Paroxysmal Atrial Fibrillation Onset Forecast and Risk Identification During Sinus Rhythm:

A Machine Learning Approach

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IRIDIA - ULB

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Current Trends in AI - 14 March 2025

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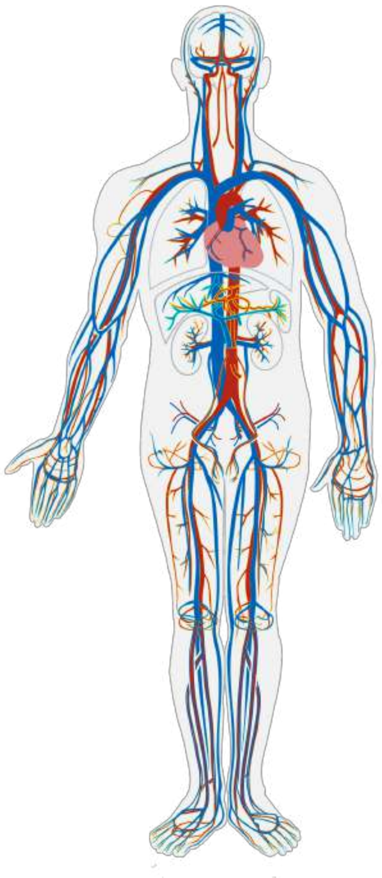
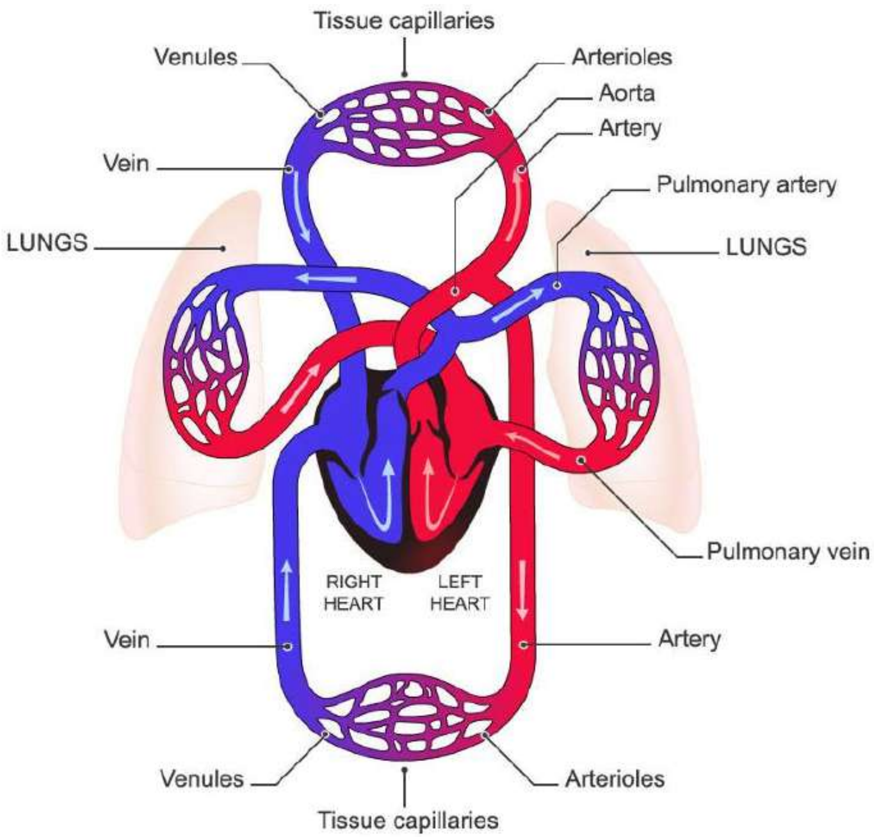
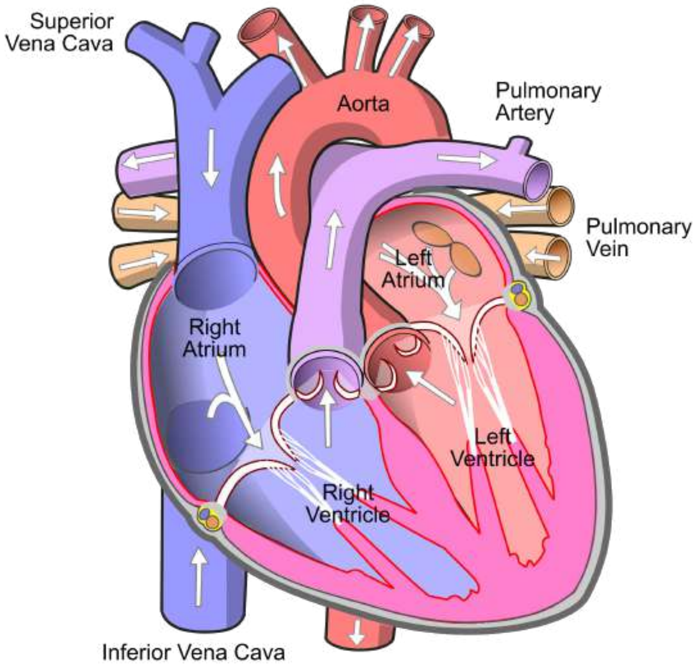
Circulatory system

