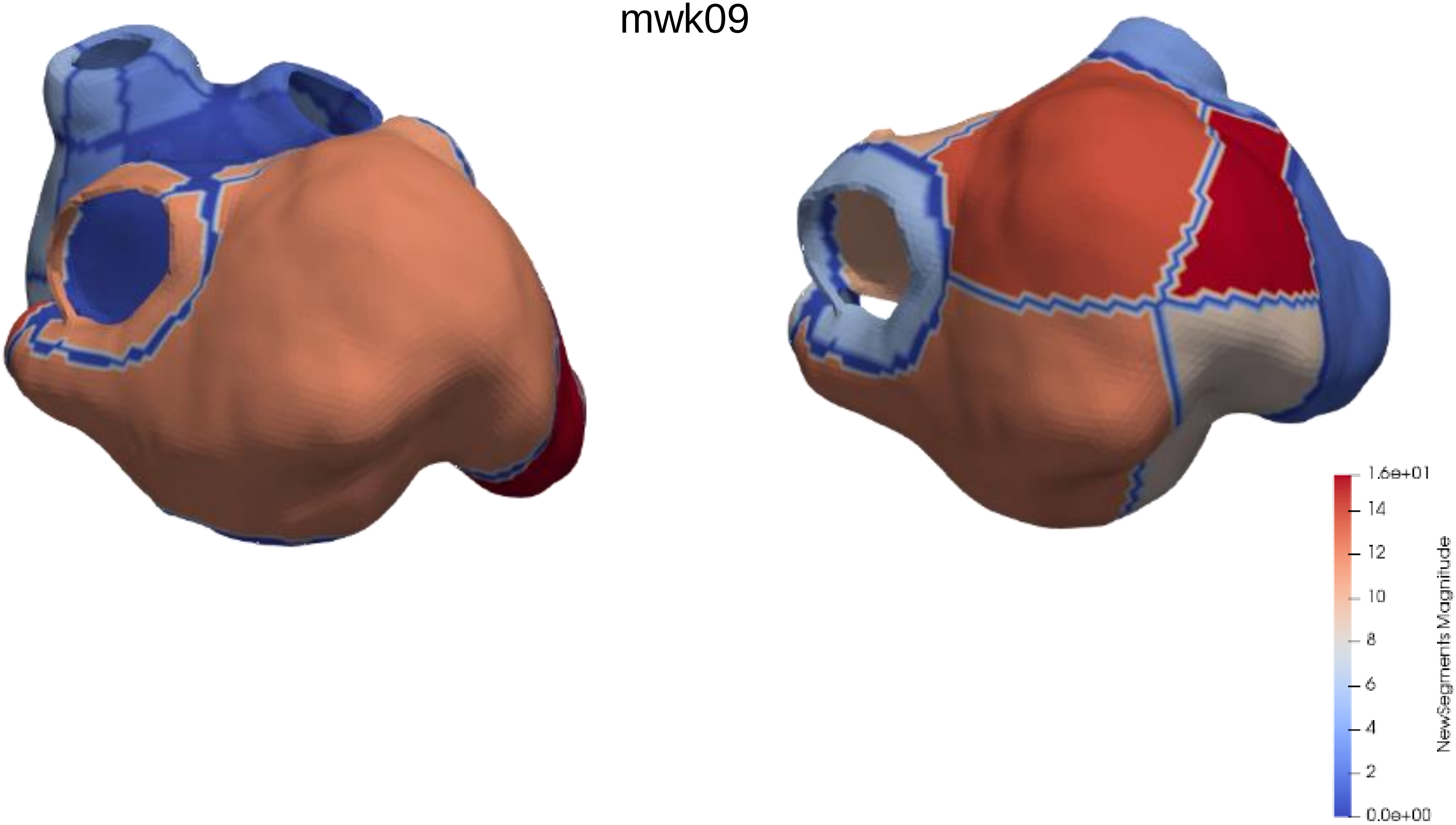
- LA segmentation



Atria Model | Segments creation

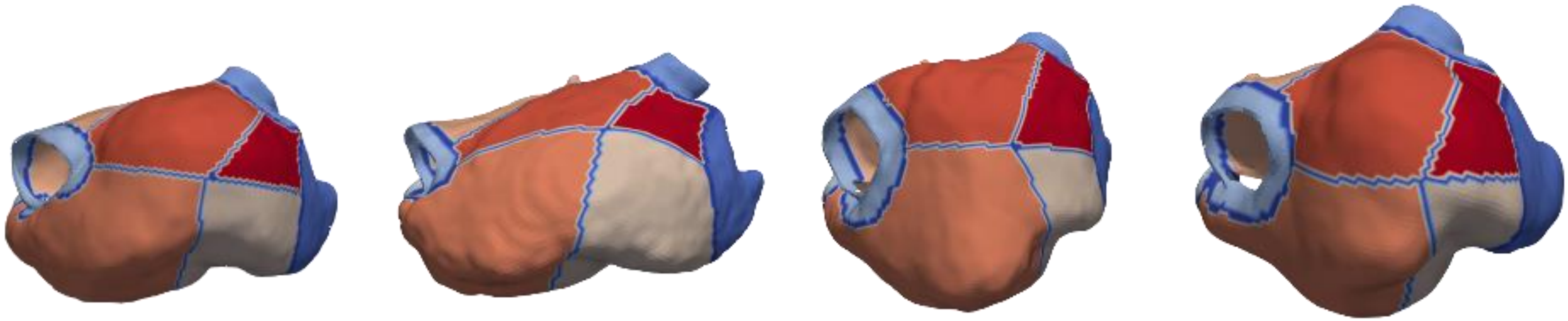
- New segmentation in the RA

mwk09

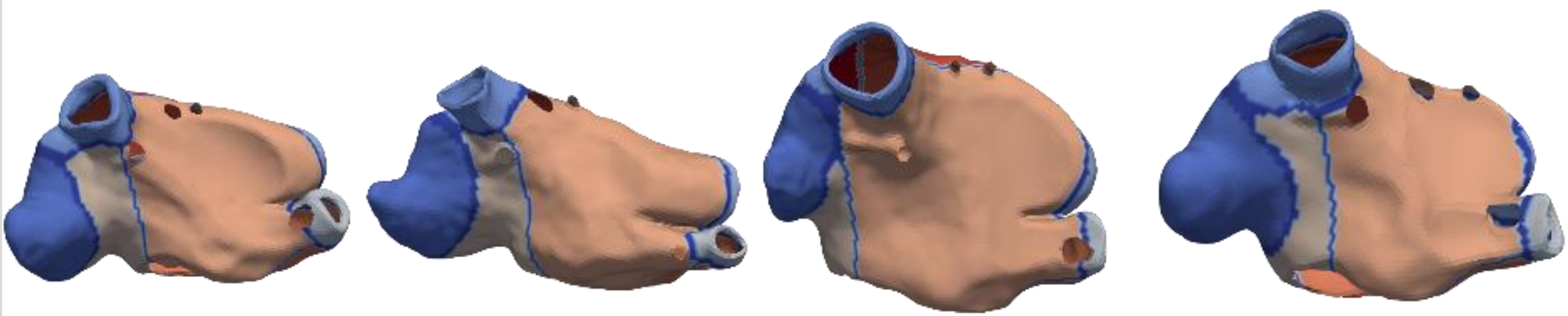


Atria Model | Segments creation

- New segmentation in the RA

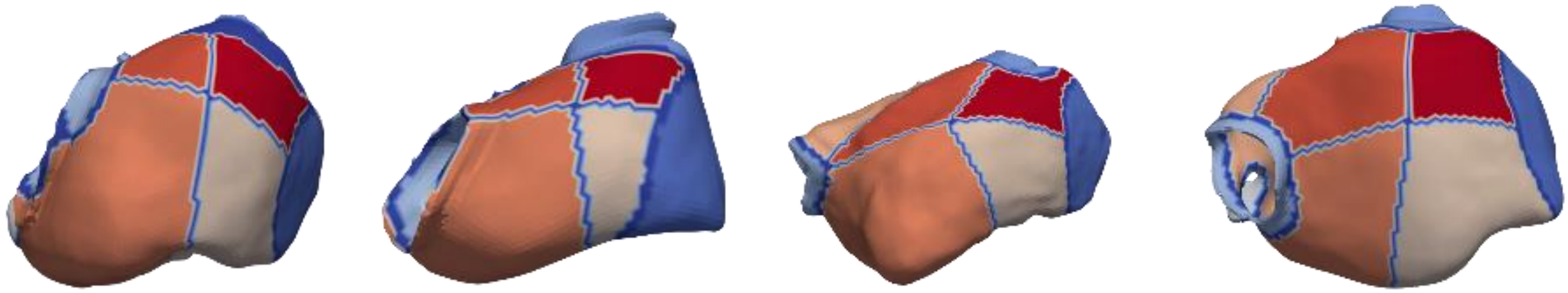


mwk09 mwk07 mwk05 mwk03

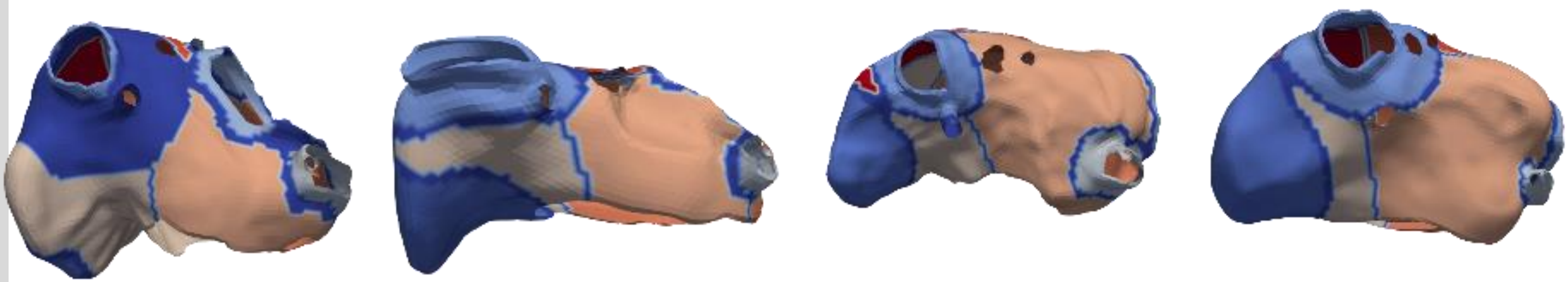


Atria Model | Segments creation

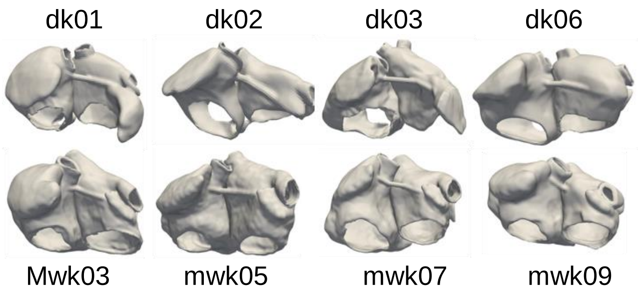
- New segmentation in the RA

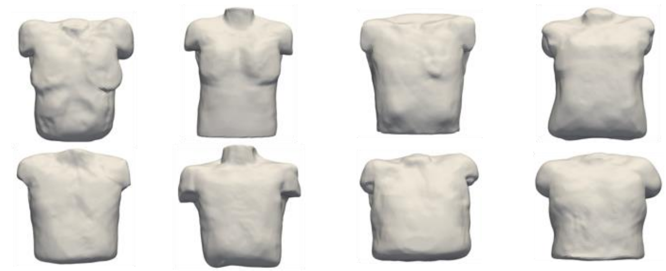


dk01 dk02 dk03 dk06



Simulation | Signal Database





8 * 8 = **64**
Atria-Torso combinations

1 rotation variation

1 translation variation

64 * 1 * 1 =
64
configurations

~200 foci
per
configuration

64 * 200 =
12800
Signals

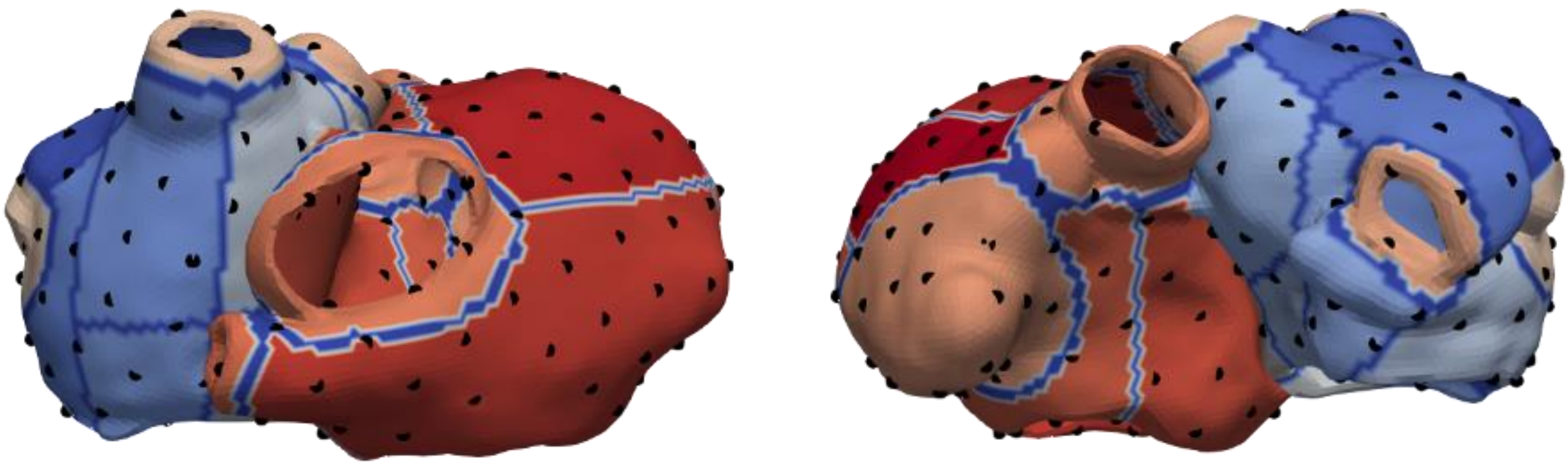
