GEORG-AUGUST-UNIVERSITÄT GÖTTINGEN IN PUBLICA COMMODA SEIT 1737

UNIVERSITÄTSMEDIZIN GÖTTINGEN
Department of Medicial Informatics
UMG

Towards Explaining Decisions of a Deep Learning Model for AF Detection in 12-lead ECGs

Signal-Based Risk Prediction in Cardiovascular Diseases (Joint Session GMDS-DGBMT)
BMT 2022, Innsbruck
September 29th

T. Bender, J. Beinecke, H. Dathe, A. C. Hauschild, D. Krefting, N. Spicher

theresa.bender@med.uni-goettingen.de

https://medizininformatik.umg.eu/

Viewpoint | Diagnostic Excellence

July 8, 2022

Rethinking Algorithm Performance Metrics for Artificial Intelligence in Diagnostic Medicine

Matthew A. Reyna, PhD, MS[1]; Elaine O. Nsoesie, PhD[2]; Gari D. Clifford, DPhil, MA, MSc[1,3]

Author Affiliations | Article Information

JAMA. 2022;328(4):329-330. doi:10.1001/jama.2022.10561

Related Articles

The promise of artificial intelligence (AI) to improve and reduce inequities in access, quality, and appropriateness of high-quality diagnosis remains largely unfulfilled. Vast clinical data sets, extensive computational capacity, and highly developed and accessible machine-learning tools have resulted in numerous publications that describe high-performing algorithmic approaches for a variety of diagnostic tasks. However, such approaches remain largely unadopted in clinical practice.

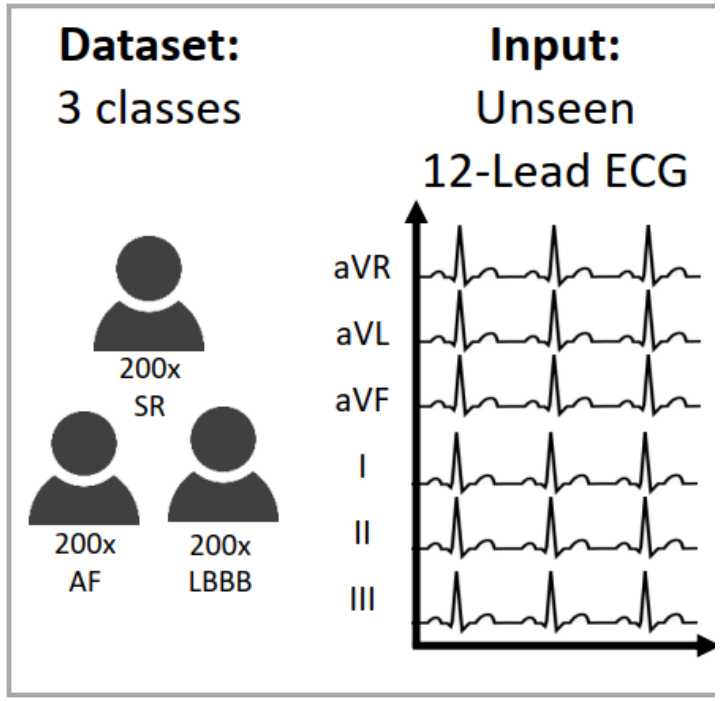
Motivation

One major reason:
Missing explainability

→ Get insights into the reasoning of deep learning models for ECG classification

https://xkcd.com/1838/

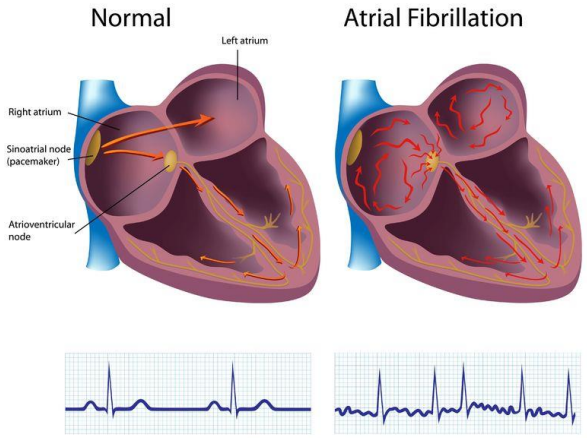
Methods



We analyze two different pathologies (China Physiological Signal Challenge 2018):

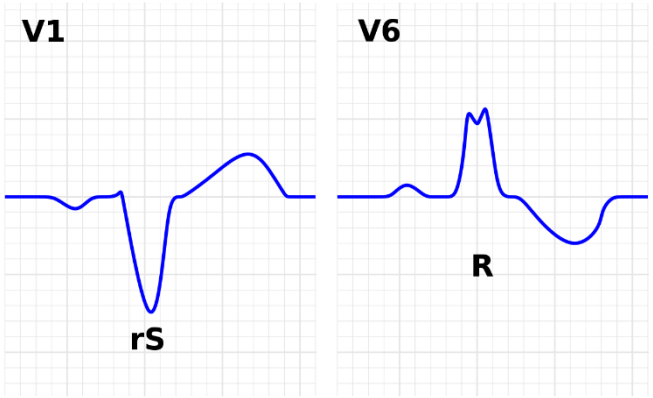
- Atrial Fibrillation: Defined by arrhythmic distances between R-waves, no P-waves as the SA node is not working
- Left Bundle Branch Block: Defined by abnormal shape of QRS-complexes

AF: *Can be identified using multiple beats only*



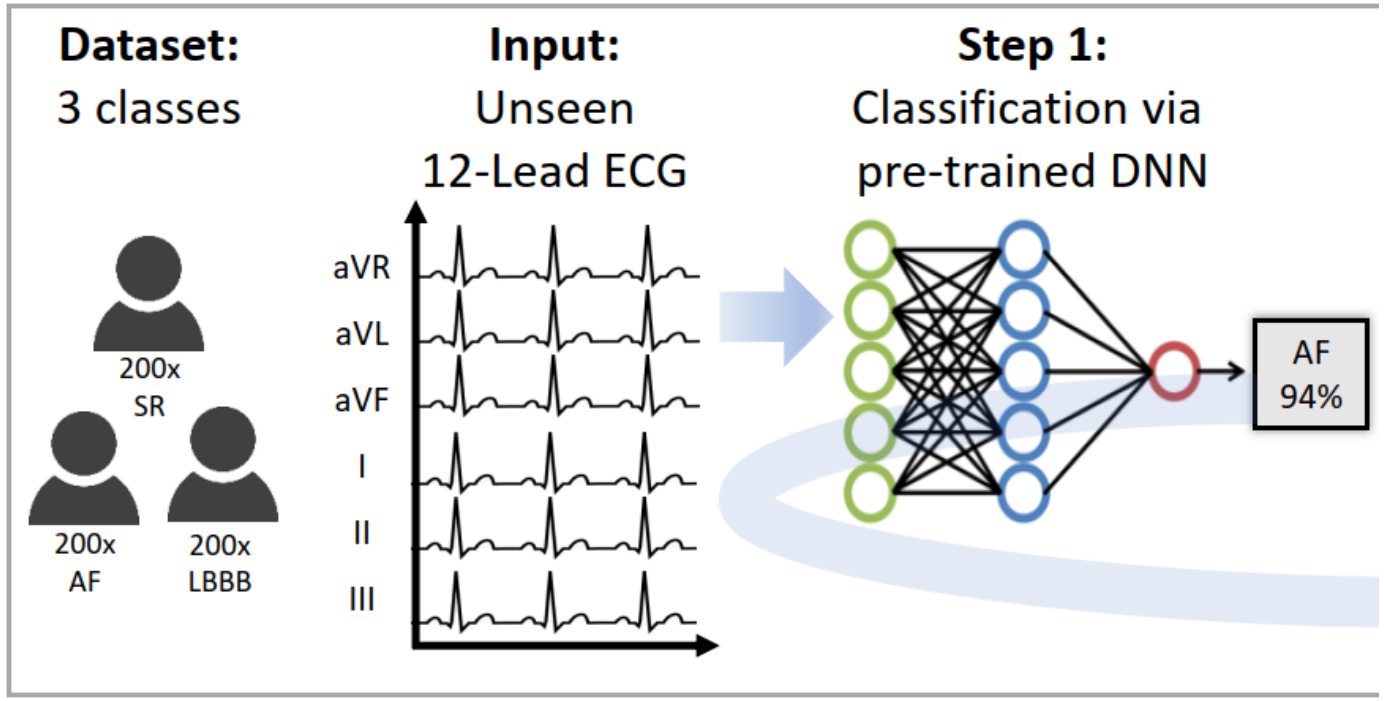
https://www.secondscount.org/heart-condition-centers/info-detail-2/what-is-atrial-fibrillation-afib-af

LBBB: *Can be identified from a single heartbeat*

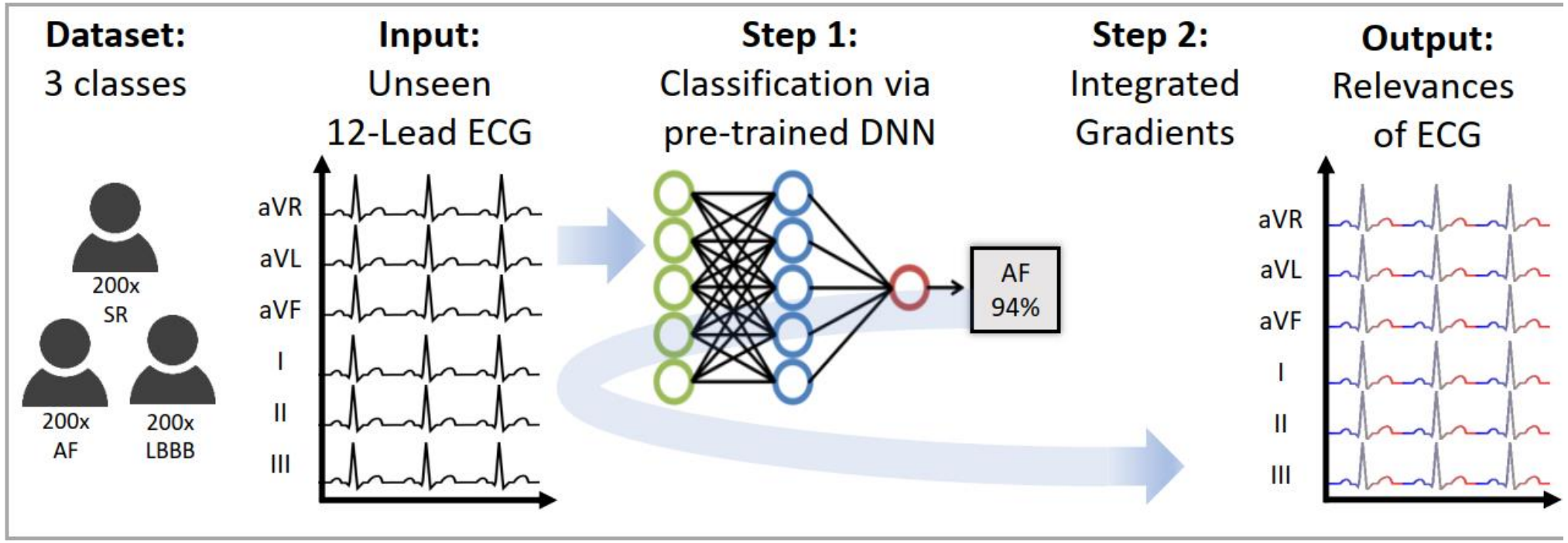


By Original: A._Rad Vector: Mrmw - Own work based on: Left bundle branch block ECG characteristics.png:, CC0, https://commons.wikimedia.org/w/index.php?curid=83141752

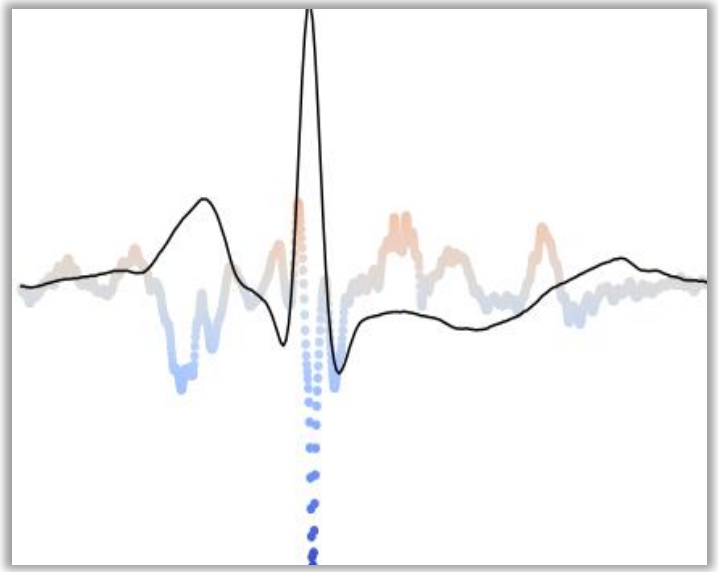
Methods


Dataset:
3 classes
200x
SR
200x
AF
200x
LBBB
Input:
Unseen
12-Lead ECG
aVR
aVL
aVF
I
II
III
Step 1:
Classification via
pre-trained DNN
AF
94%