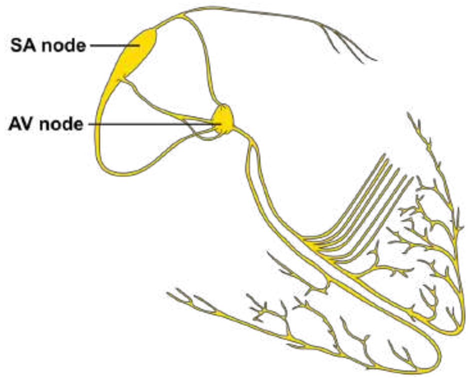




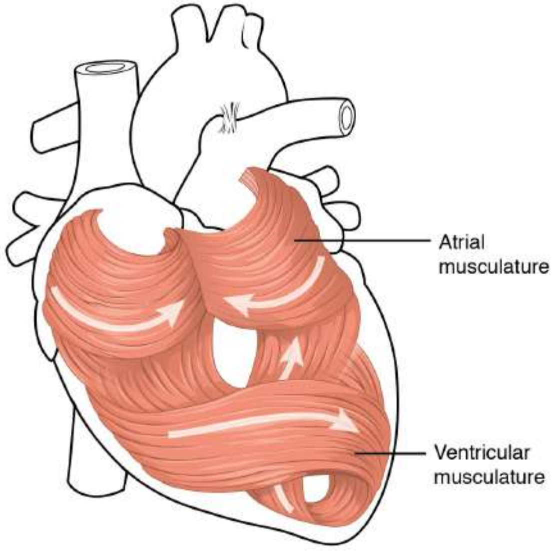
Human heart



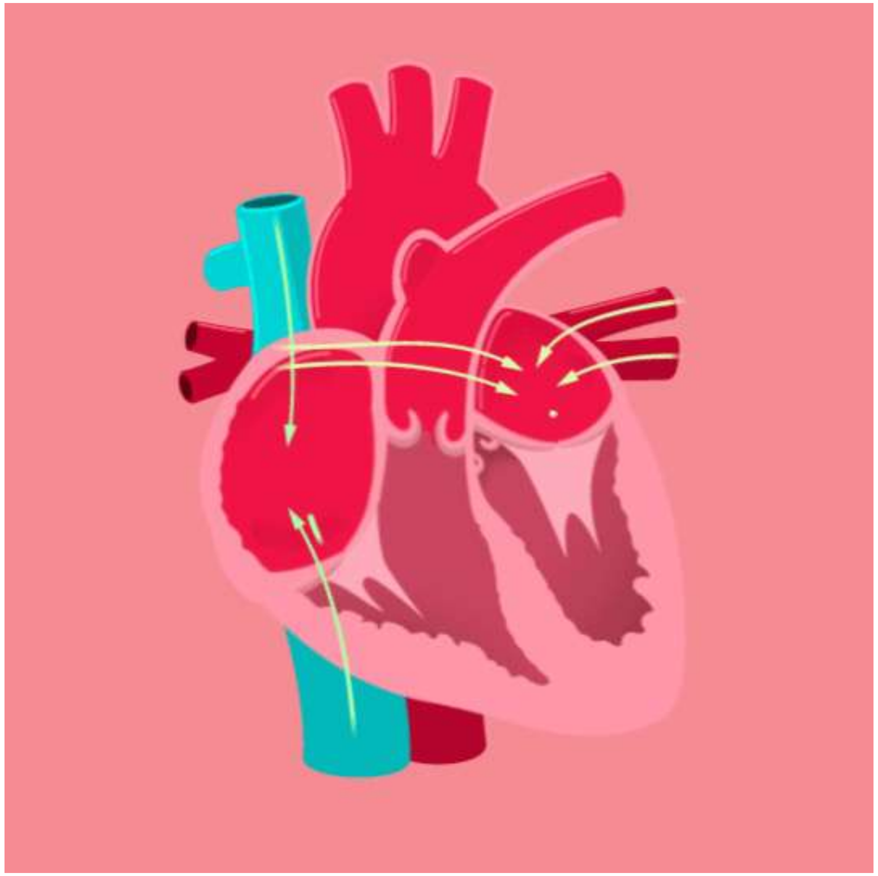