Training Dataset

Validation Dataset

Testing Dataset

Simulation | Fast-marching

- Selection of ~200 ectopic foci per atria model

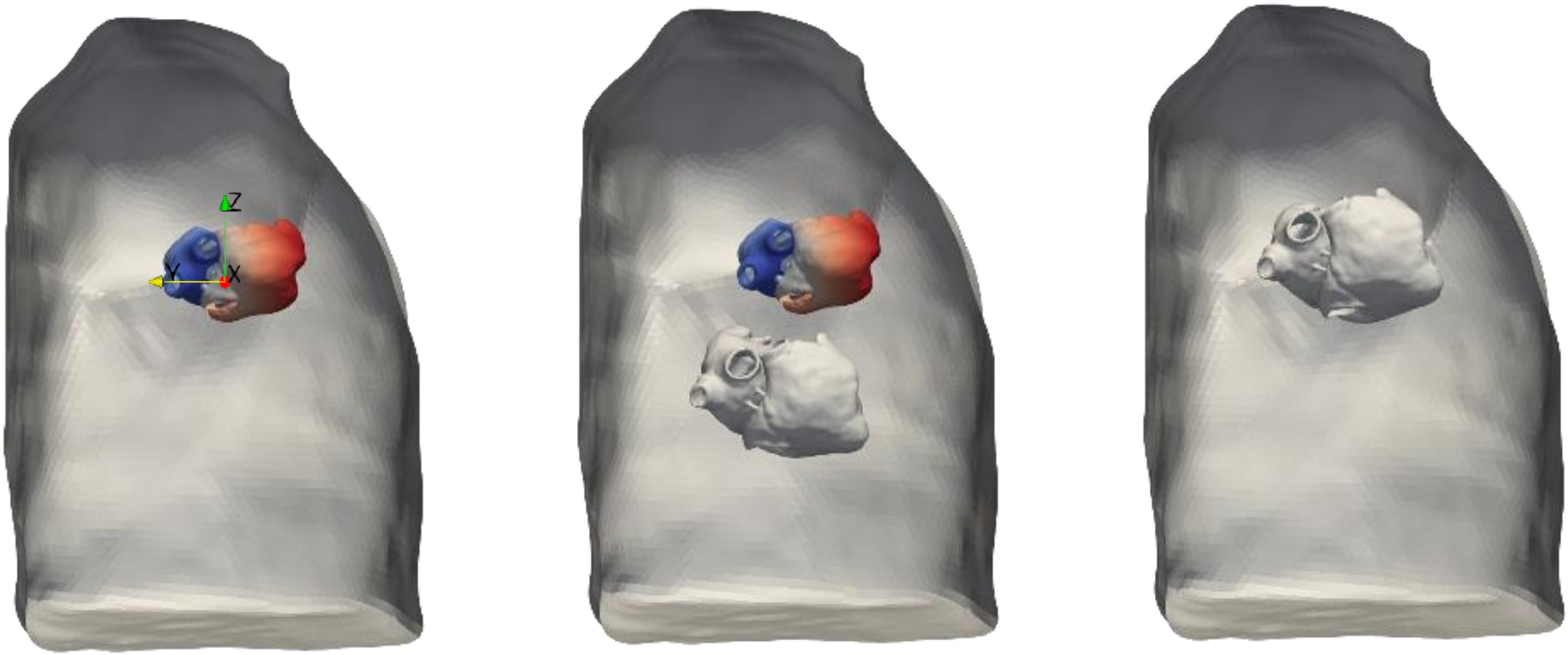


Simulation | Torso Model

- We decided to work with an **homogeneous torso**
- If the initial classification is successfully, a heterogeneous torso could be used to improve it.

Simulation | Atria-Torso combinations

- Calculation of the torso's centre of mass for the correct placement of atria

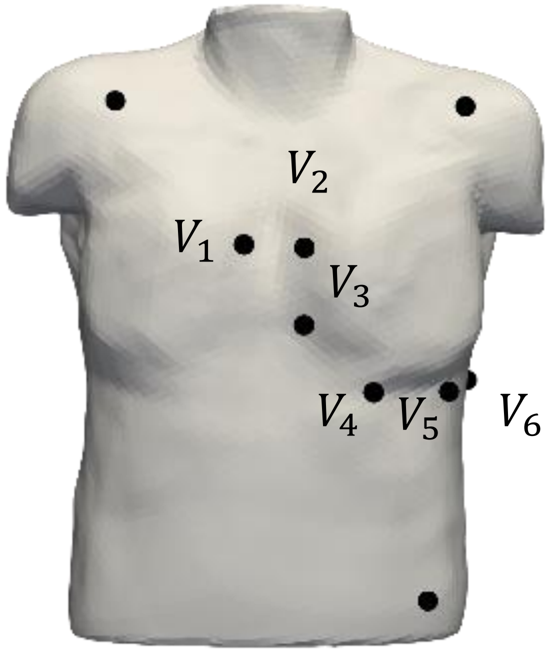


Simulation | Atria-Torso combinations

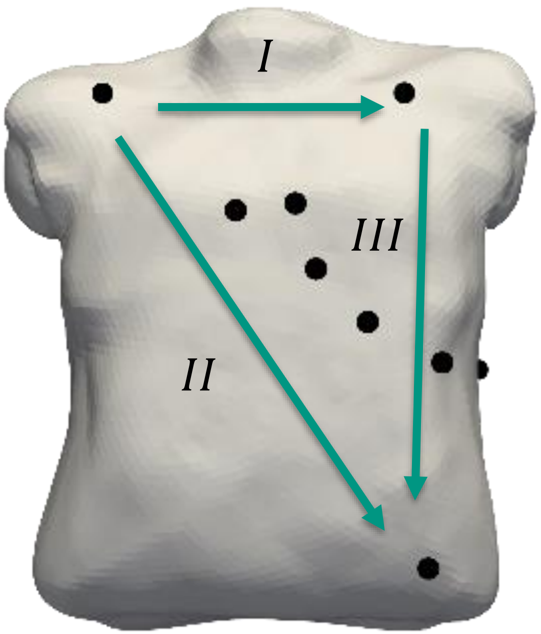
- The torso is fixed and the atria changes around it.
- Equally distributed translations (y: 0…20 mm | x,z: −10…10 mm)
- Equally distributed rotations around (x,y,z: −10…10°)