Methods

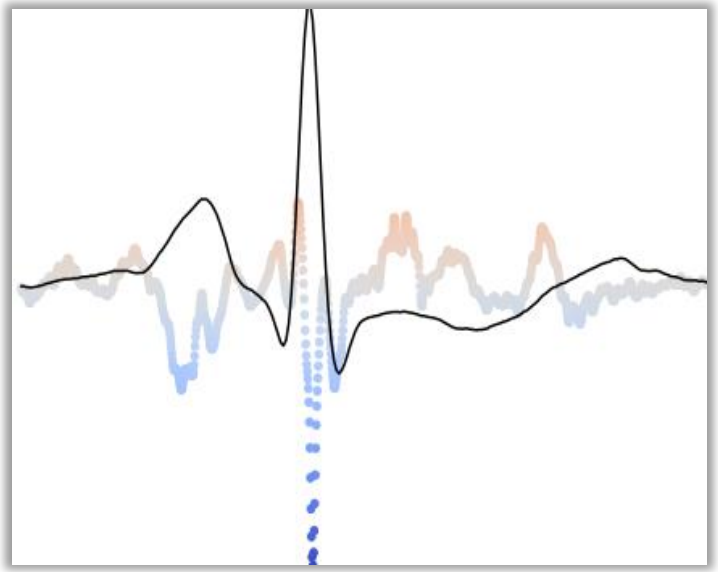

Dataset:
3 classes
200x
SR
200x
AF
200x
LBBB
Input:
Unseen
12-Lead ECG
aVR
aVL
aVF
I
II
III
Step 1:
Classification via
pre-trained DNN
AF
94%
Step 2:
Integrated
Gradients
Output:
Relevances
of ECG
aVR
aVL
aVF
I
II
III