Simulation | 12-lead ECG

- Use of 9-electrode ECG + calculation of augmented limb leads (aVL, aVR, aVF)



precordial electrodes



limb leads

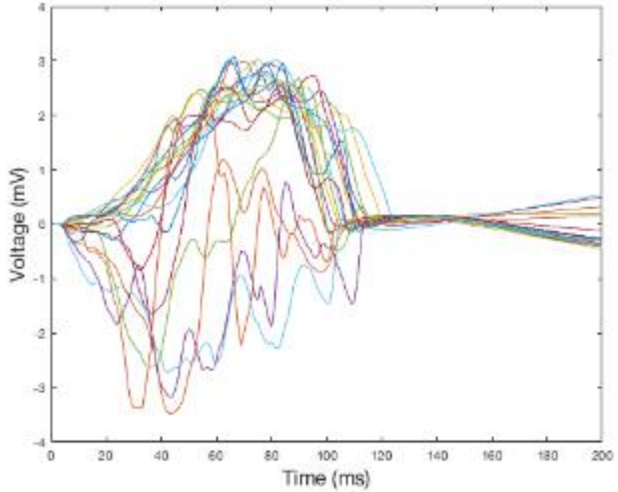
$$aVL = LA - (1/2)(RA + LL)$$

$$aVR = RA - (1/2)(LA + LL)$$

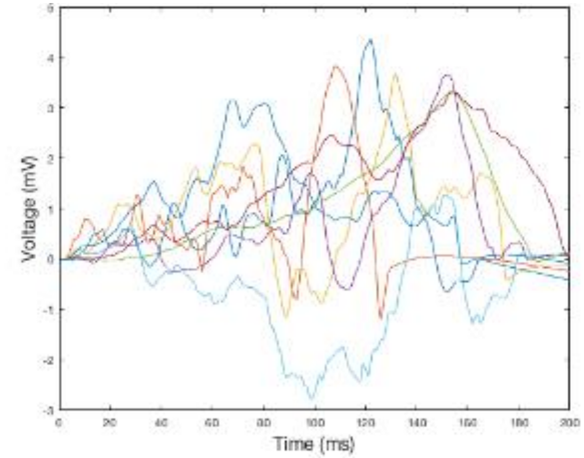
$$aVF = LL - (1/2)(RA + LA)$$

Simulation | 12-lead ECG

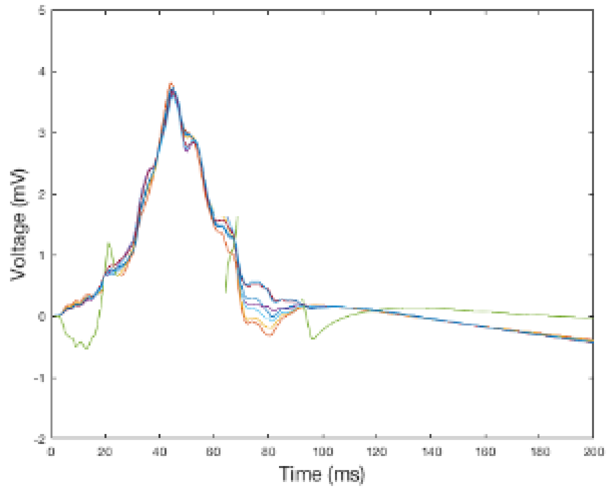
Multiple triggers in one atria-torso combination



One foci in the same atria but different torsos

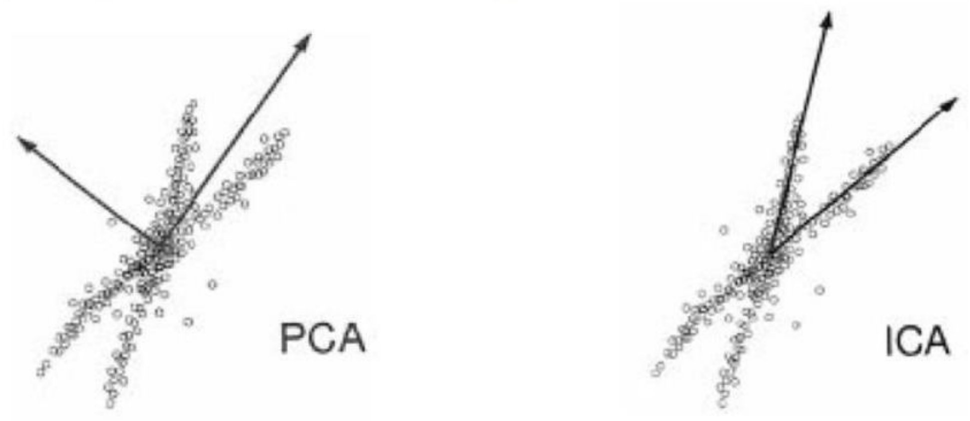


One foci in the same torso but different atrias



Feature extraction | PCA vs Fast-ICA

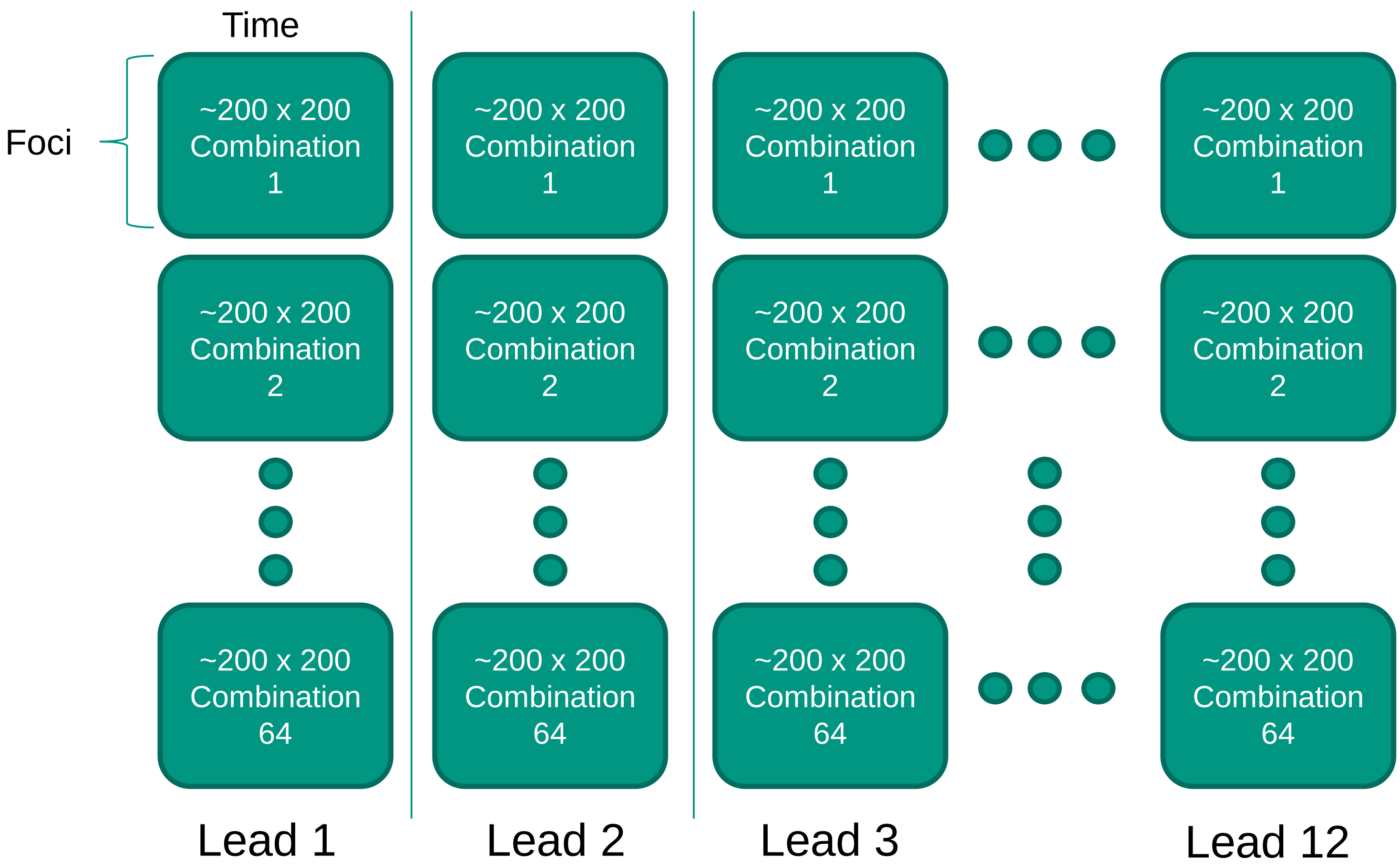
- Simple synthetic data example:



- PCA aims to **de-correlating** observables (second order statistics)
- ICA aims at **independence** (including higher order moments)

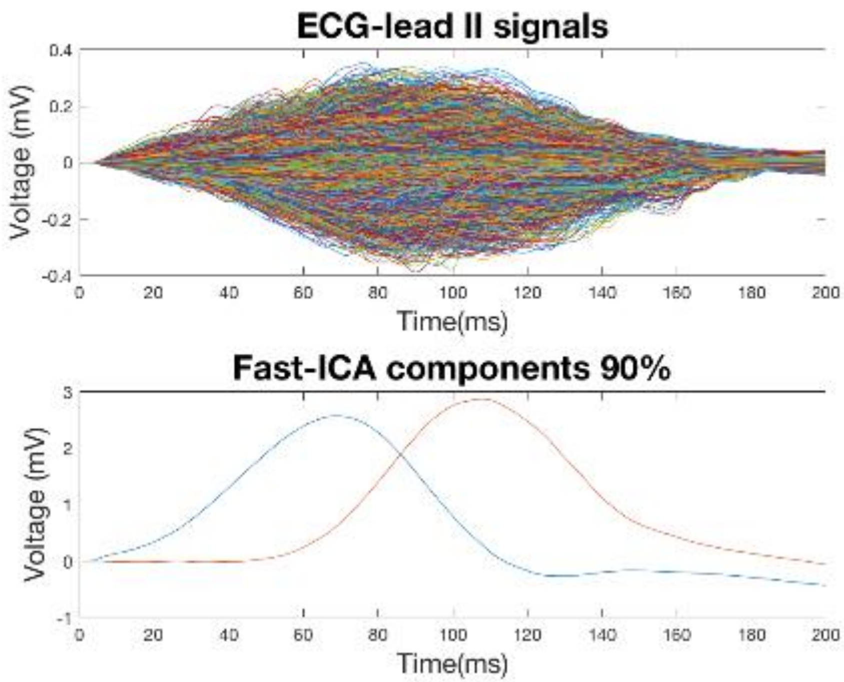
Feature extraction | **Fast-ICA**

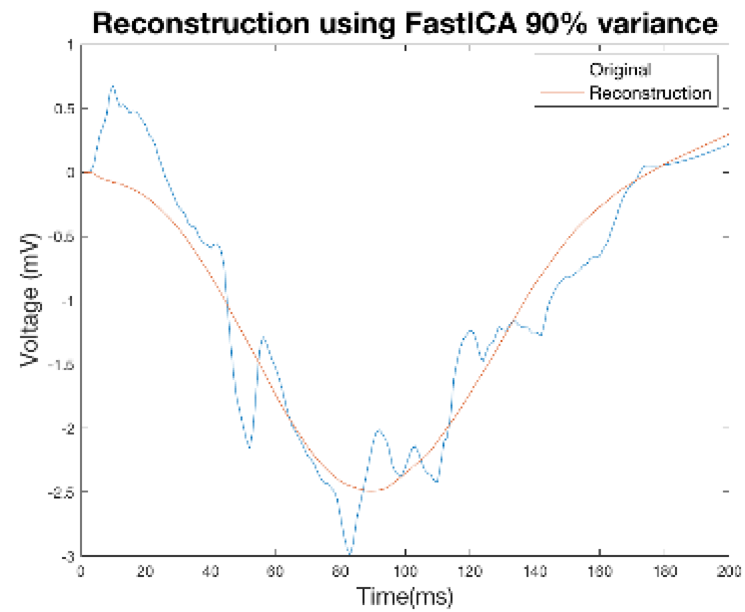
- The goal of FastICA is to rotate your data so that each axis looks as non-Gaussian as possible.



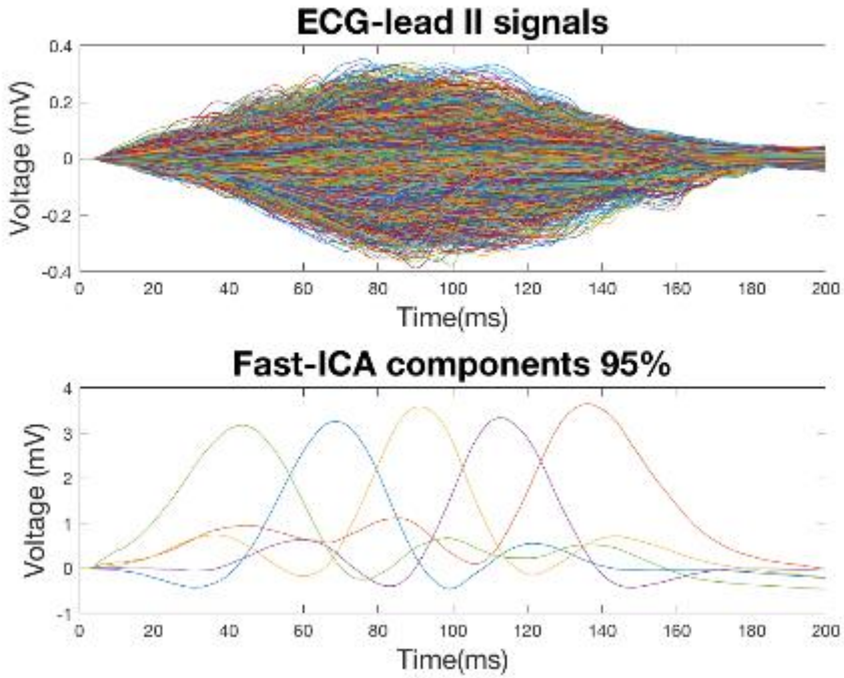
Feature extraction | Fast-ICA 90% variance

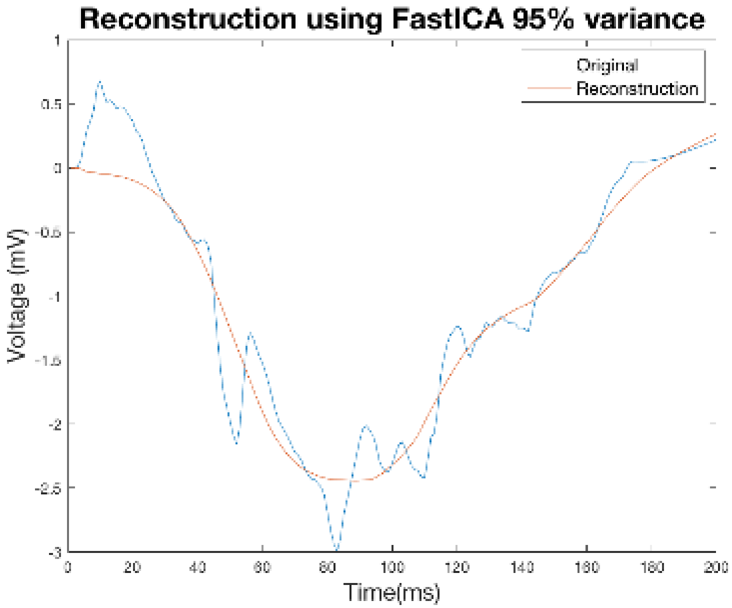
- Variance selection for signal reconstruction





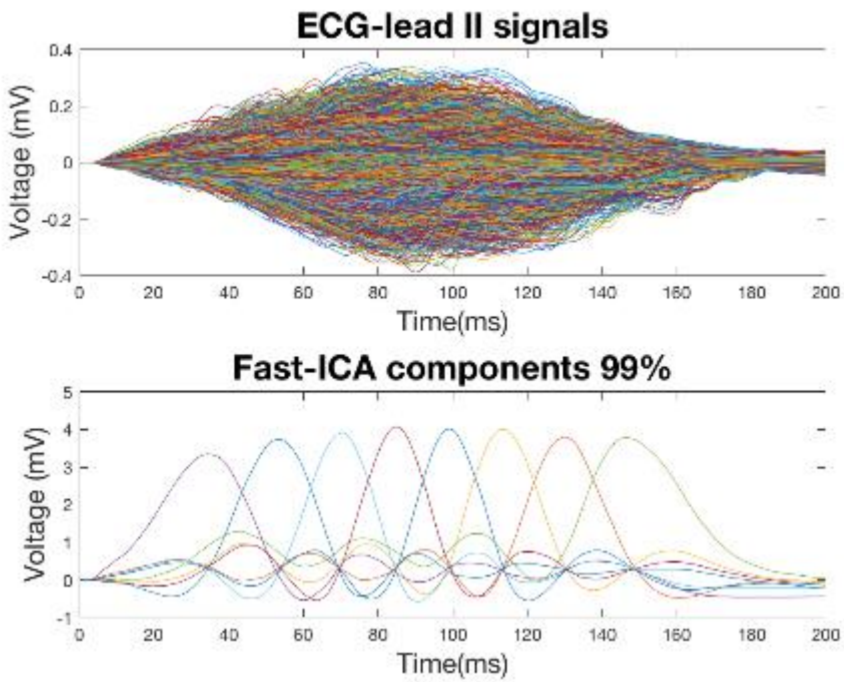
- Variance selection for signal reconstruction

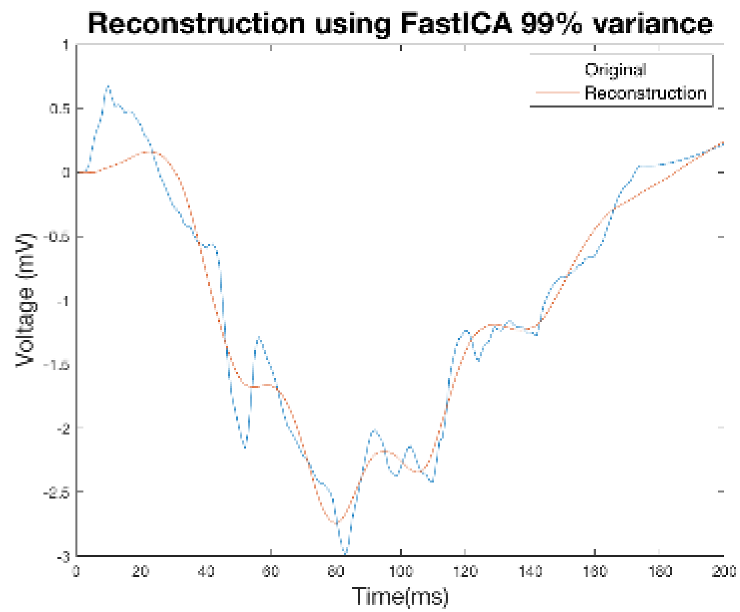




Feature extraction | **Fast-ICA 99% variance**

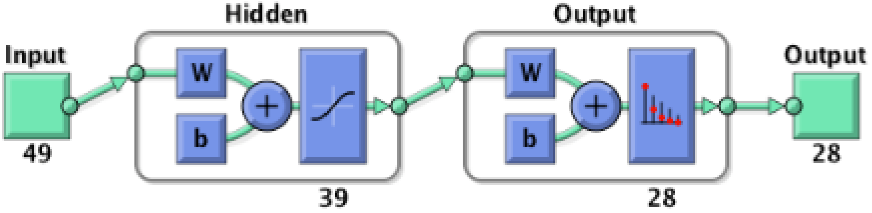
- Variance selection for signal reconstruction





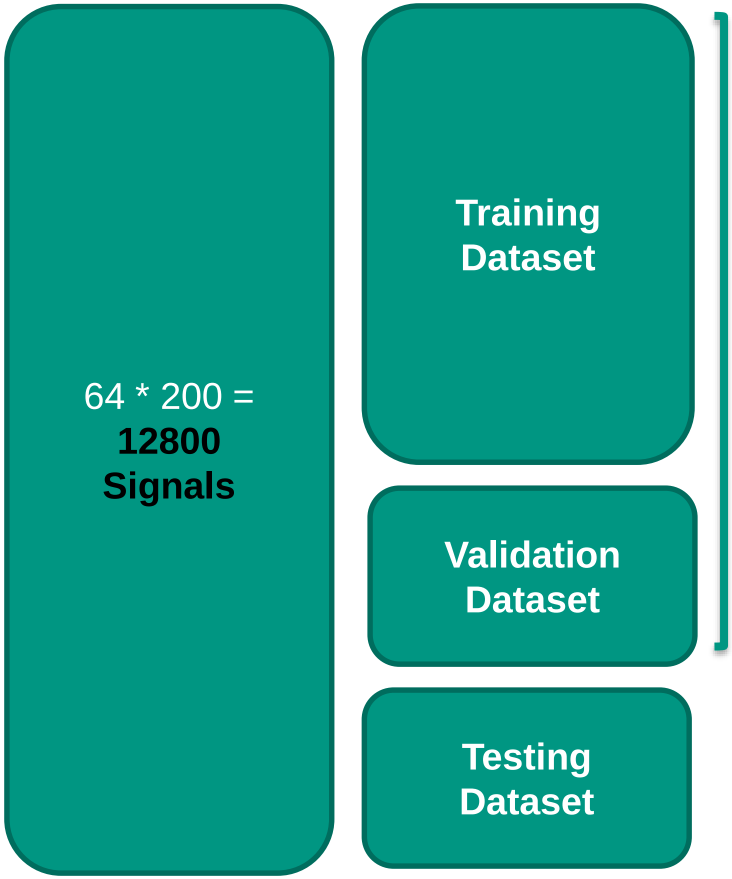
Classification | Neural Network

- **Feedforward networks** consist of a series of layers
- Feedforward networks can be used for any kind of input to output mapping



- A feedforward network with one **hidden layer** and enough neurons in the hidden layers, can fit finite input-output mapping problem

Classification | Neural Network



- **Training**: These are presented to the network during training, and the network adjusted according to ist error.
- **Validation**: These are used to measure network generalization, and to halt training when generalization stops improving.
- **Testing**: These have no effect on training and so provide and independent measure of network performance during and after training

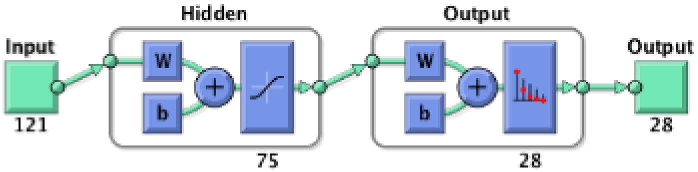
Classification | Overfitting

- Improving the network's ability to generalize helps prevent **overfitting**
- Overfitting occurs when a network **has memorized the training set** but has not learned to generalize to new inputs.
- Overfitting produces a relatively **small error on the training** set but a much **larger error** when **new data** is presented to the network
- **Early stopping** uses two different data sets: the **training set**, to update the weights and biases, and the **validation set**, to stop training when the network begins to overfit the data.