Methods

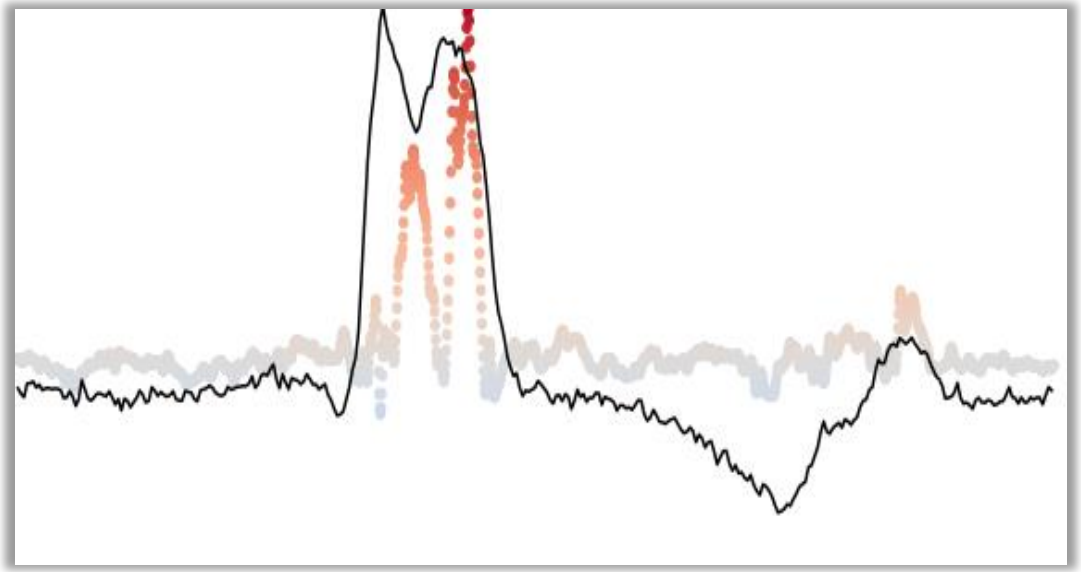


Healthy ECG

Methods

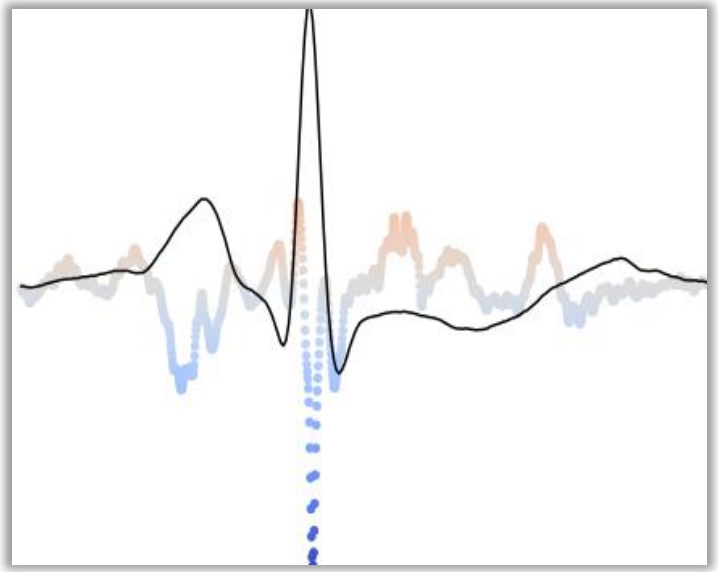


Healthy ECG

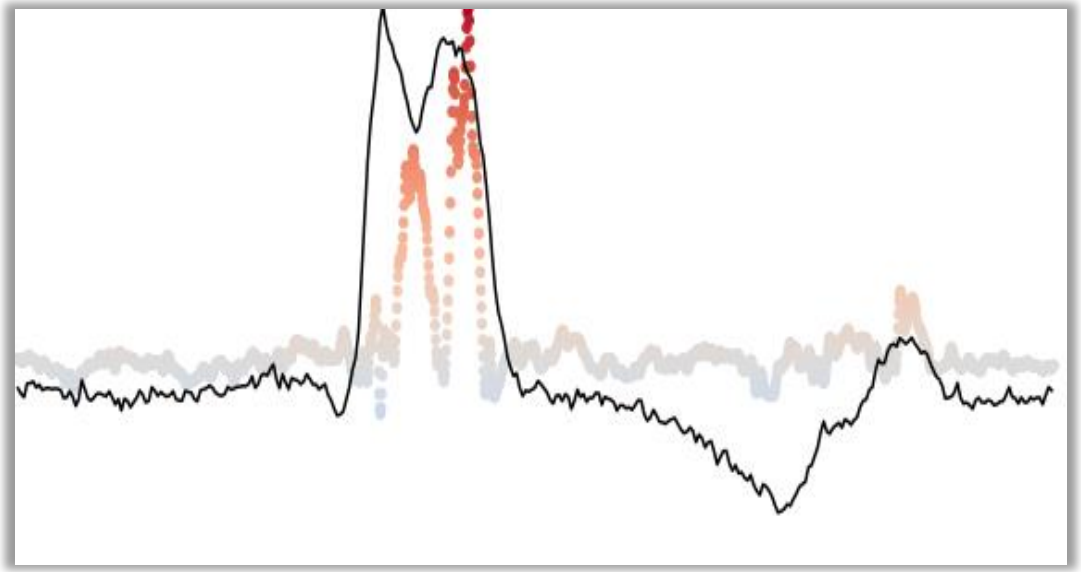


LBBB

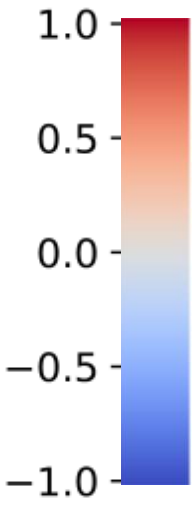
Methods



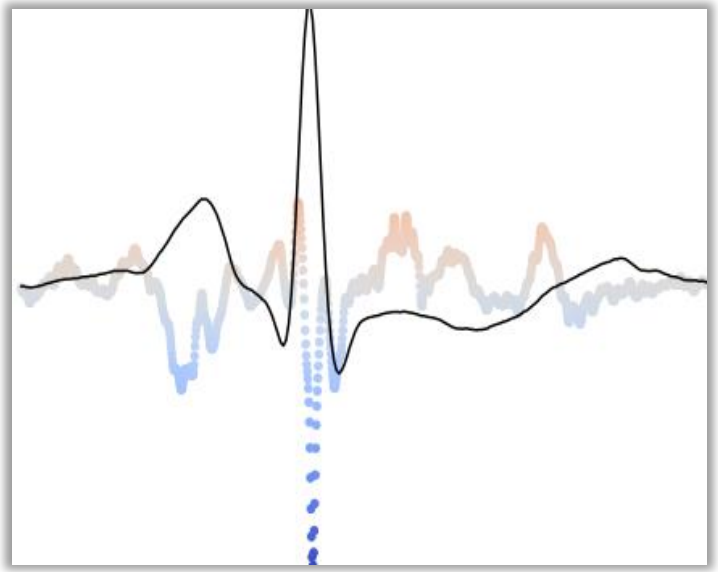
Healthy ECG



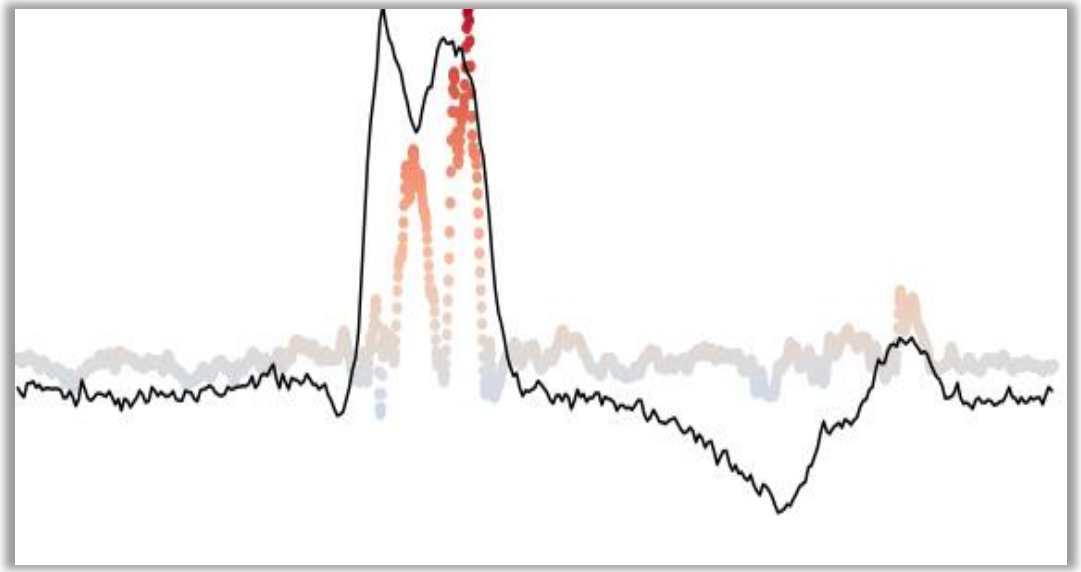
LBBB



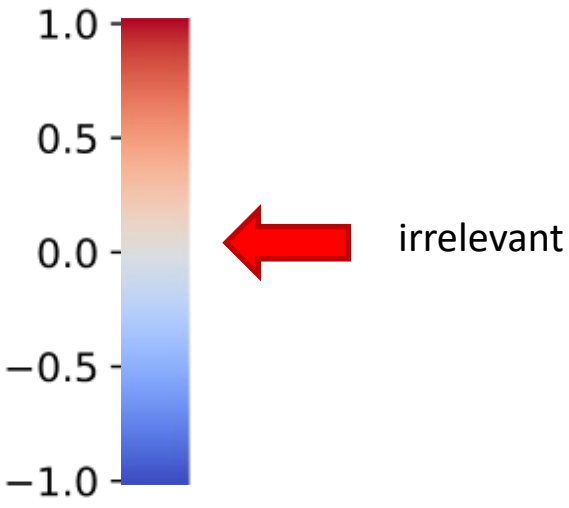
Methods



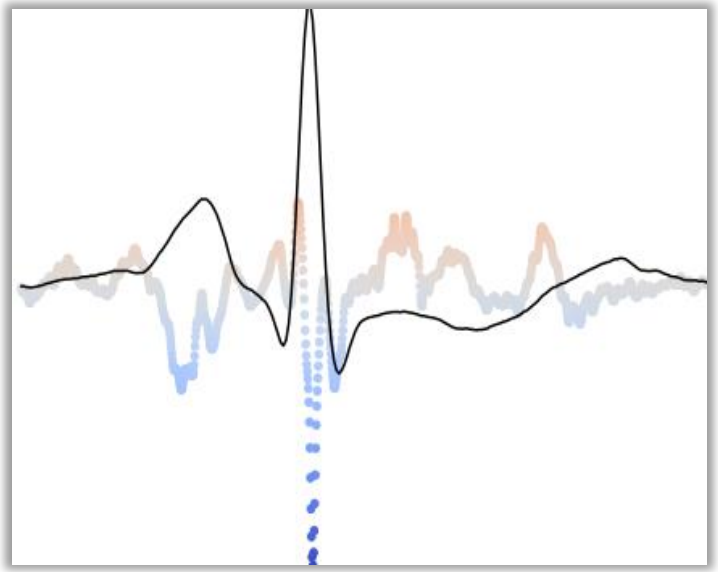
Healthy ECG



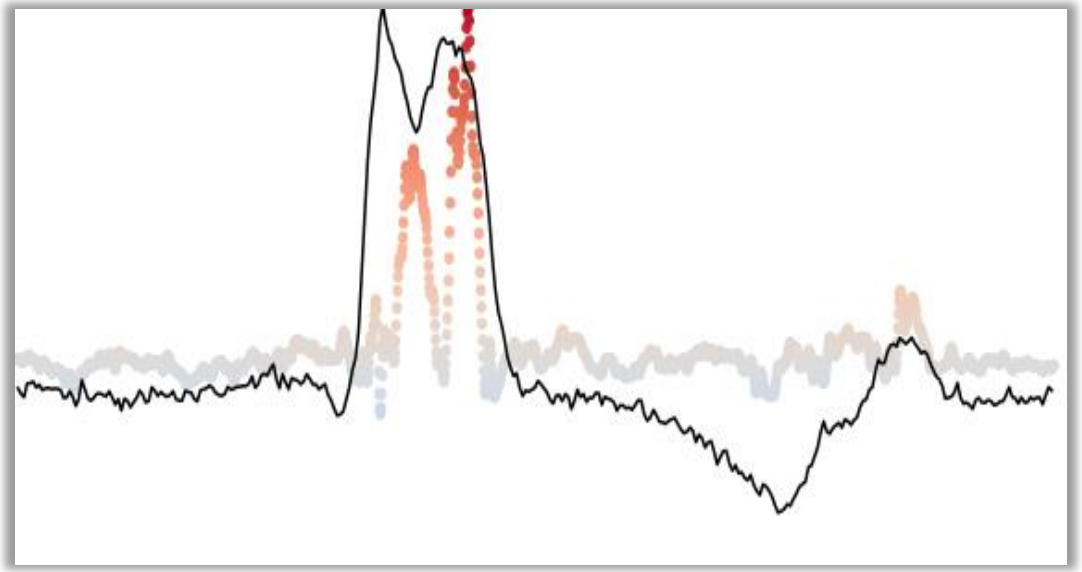
LBBB



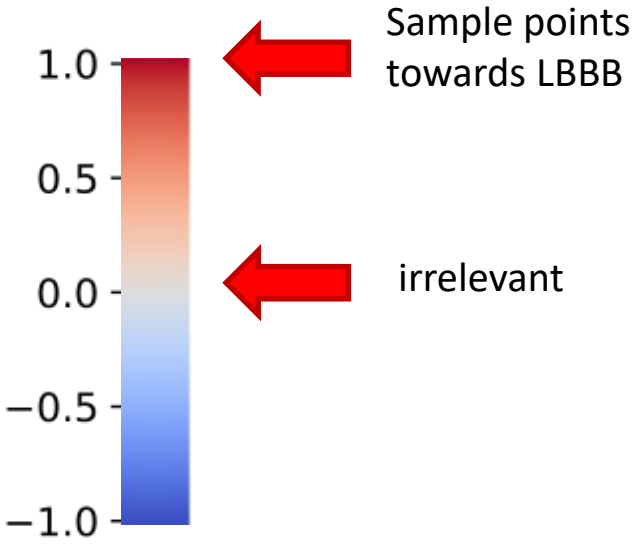
Methods



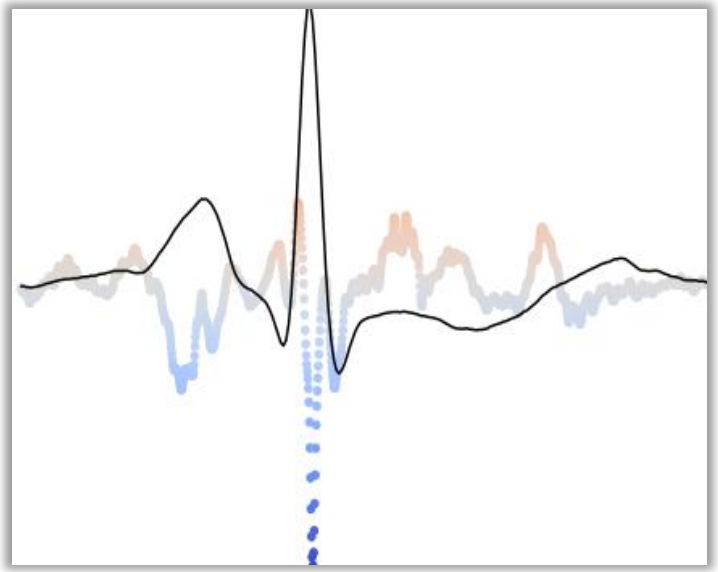
Healthy ECG



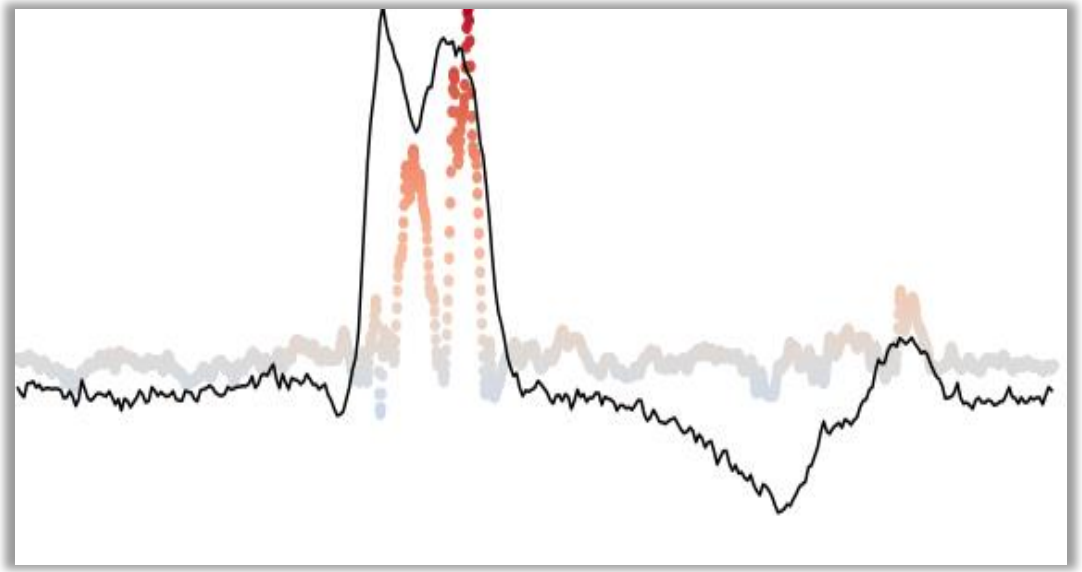
LBBB



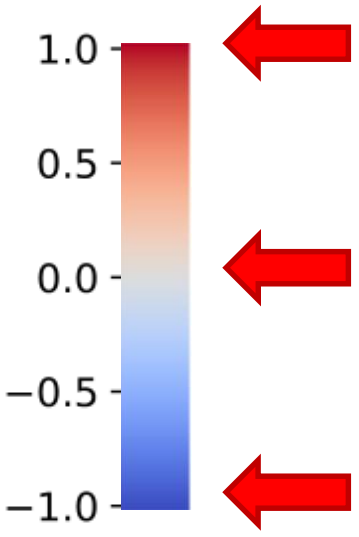
Methods



Healthy ECG



LBBB

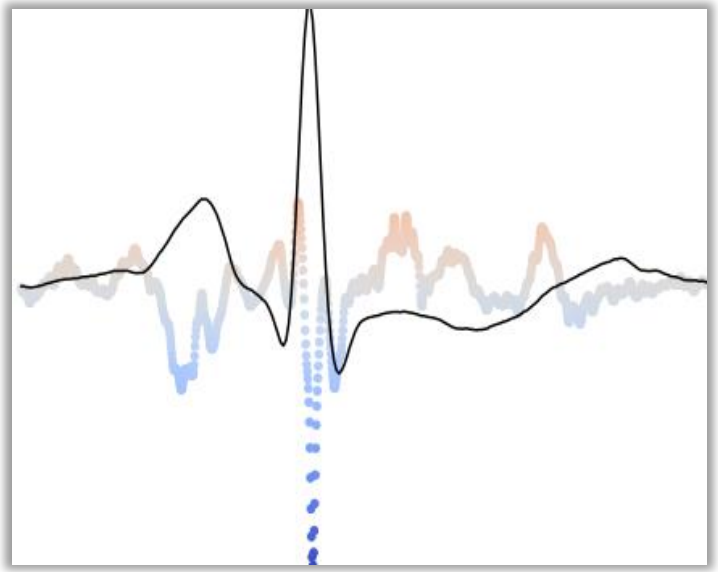


Sample points towards LBBB

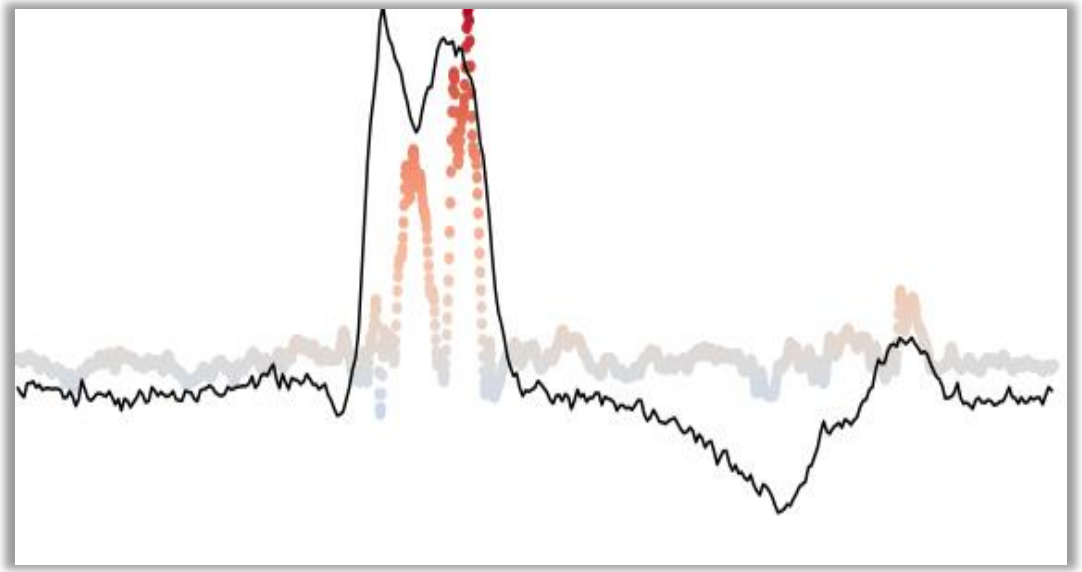
irrelevant

Sample points against LBBB (towards Sinus Rhythm)

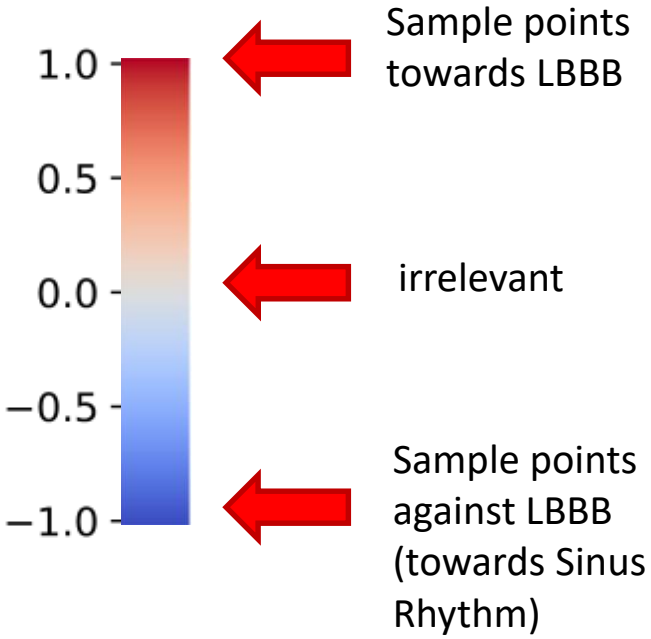
Methods



Healthy ECG

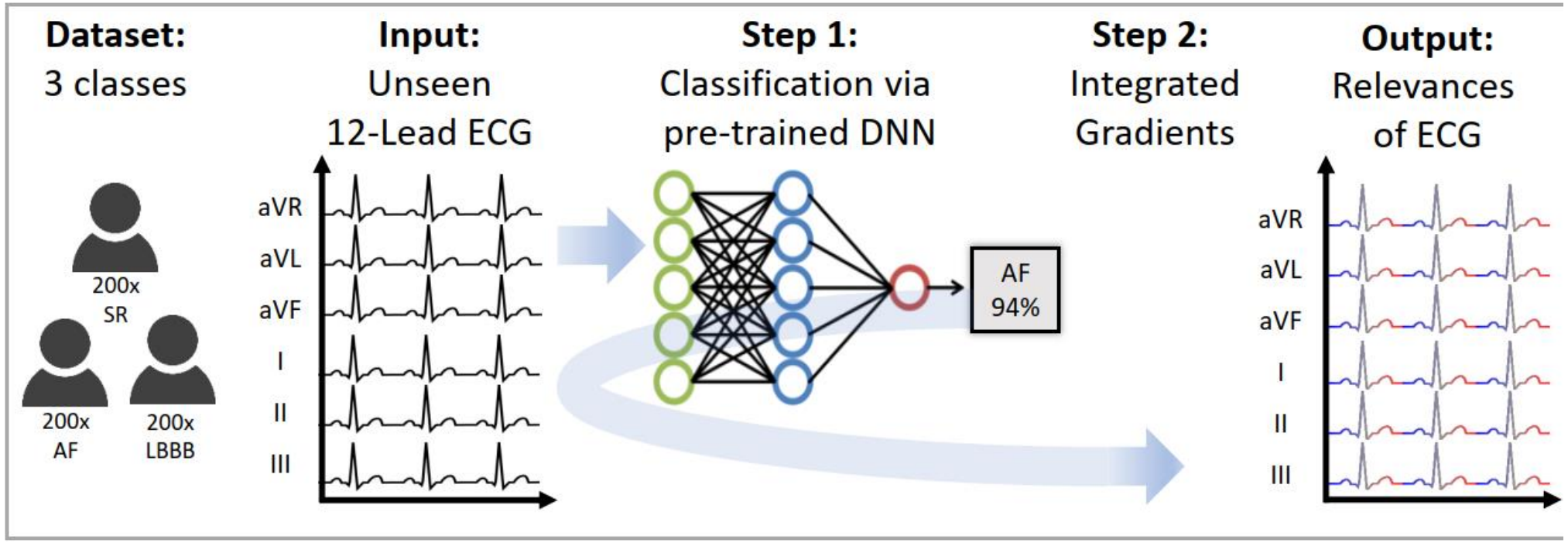


LBBB

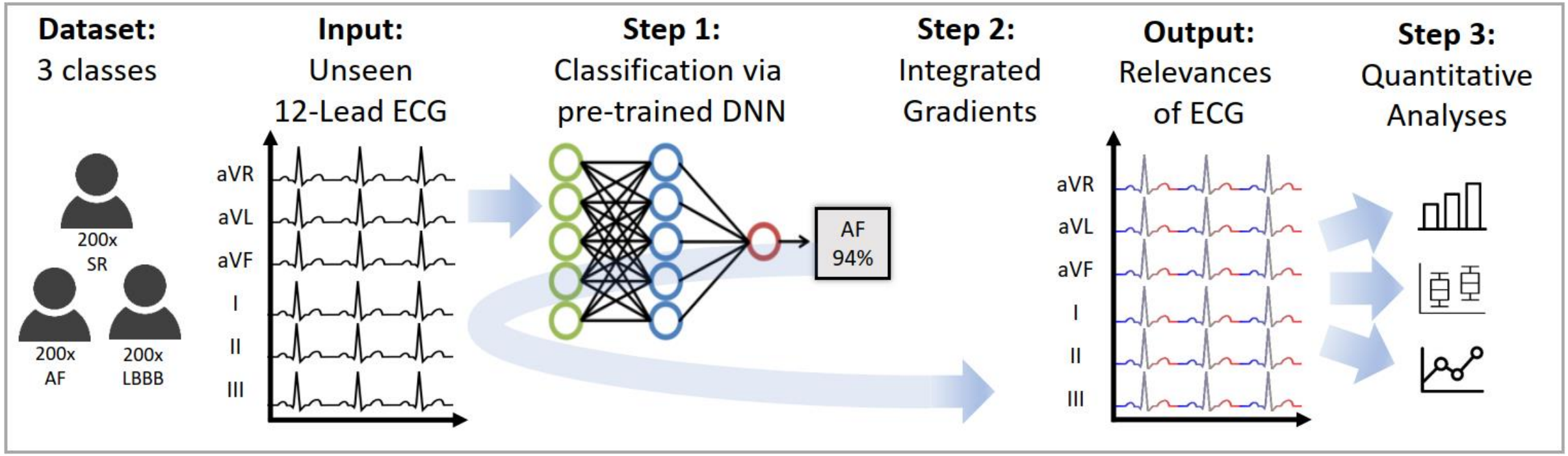


However, this gives only anecdotical proof for a single heart beat of a single patient.
How can we generalize results?

Methods

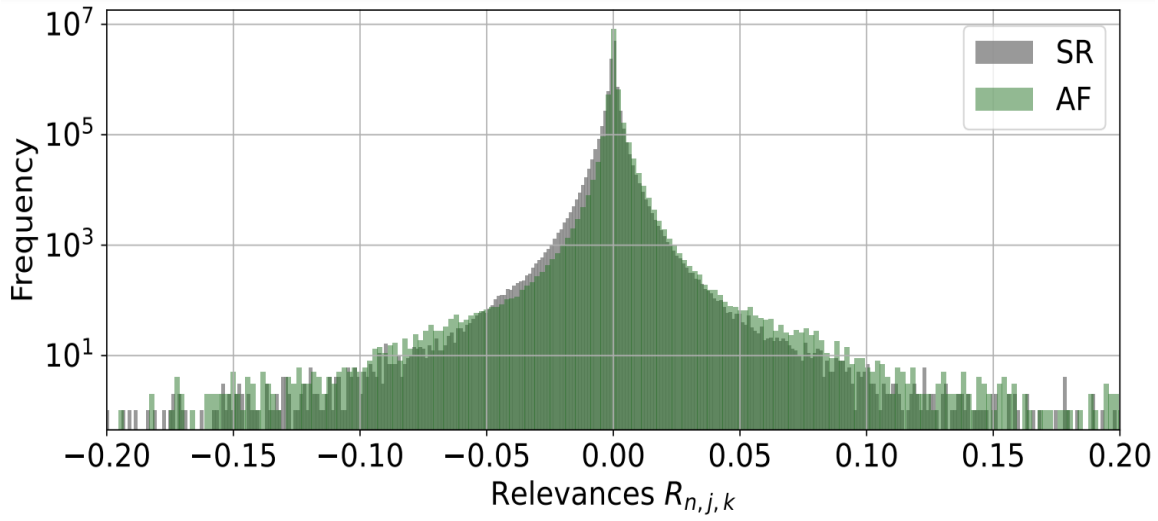

Dataset:
3 classes
200x
SR
200x
AF
200x
LBBB
Input:
Unseen
12-Lead ECG
aVR
aVL
aVF
I
II
III
Step 1:
Classification via
pre-trained DNN
AF
94%
Step 2:
Integrated
Gradients
Output:
Relevances
of ECG
aVR
aVL
aVF
I
II
III

Methods

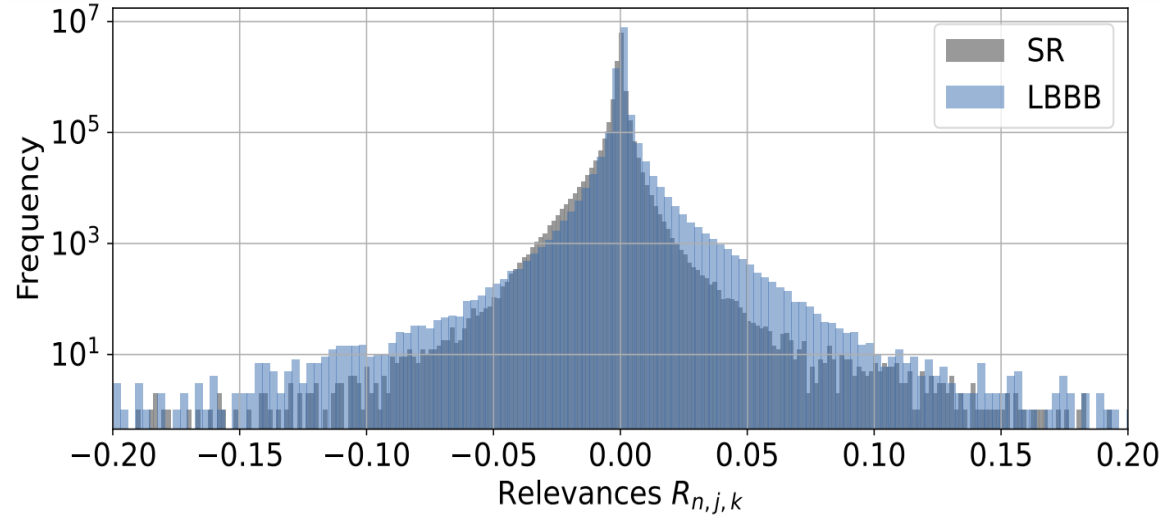

Dataset:
3 classes
200x
SR
200x
AF
200x
LBBB
Input:
Unseen
12-Lead ECG
aVR
aVL
aVF
I
II
III
Step 1:
Classification via
pre-trained DNN
AF
94%
Step 2:
Integrated
Gradients
Output:
Relevances
of ECG
aVR
aVL
aVF
I
II
III
Step 3:
Quantitative
Analyses