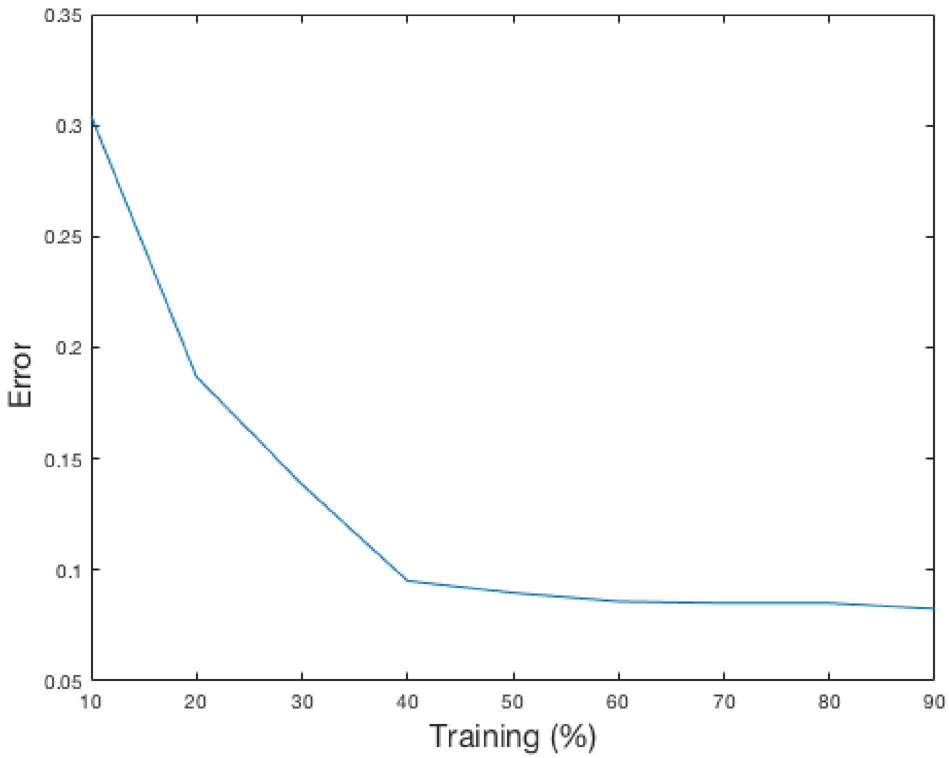
Classification | Error vs training database size

- To avoid overfitting, the **percentage** used on the Training, Validation and Test is important.

- FastICA 99%
- 75 Hidden neurons



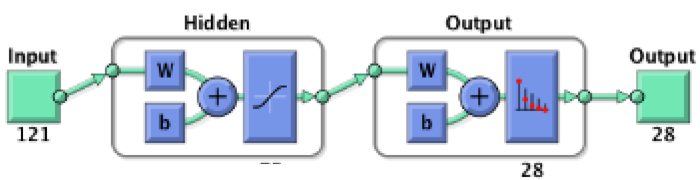
Average error (training, validation, test) vs training size



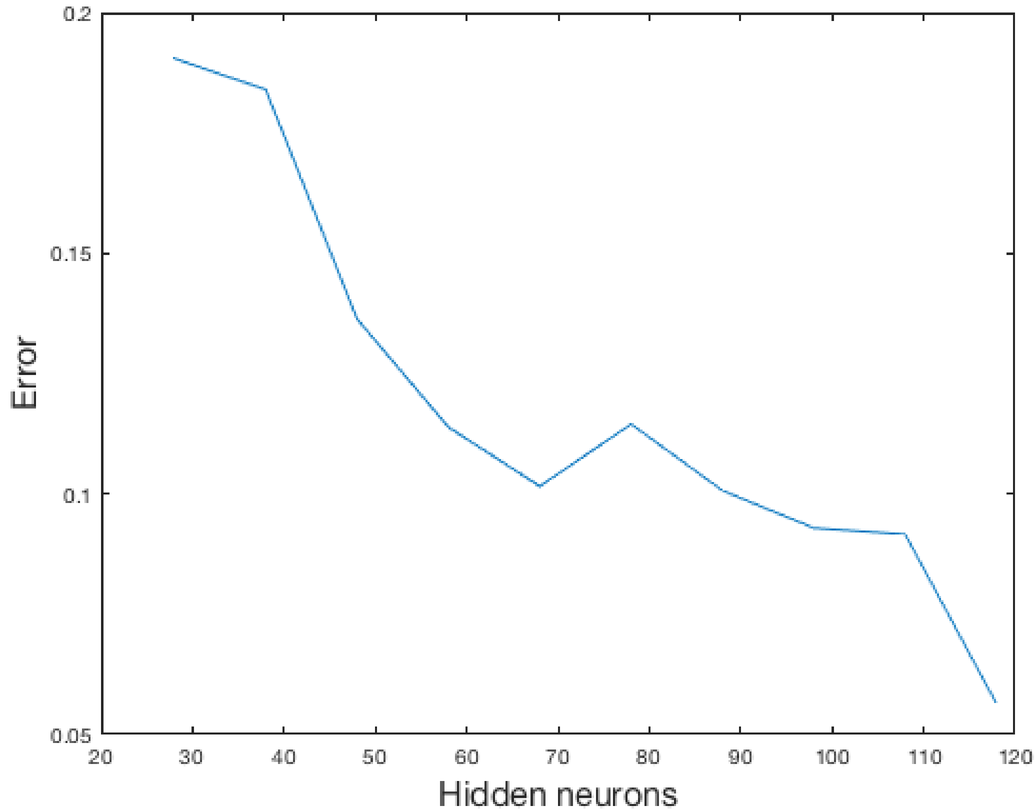
Classification | Error vs hidden neurons

- To avoid overfitting, the number of **hidden neurons** should be between the number of features and the number of classes

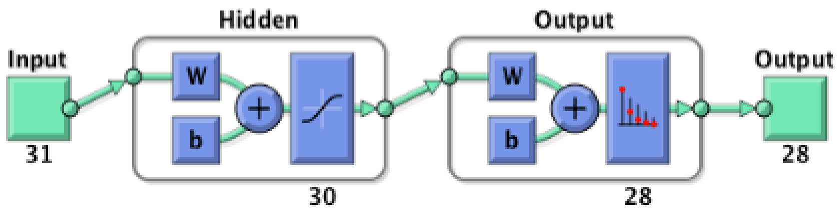
- FastICA 99%
- 60% Training
- 20% Validation
- 20% Testing