Results

AF

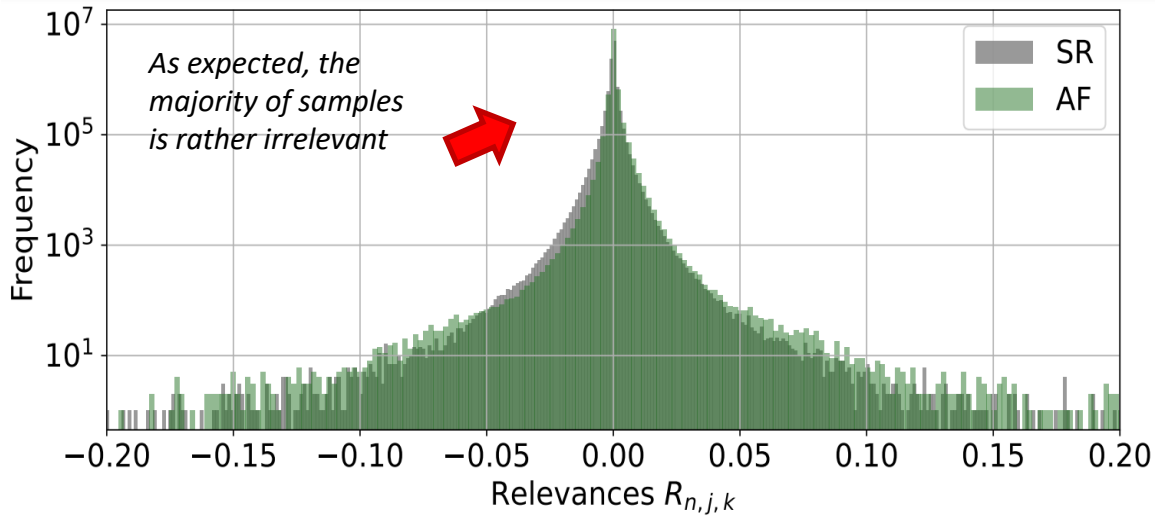


LBBB

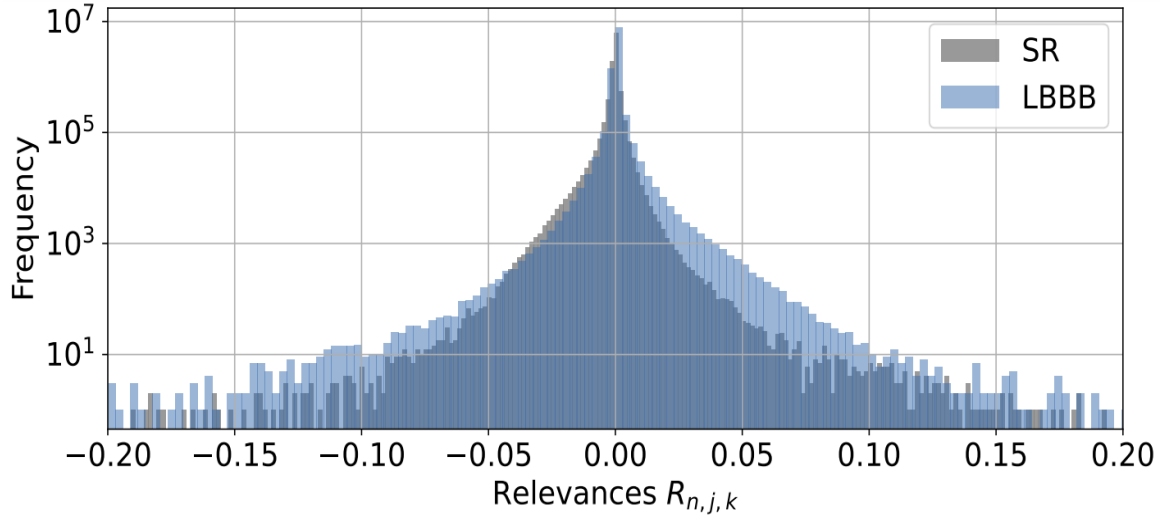


Results

AF

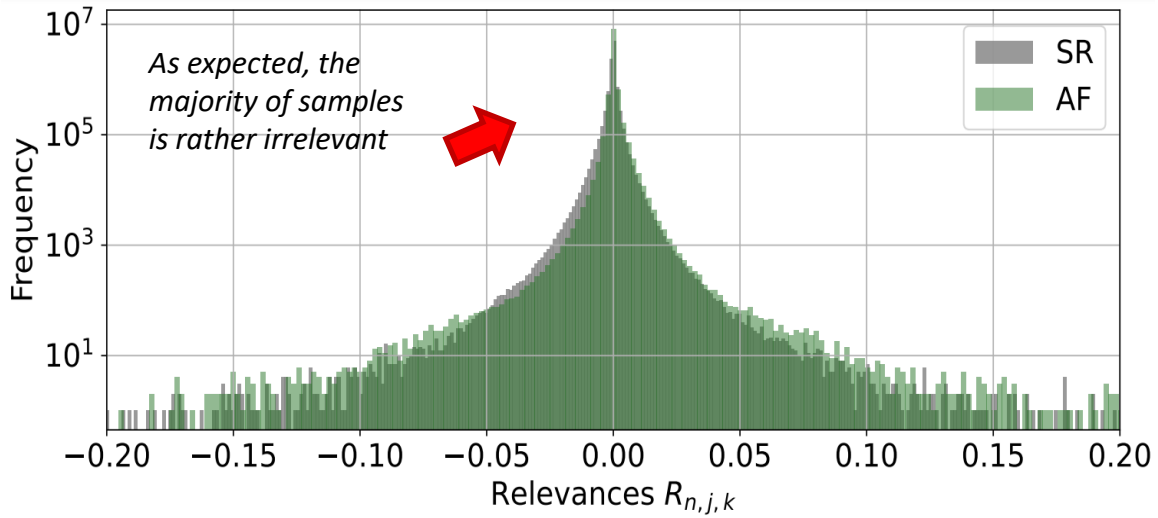


LBBB

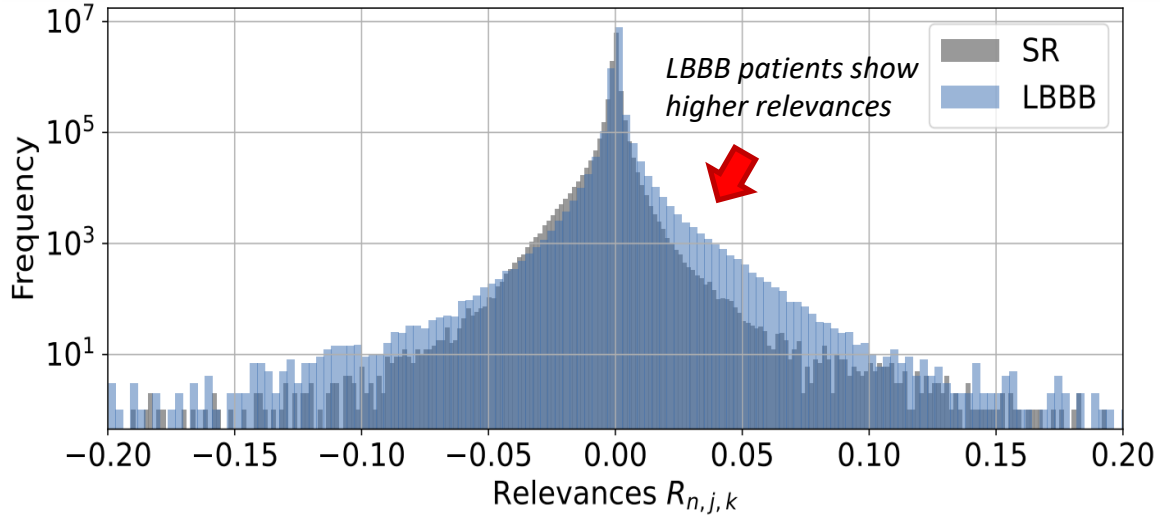


Results

AF

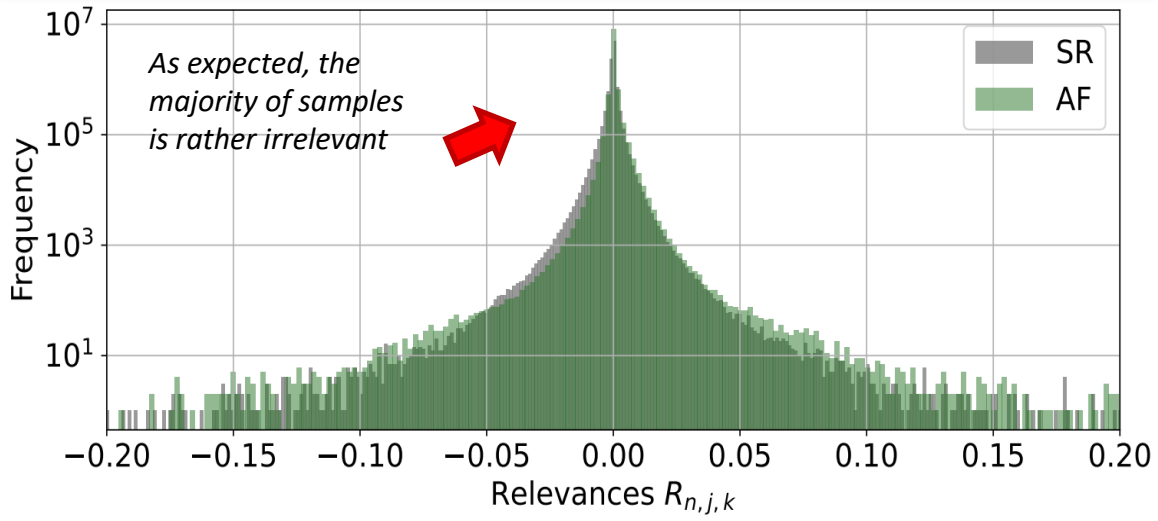


LBBB

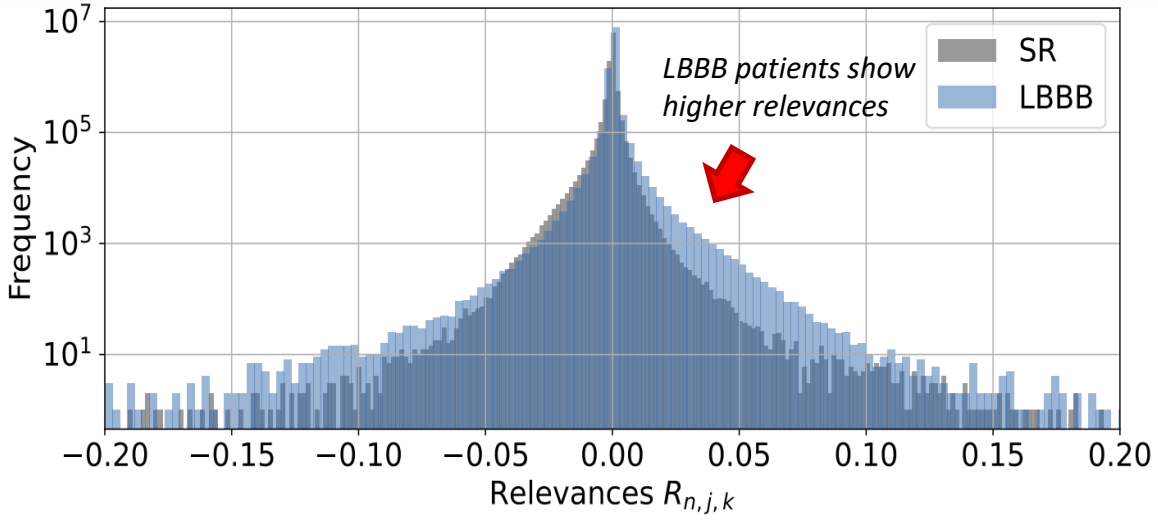


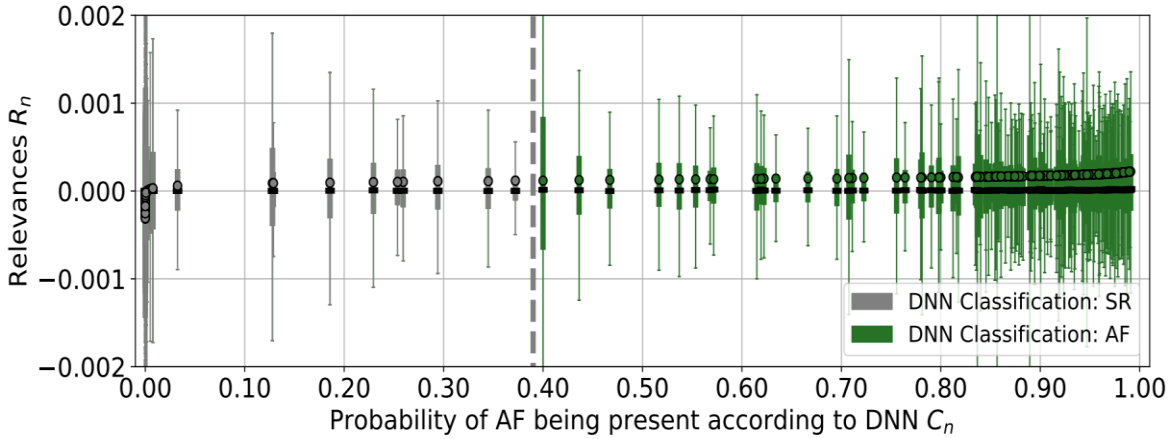
Results

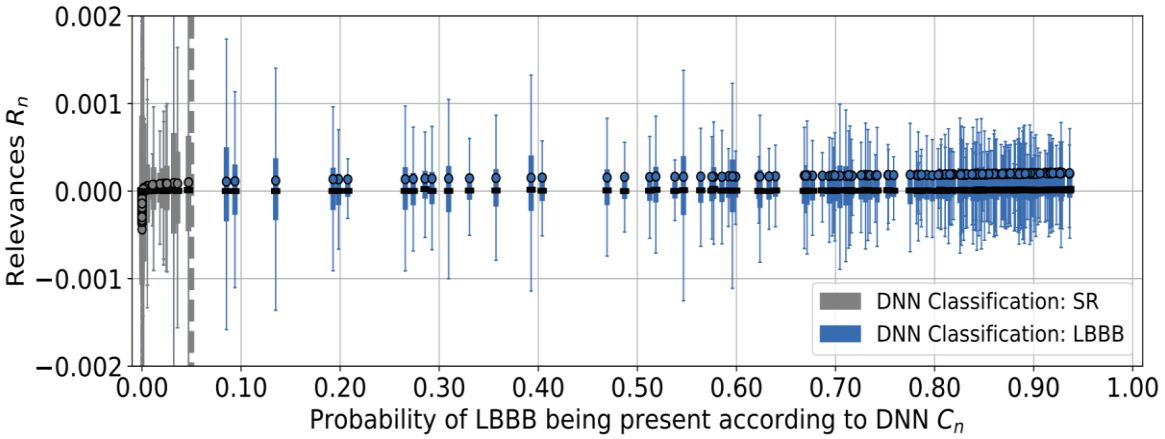
AF



LBBB

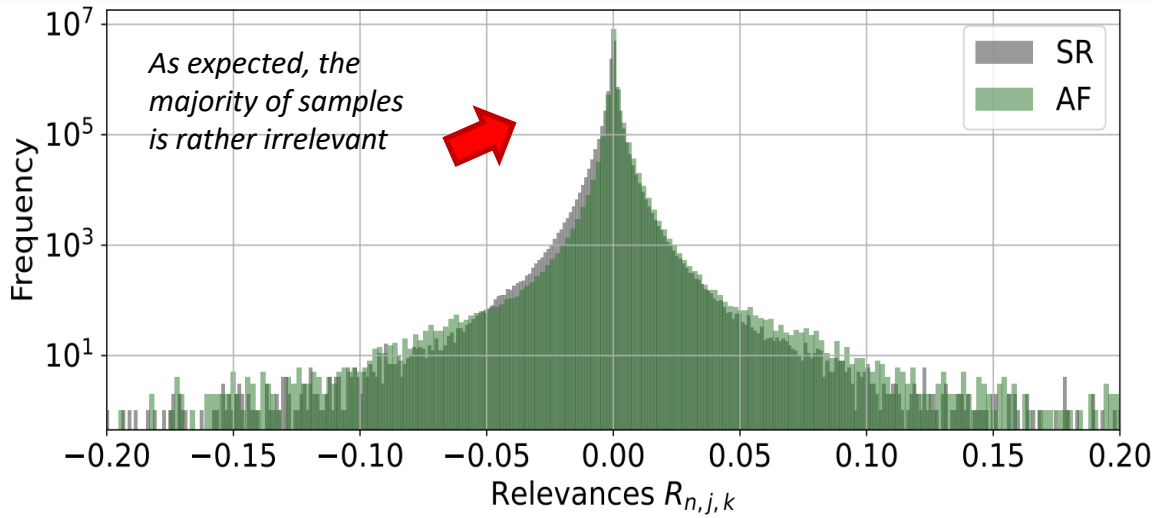




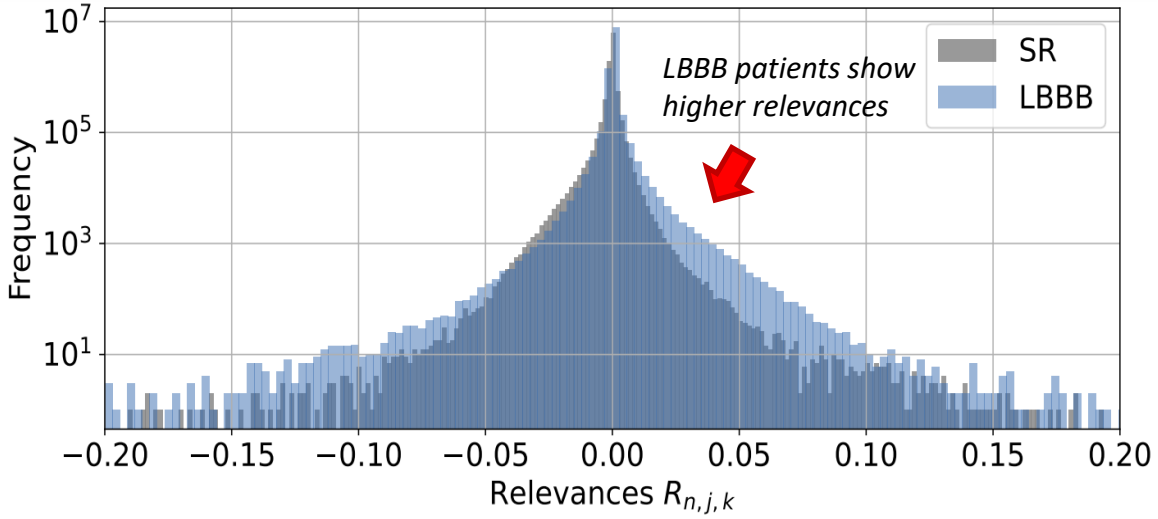


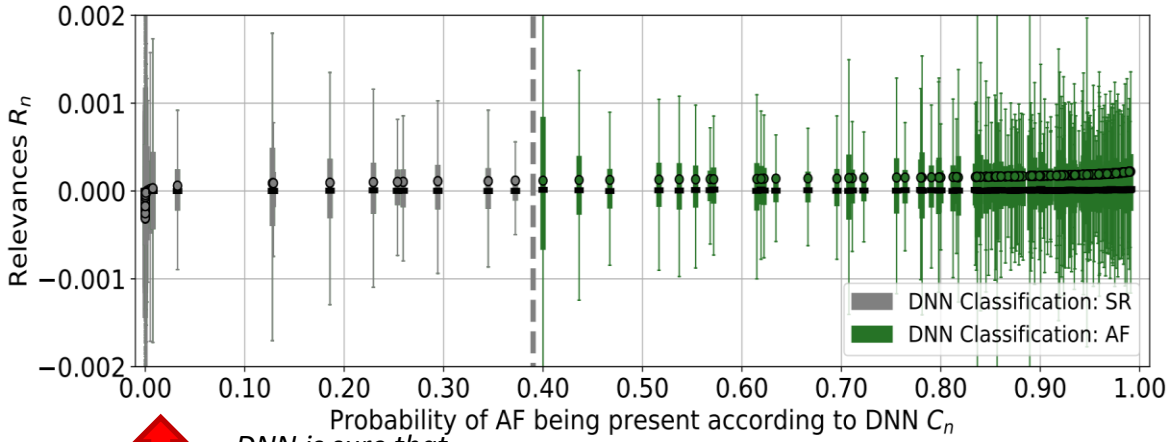
Results

AF

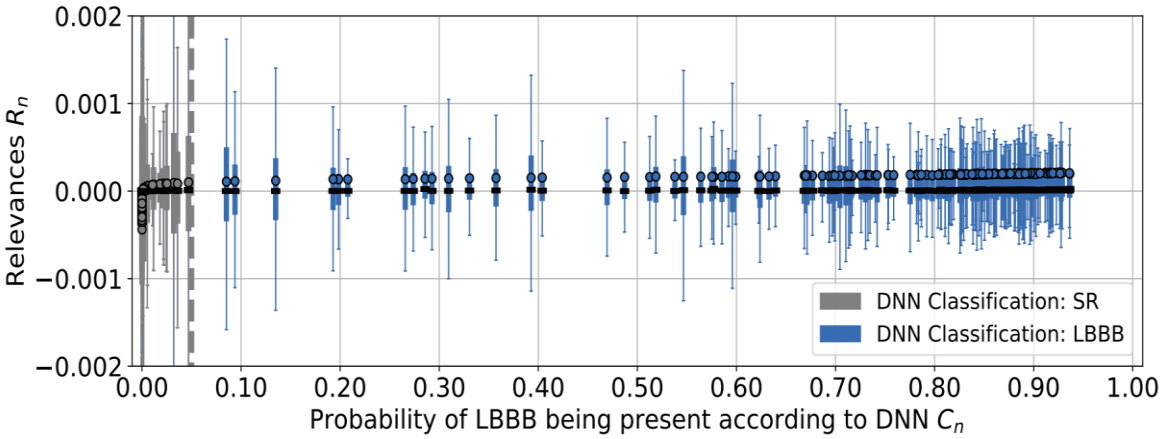