Average error (training, validation, test) vs hidden neurons

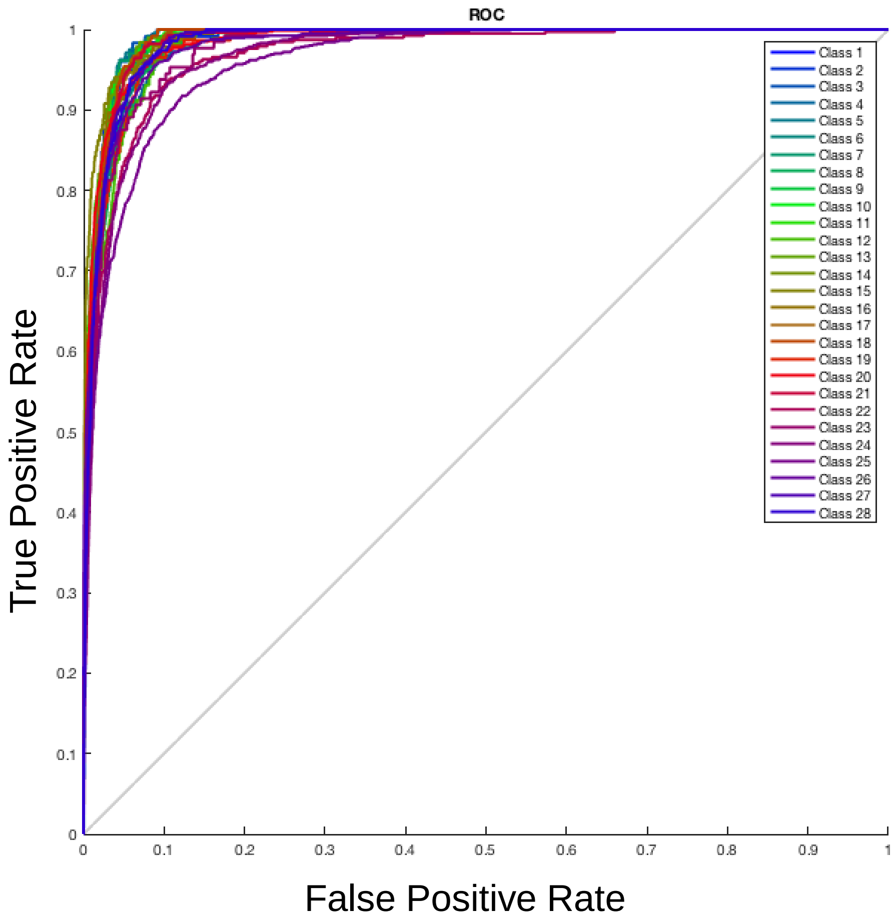


Classification | Neural Network PCA 90%

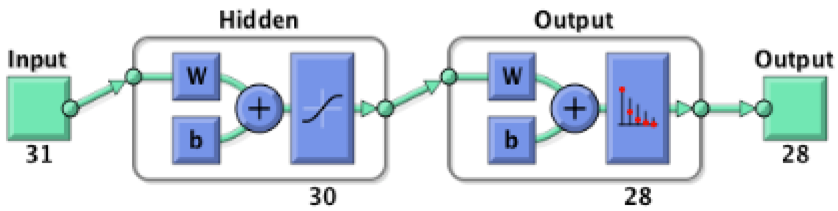


$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

Testing Accuracy
70.1 %

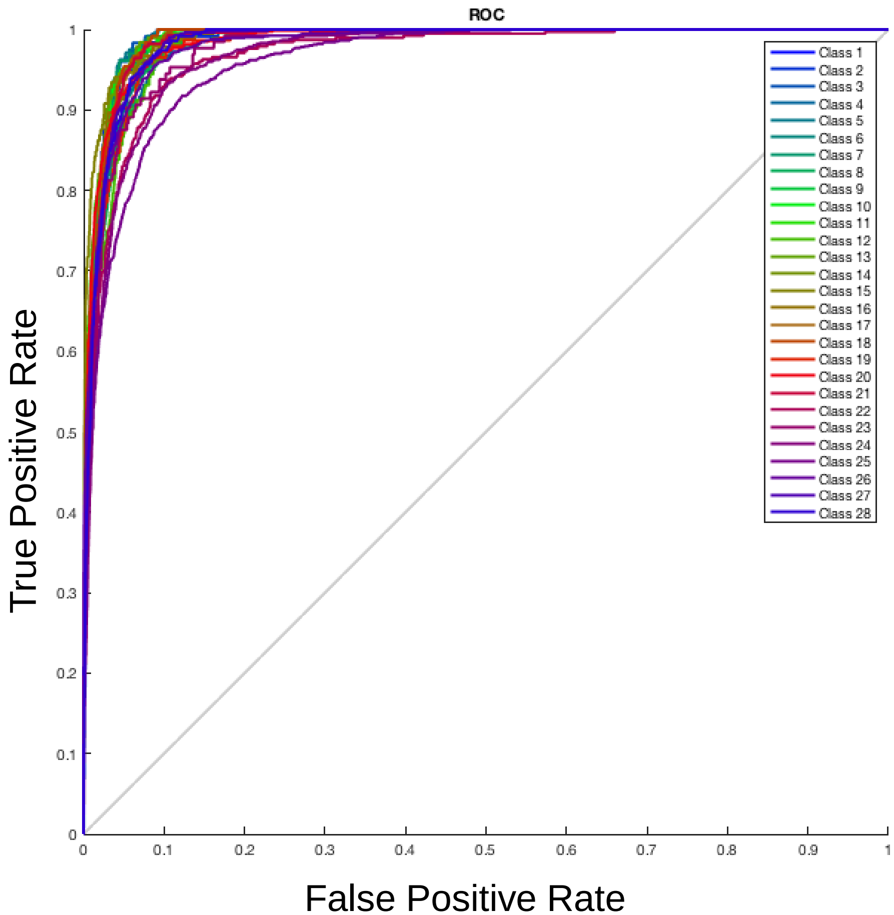


Classification | Neural Network Fast-ICA 90%

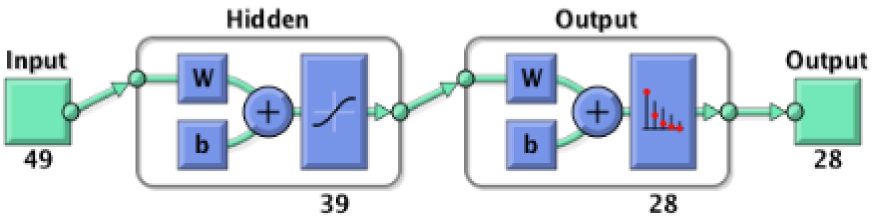


$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

Testing Accuracy
71.4 %

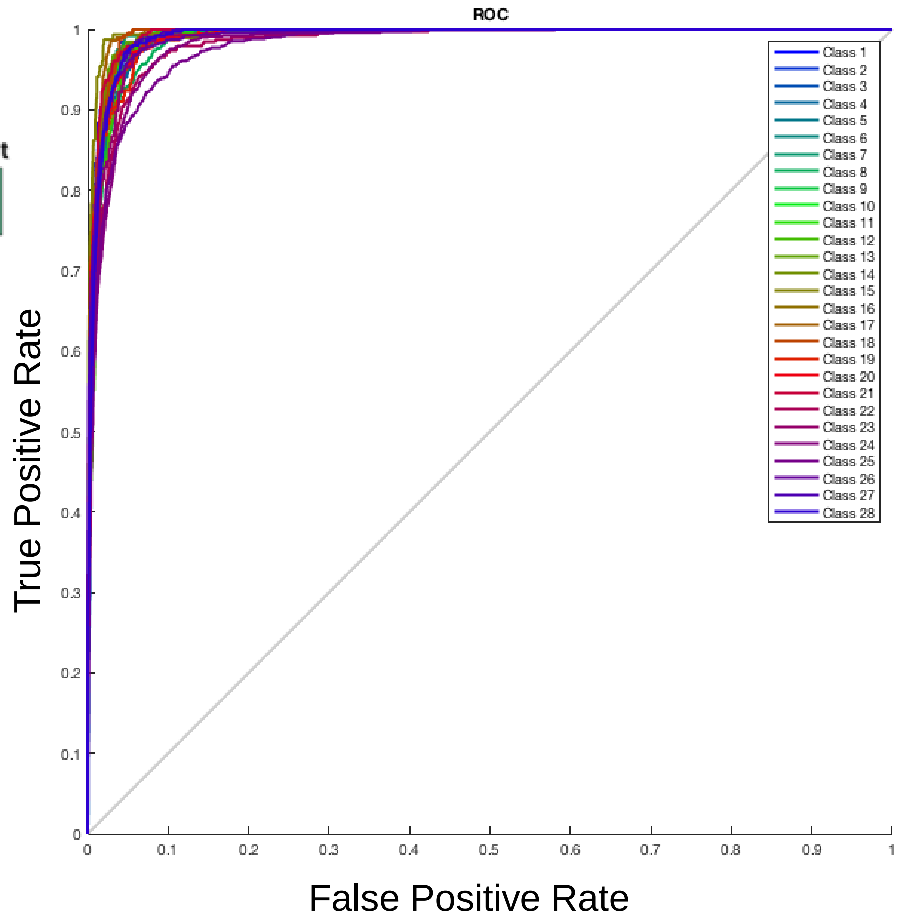


Classification | Neural Network PCA 95%

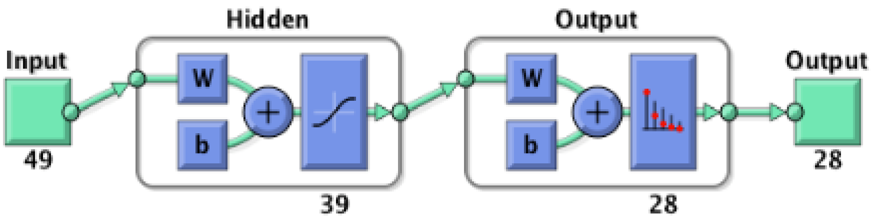


$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

Testing Accuracy
73.2 %

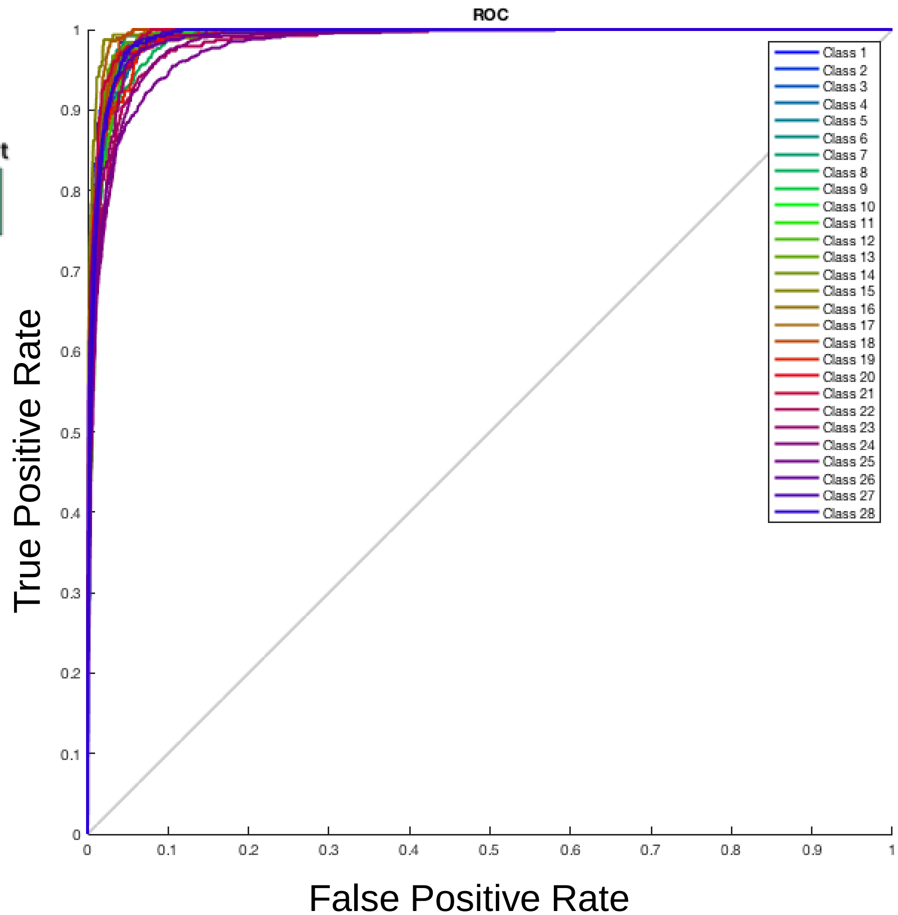


Classification | Neural Network Fast-ICA 95%

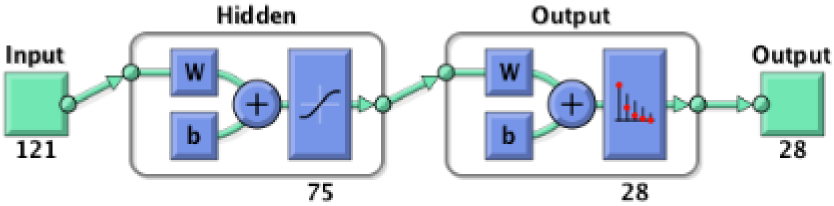


$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

Testing Accuracy
75.2 %

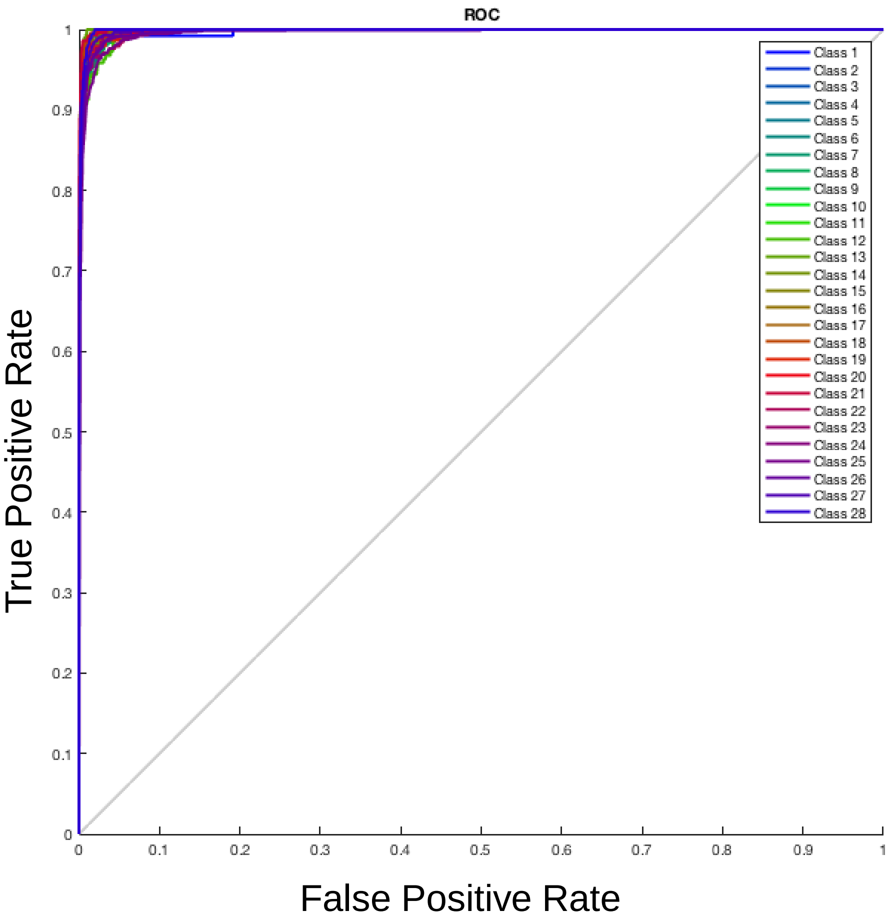


Classification | Neural Network PCA 99%

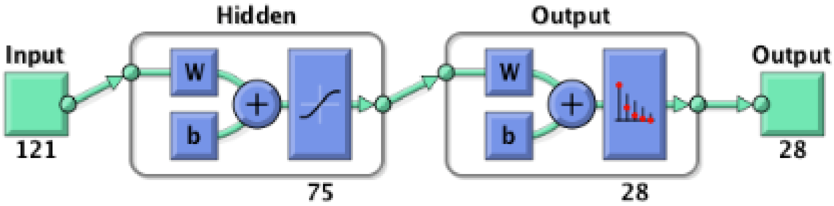


$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

Testing Accuracy
82.2 %

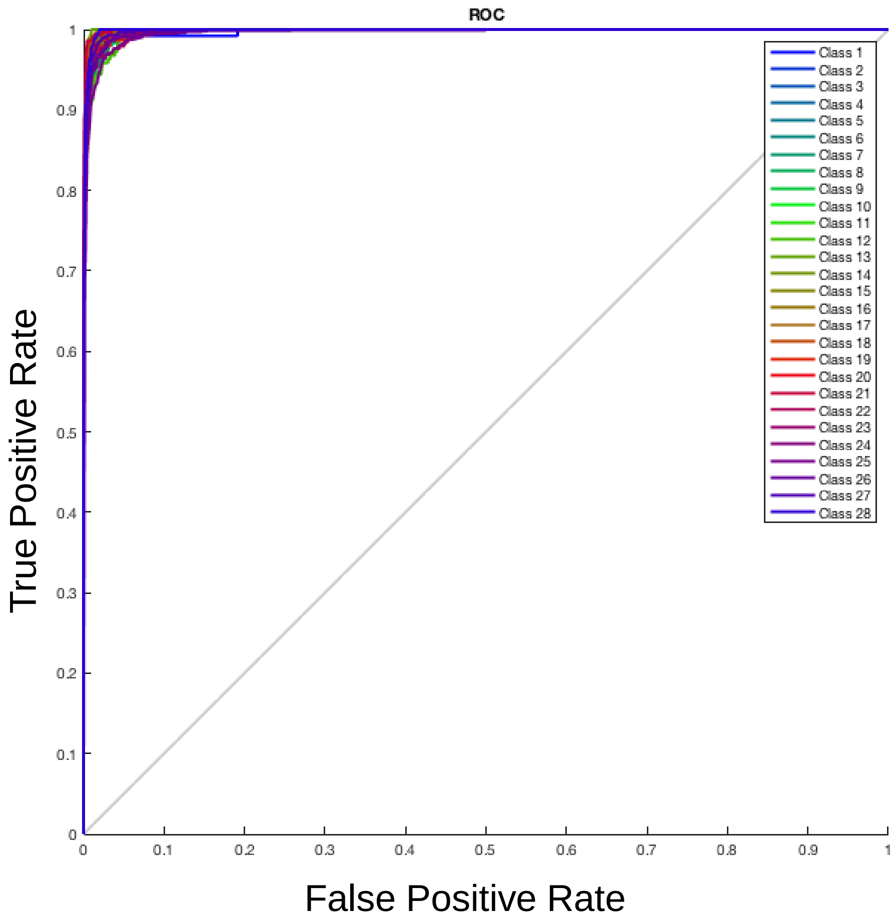


Classification | Neural Network Fast-ICA 99%



$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

Testing Accuracy
86.2 %



Classification | Results interpretation

- Geometrical interpretation

Left Atrium

1	2	3	4	5	6	7	8	9	10	11	12	13	14
76.7%	79.5%	77.3%	81.5%	82.5%	82.4%	83.2%	87.5%	90.9%	85.0%	90.0%	72.7%	87.5%	79.3%
23.3%	20.5%	22.7%	18.5%	17.5%	17.6%	16.8%	12.5%	9.1%	15.0%	10.0%	27.3%	12.5%	20.7%

Pulmonary veins wall

LA Appendix

Right Atrium

Pulmonary veins

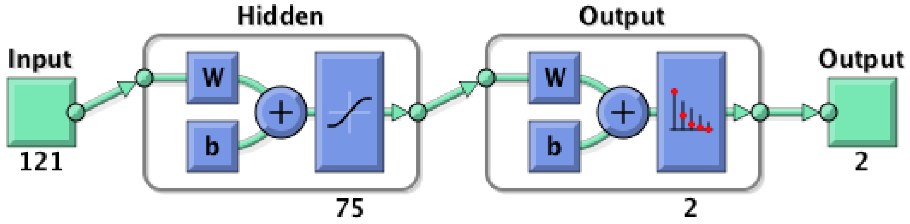
15	16	17	18	19	20	21	22	23	24	25	26	27	28
84.2%	87.0%	89.0%	80.8%	70.1%	92.9%	90.7%	73.1%	74.2%	93.3%	85.6%	91.7%	90.9%	89.2%
15.8%	13.0%	11.0%	19.2%	29.9%	7.1%	9.3%	26.9%	25.8%	6.7%	14.4%	8.3%	9.1%	10.8%

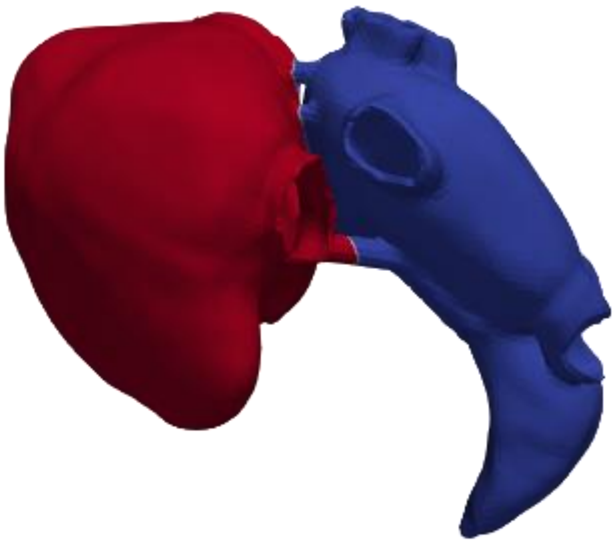
RA Appendix

RA Posterior wall

Classification | Neural Network Left vs Right

- It is also desirable to know the Accuracy of the NN when the classification of Left and Right atriums.