LBBB



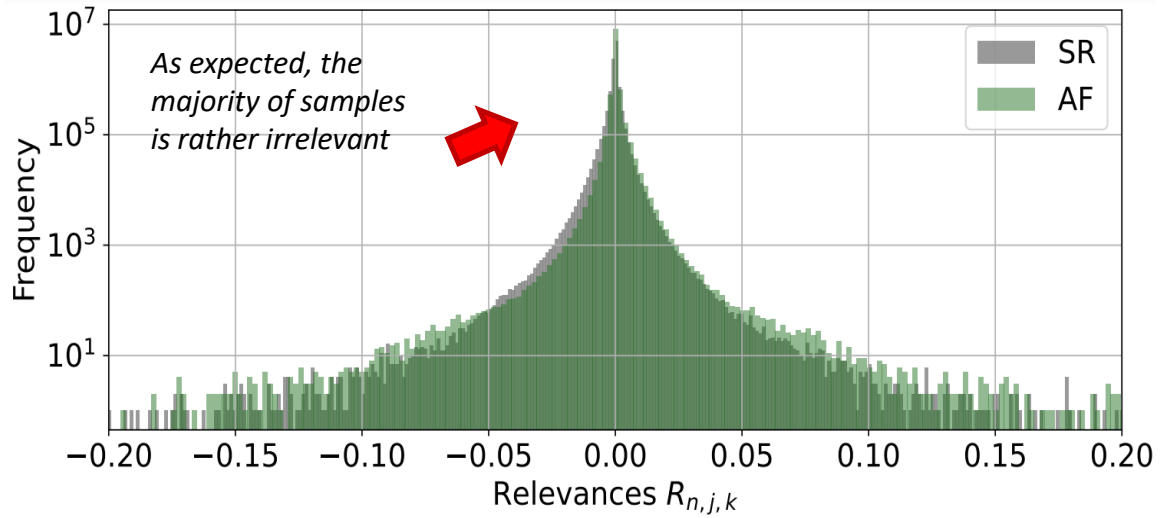


DNN is sure that these are Sinus Rhythm

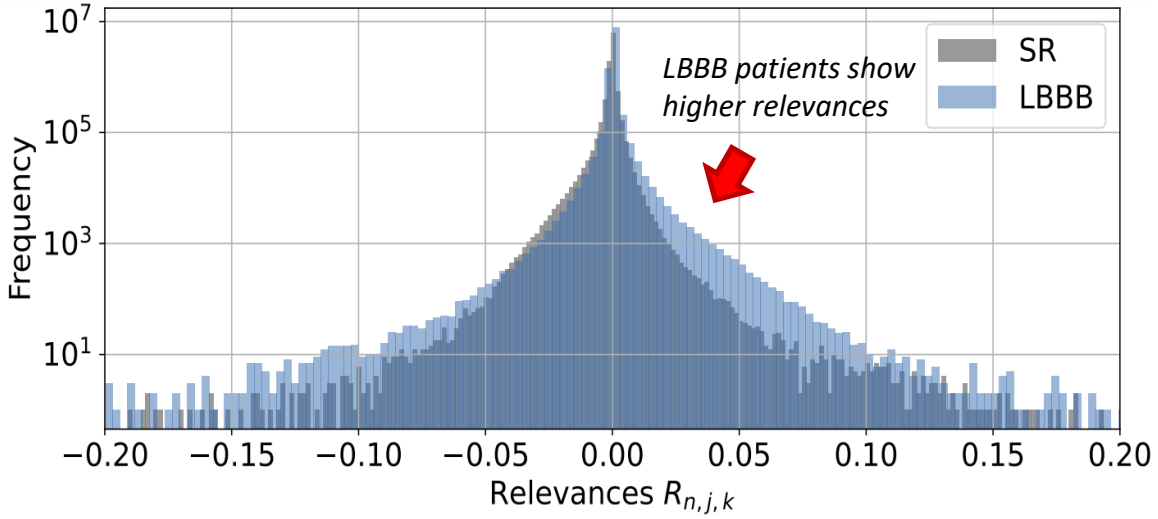


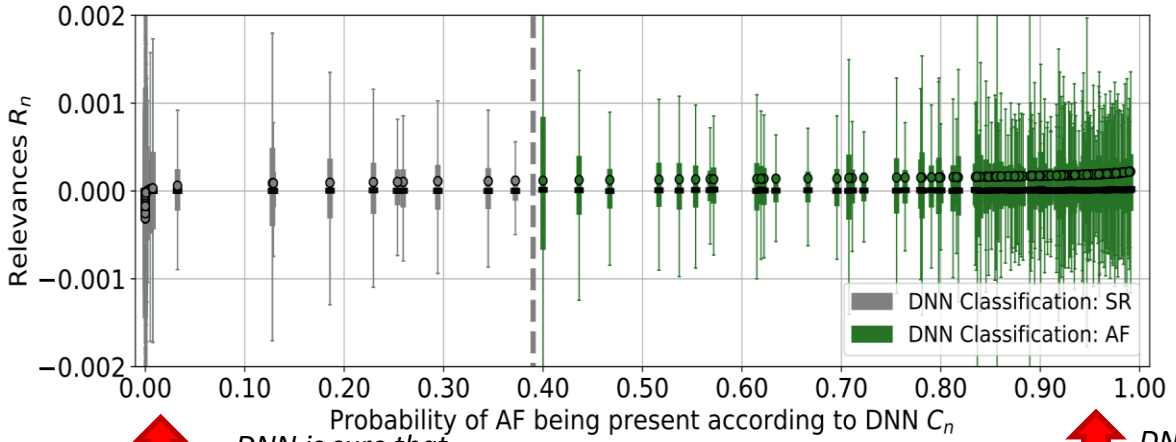
Results

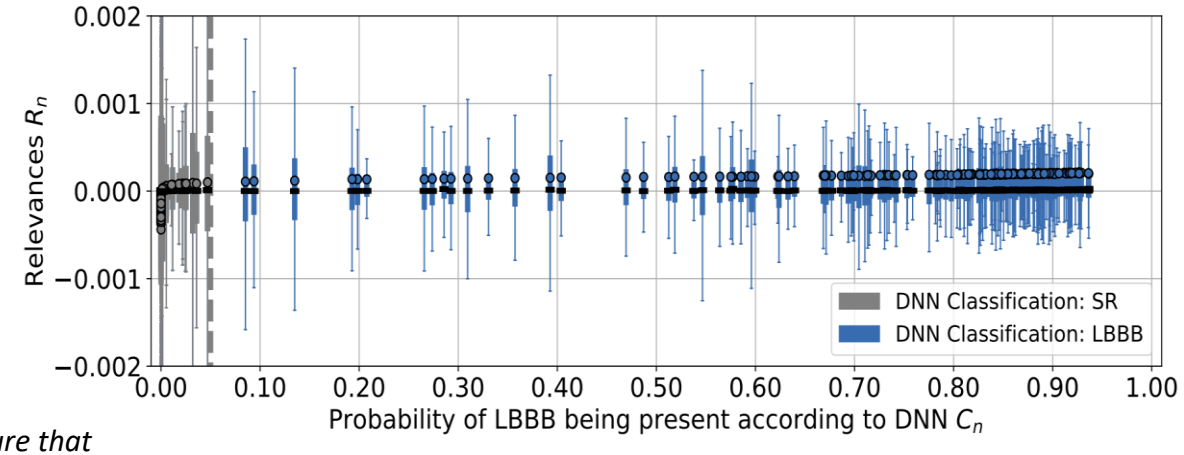
AF



LBBB



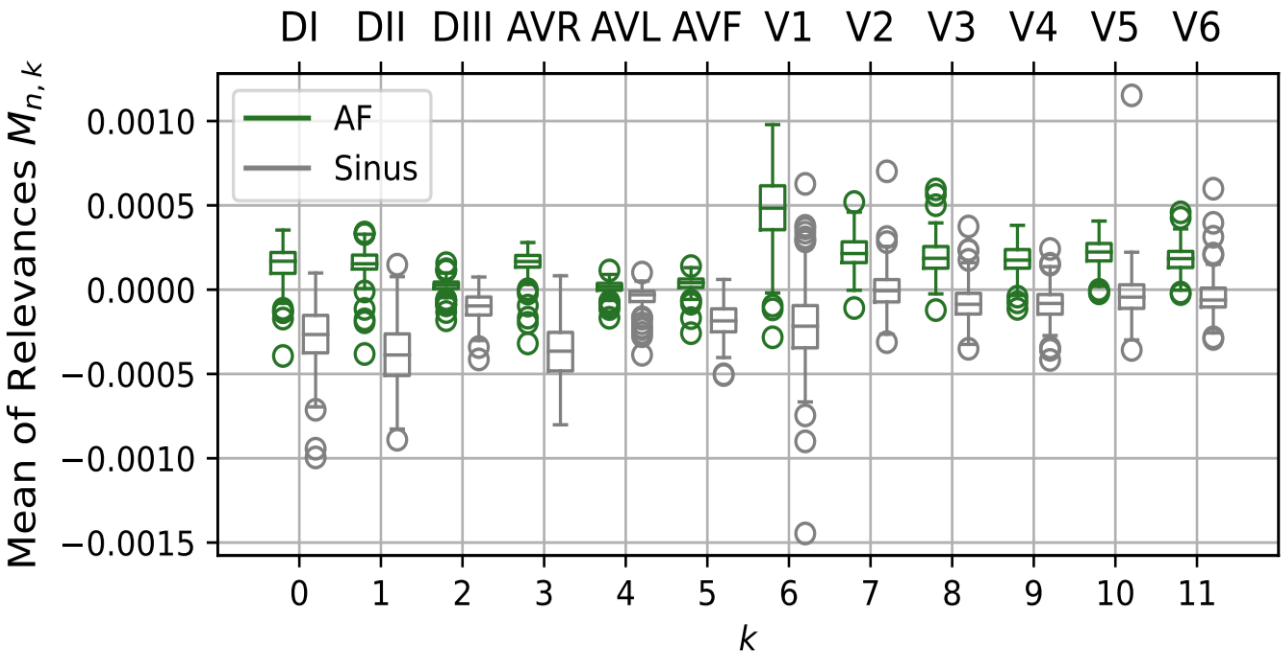




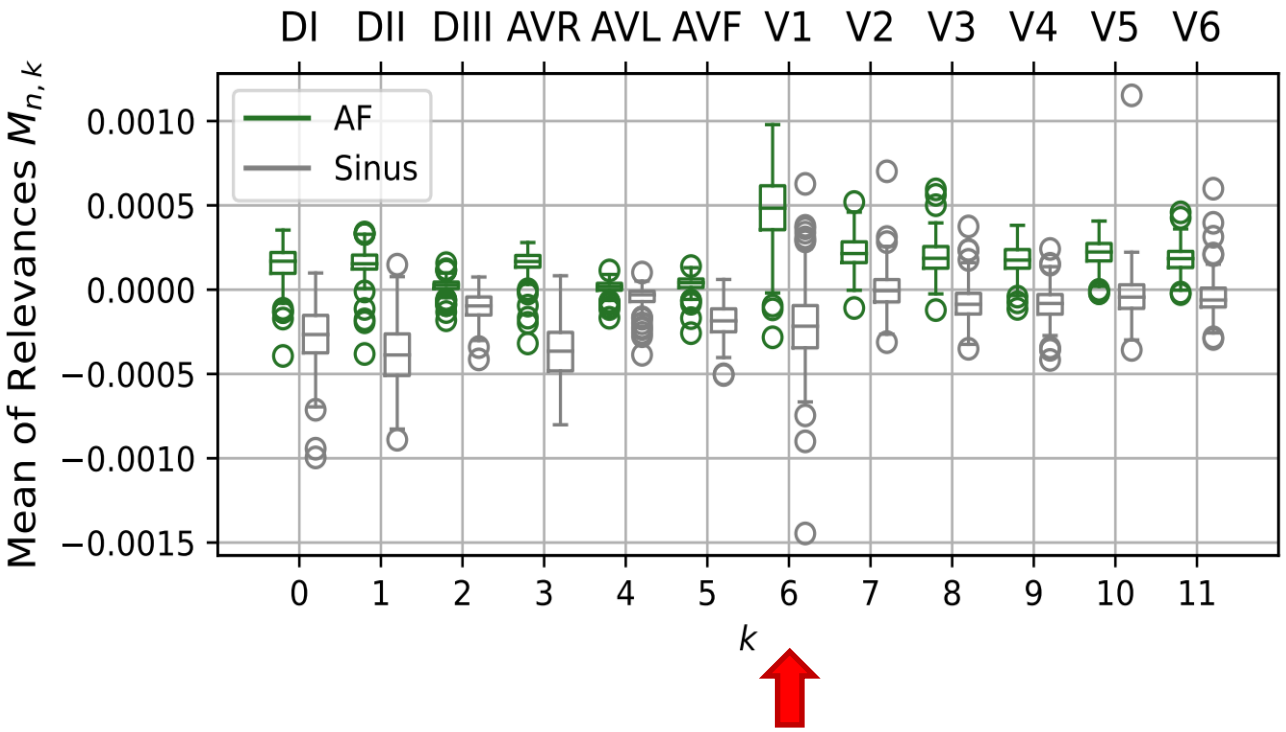
DNN is sure that these are Sinus Rhythm

DNN is sure that these are AF

Results


DI
DII
DIII
AVR
AVL
AVF
V1
V2
V3
V4
V5
V6
AF
Sinus
Mean of Relevances $M_{n,k}$
0.0010
0.0005
0.0000
−0.0005
−0.0010
−0.0015
0
1
2
3
4
5
6
7
8
9
10
11
k

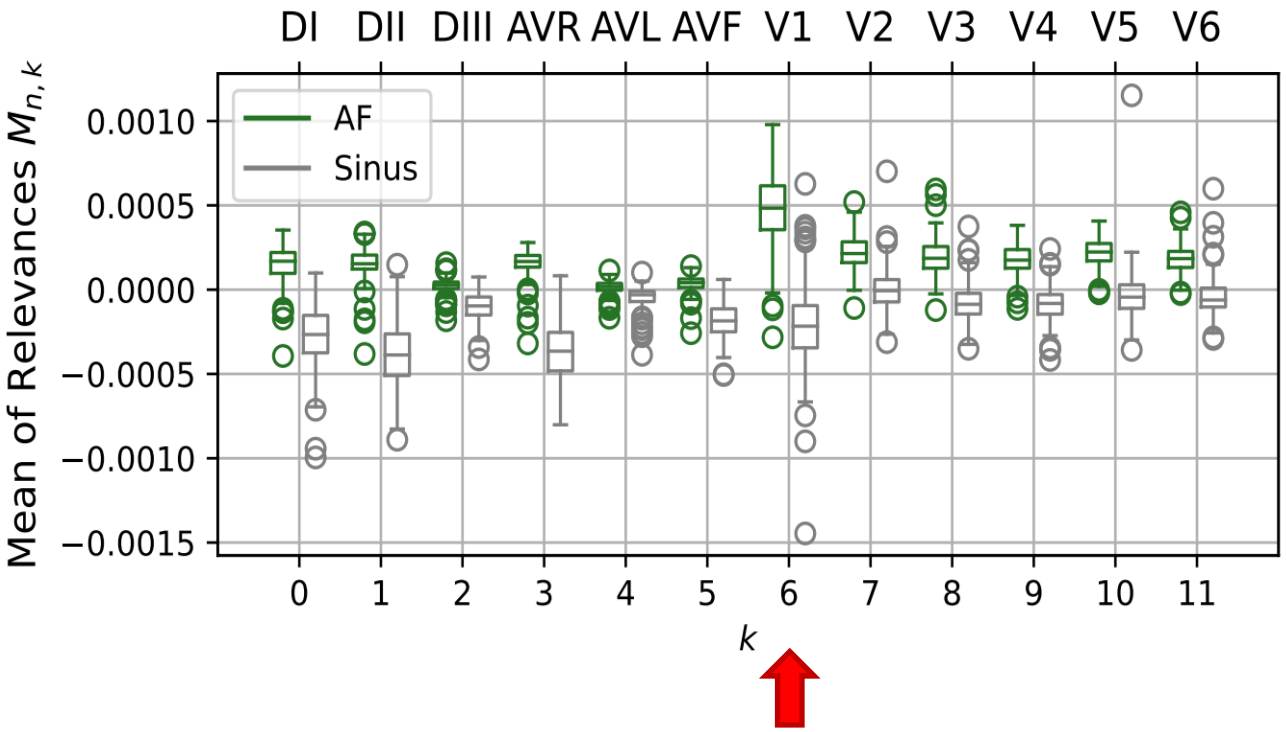