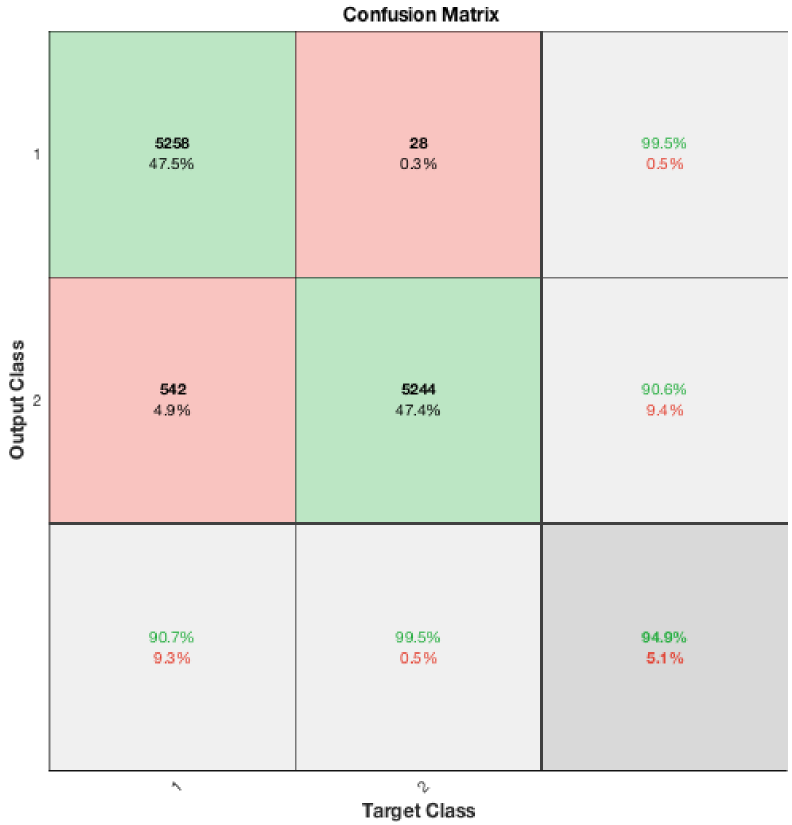


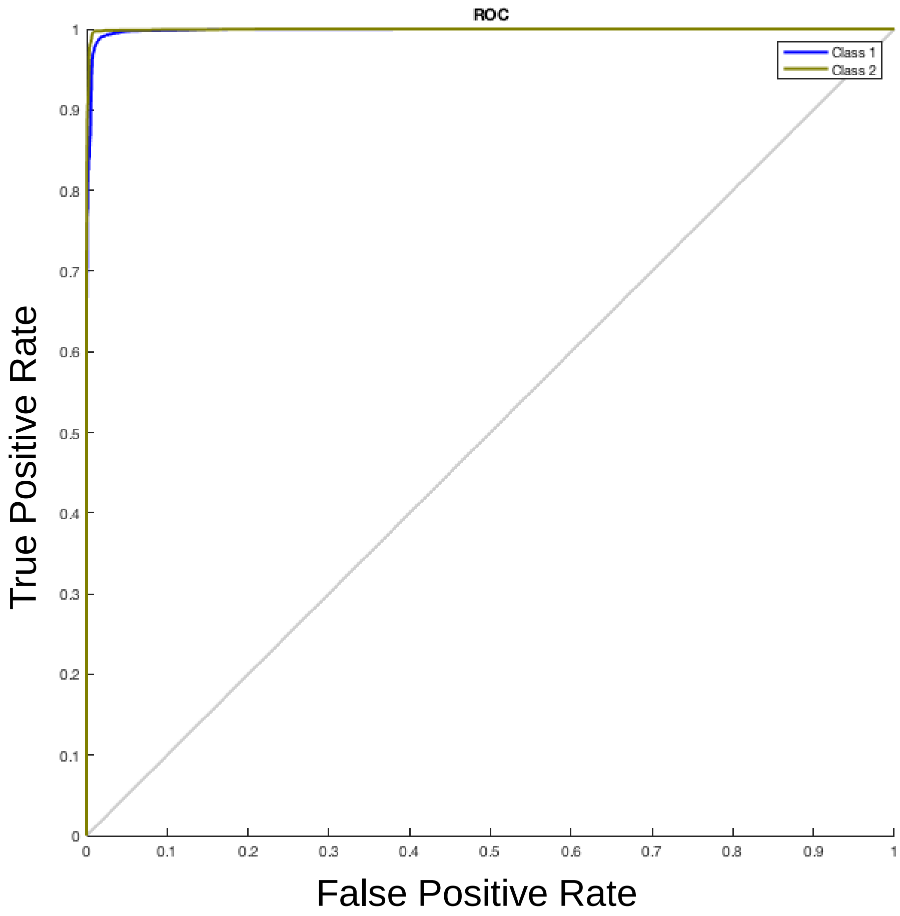


- Fast-ICA 99%
- Random division: 60% Training, 20% Validation, 20% Testing

Classification | Neural Network Left vs Right

- Results



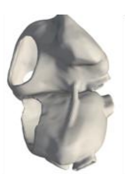


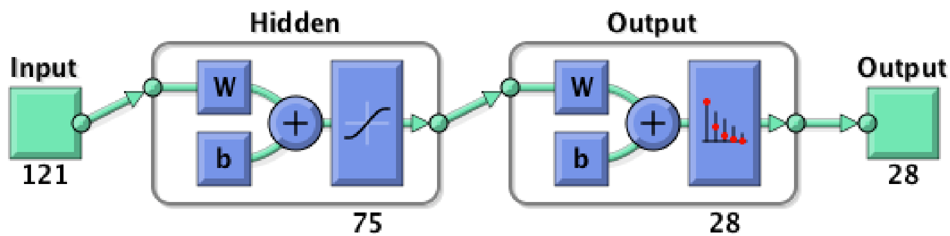
- Using all the atria models to Training and Validating, except one, which is used as Testing

Training Dataset

Validation Dataset

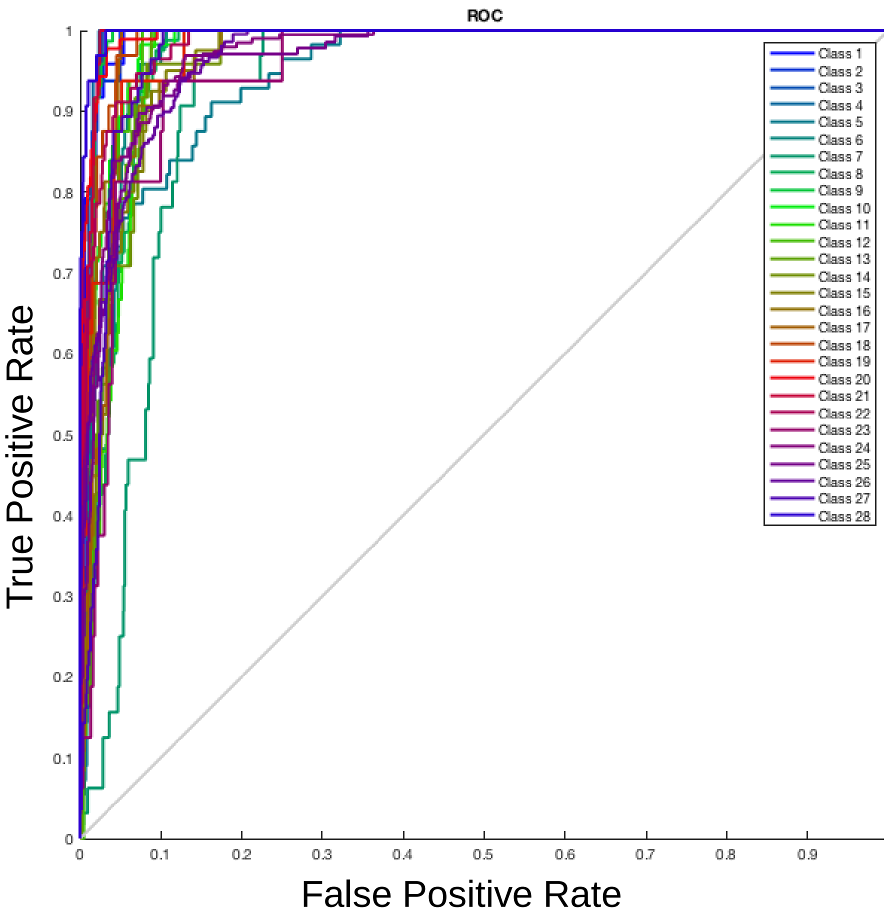
Testing Dataset





Classification | Neural Network – Atria Model

- The Accuracy is worse compared with the random data division



	dk06	mwk03	mwk05	mwk07
Acc	49.8 %	35.2 %	56.1 %	53.3 %

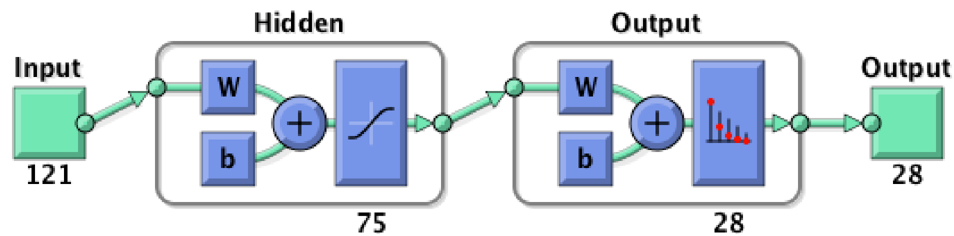
Classification | Neural Network – Torso Model

- Using all the torso models to Training and Validating, except one, which is used as Testing

Training Dataset

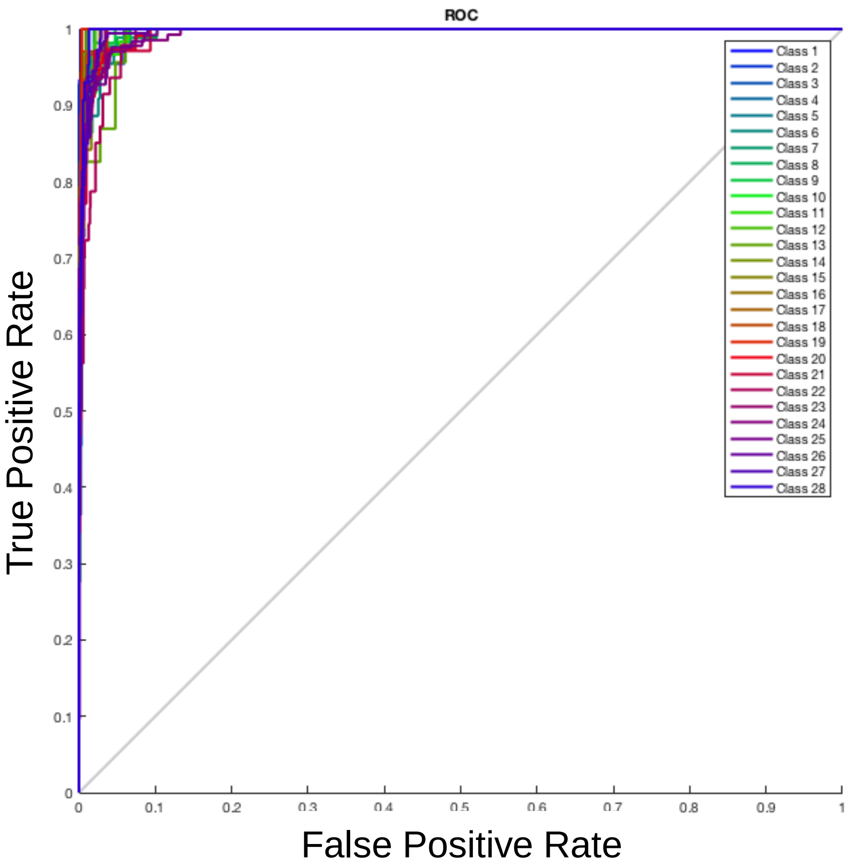
Validation Dataset

Testing Dataset



Classification | Neural Network – Torso Model

- The Accuracy is the same as the one with the random data division



	dk01	dk02	dk03	dk06
Acc	85.2 %	84.1 %	80.3 %	81.6 %

Conclusions

- Classification depends more on **atria** than on torso models
- Classification performs better in **larger segments** and in the ones with **more distance to the Septum**
- **RA segments** are better to classify than LA ones
- Classification performs better on **Fast-ICA** features than on PCA
- Classification performs better on **higher variance features**
- **RA and LA** are correctly differentiated in most of the cases
- **RA and LA appendices** are found with high accuracy
- **Pulmonary veins** and the space between them are the segments with worst classification

Conclusions

- **Geometrical aspects**:
  - Classification depends more on **atria** than on torso models
  - Classification performs better in **segments** with **more distance to the Septum**
  - **RA and LA** are correctly differentiated in most of the cases
  - **RA and LA appendices** are found with high accuracy
  - **Pulmonary veins** and the space between them are the segments with worst classification
- **Classification aspects**
  - Classification performs better in **larger segments**
  - Classification performs better on **Fast-ICA** features than on PCA
  - Classification performs better on **higher variance features**

Conclusions | Future work

- Definition of **larger segments** on LA
- Addition of **probabilities to the input segments**
- **More triggers**
- **More rotations and translations**
- **More or different features**
- **Heterogeneous torso**
- **Excitations** with **anisotropic** and **varying conduction velocities**
- If neither of this task improve the classification, **more ECG leads** or **BSPM** should be used

THANKS FOR YOUR ATTENTION

Questions?

INSTITUTE OF BIOMEDICAL ENGINEERING