Results


DI DII DIII AVR AVL AVF V1 V2 V3 V4 V5 V6
AF
Sinus
Mean of Relevances $M_{n,k}$
0.0010
0.0005
0.0000
−0.0005
−0.0010
−0.0015
0 1 2 3 4 5 6 7 8 9 10 11
k

Results

recordings.[20–22] It has been suggested to analyse lead V1 when using a standard 12-lead ECG or, as proposed previously by Waktare *et al.*,[23] a 'bipolar modification of V1' covering the atria (low C1) when applying different ECG recording systems, as the largest fibrillatory waves are usually found in these leads.

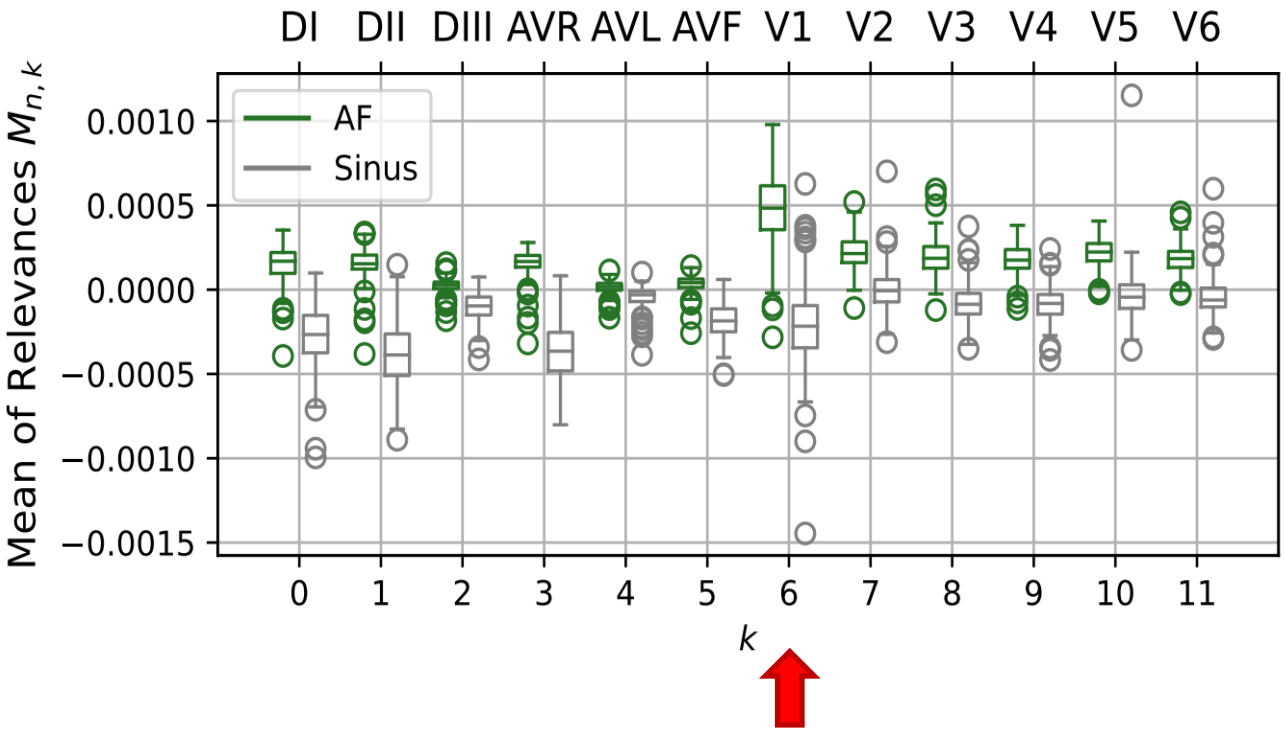
Bollmann et al. (2006) https://doi.org/10.1093/europace/eul113

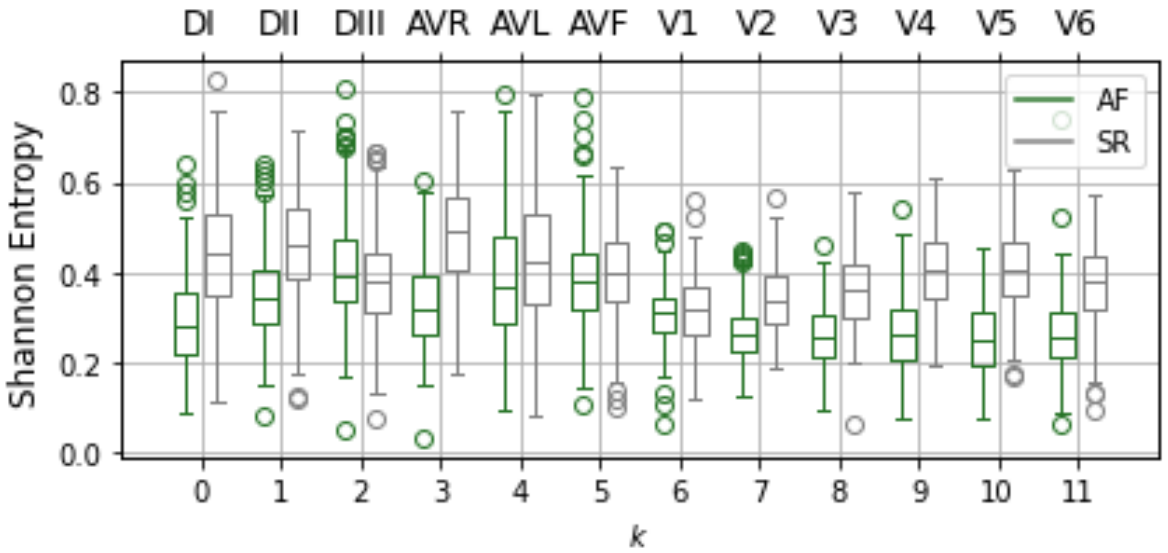


Results

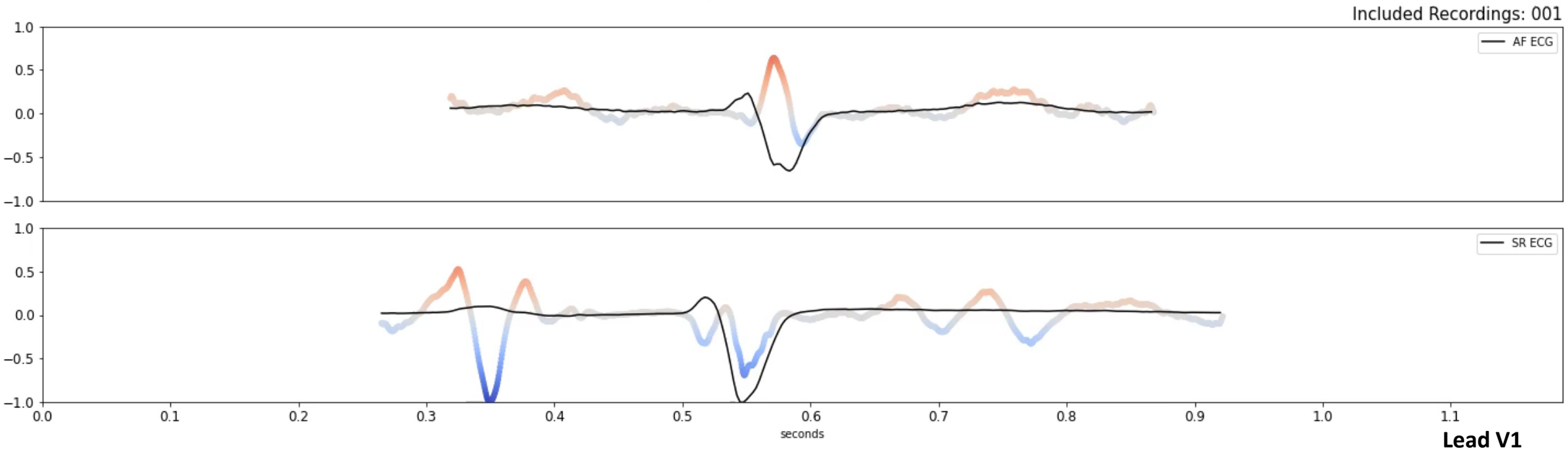
recordings.[20–22] It has been suggested to analyse lead V1 when using a standard 12-lead ECG or, as proposed previously by Waktare *et al.*,[23] a 'bipolar modification of V1' covering the atria (low C1) when applying different ECG recording systems, as the largest fibrillatory waves are usually found in these leads.

Bollmann et al. (2006) https://doi.org/10.1093/europace/eul113



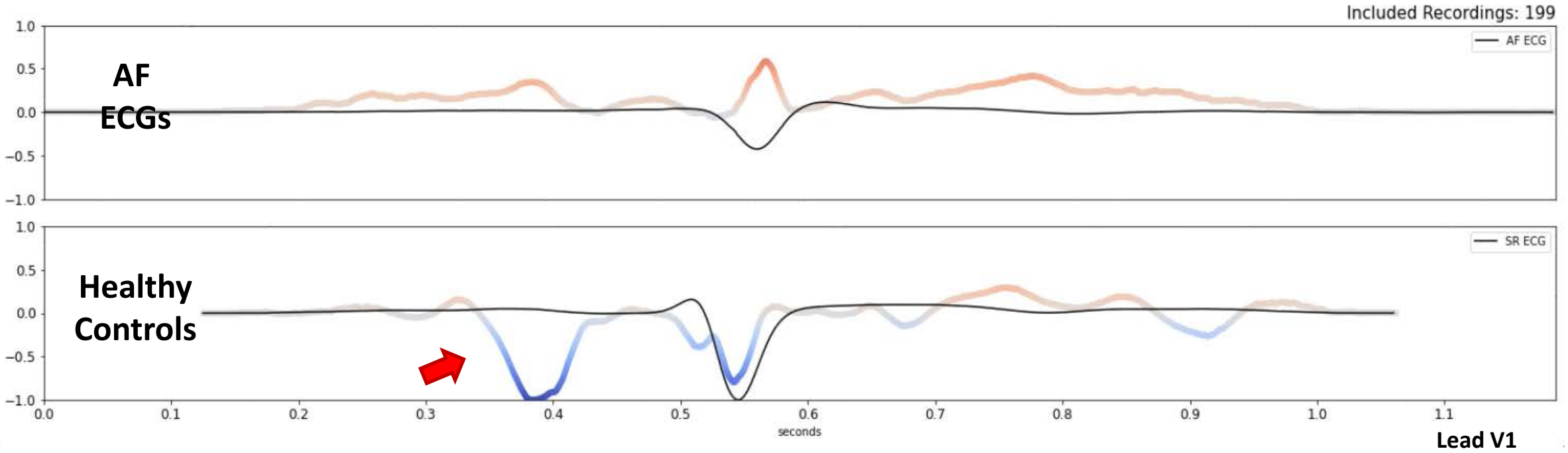


Results



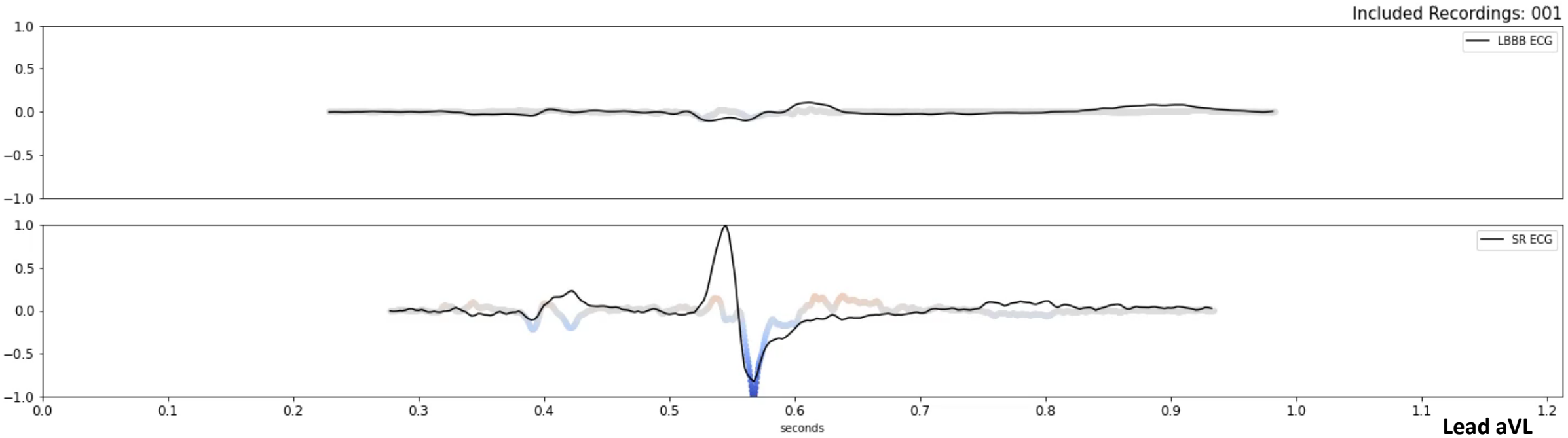
Lead V1

Results



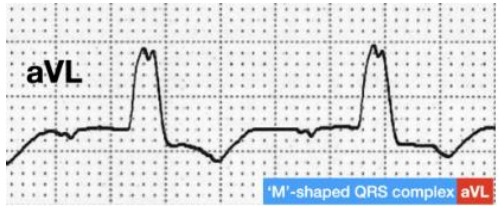
- P-waves are a clear counter-sign to AF (in AF the sinus node is inactive)

Results

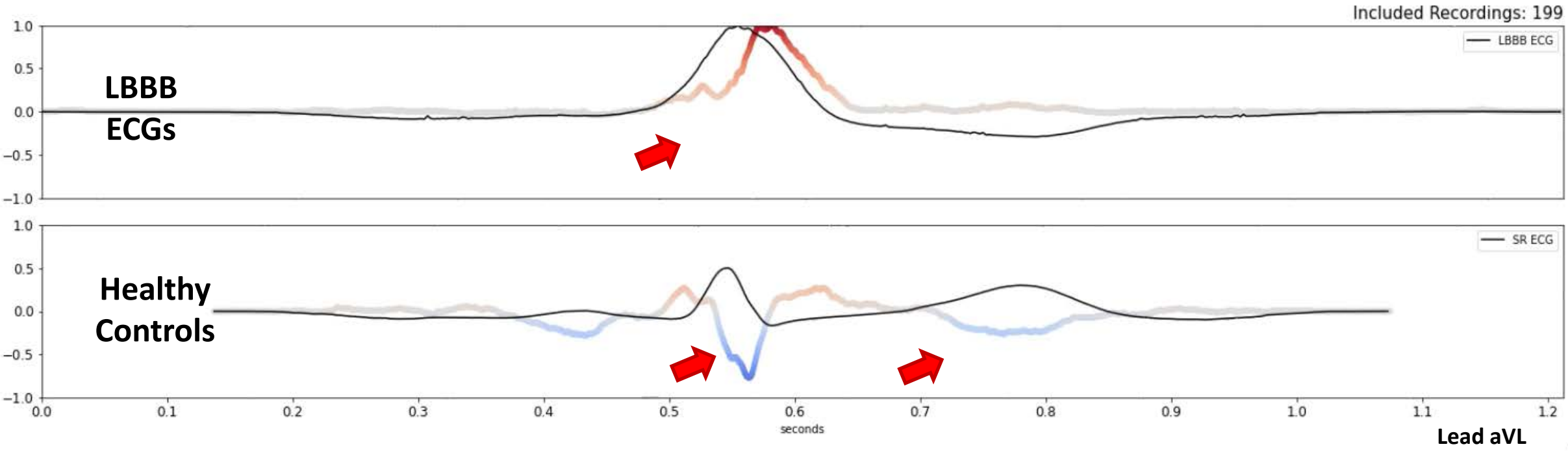


Lead aVL

Results



https://litfl.com/left-bundle-branch-block-lbbb-ecg-library/



- Abnormal QRS complexes are signs for LBBB
- T-waves with positive amplitude in lead aVL are counter-signs to LBBB

Conclusion

We can conclude that the DNN learned cardiology textbook knowledge for the whole cardiac cycle.

A limitation of our analysis is that we cannot infer any time-dependent information of the relevances.

In future work…
…we will analyse the entropy of unaggregated (raw) data
…we will use the methods proposed in this work for developing an interactive tool for clinical practice which offers cardiologists an intuitive overview of the DNN's reasoning, supporting them in their decision whether to trust the DNN's classification, or not.

Contact

Theresa Bender

University Medical Center Göttingen
Department of Medical Informatics
Robert-Koch-Str. 40
37075 Göttingen

Tel.: +49 551 39-61527
E-Mail: theresa.bender@med.uni-goettingen.de

Web: https://medizininformatik.umg.eu/
ORCID ID: https://orcid.org/0000-0001-6721-7034

Thank you!