Nervous system



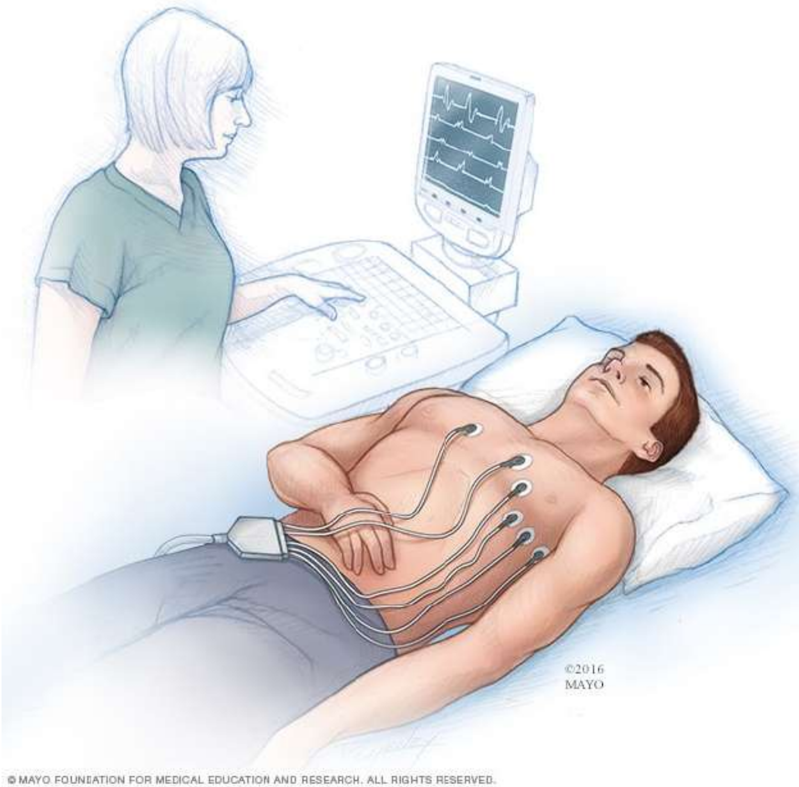
Heart muscles



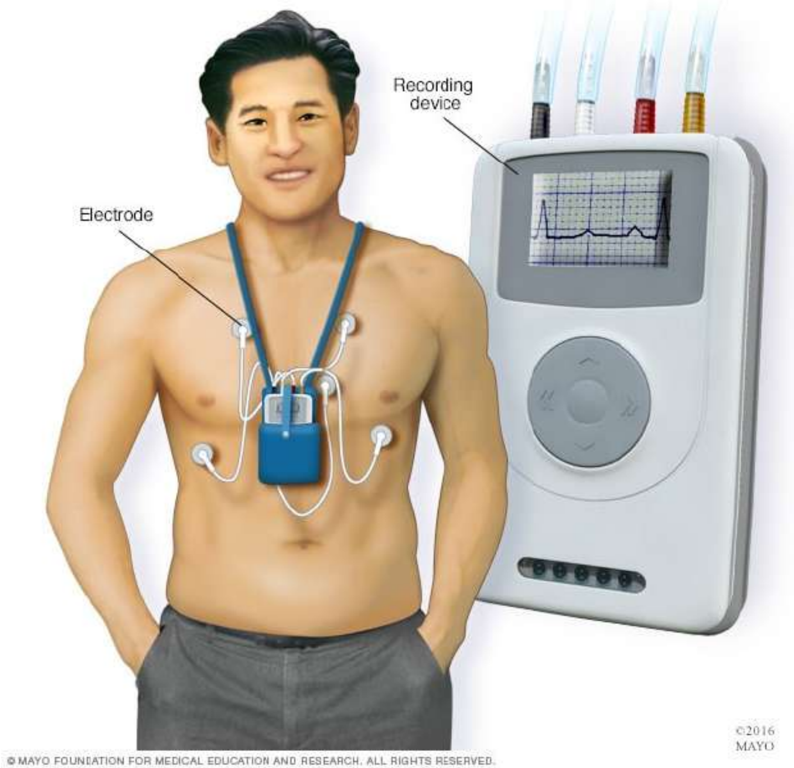
Heartbeat



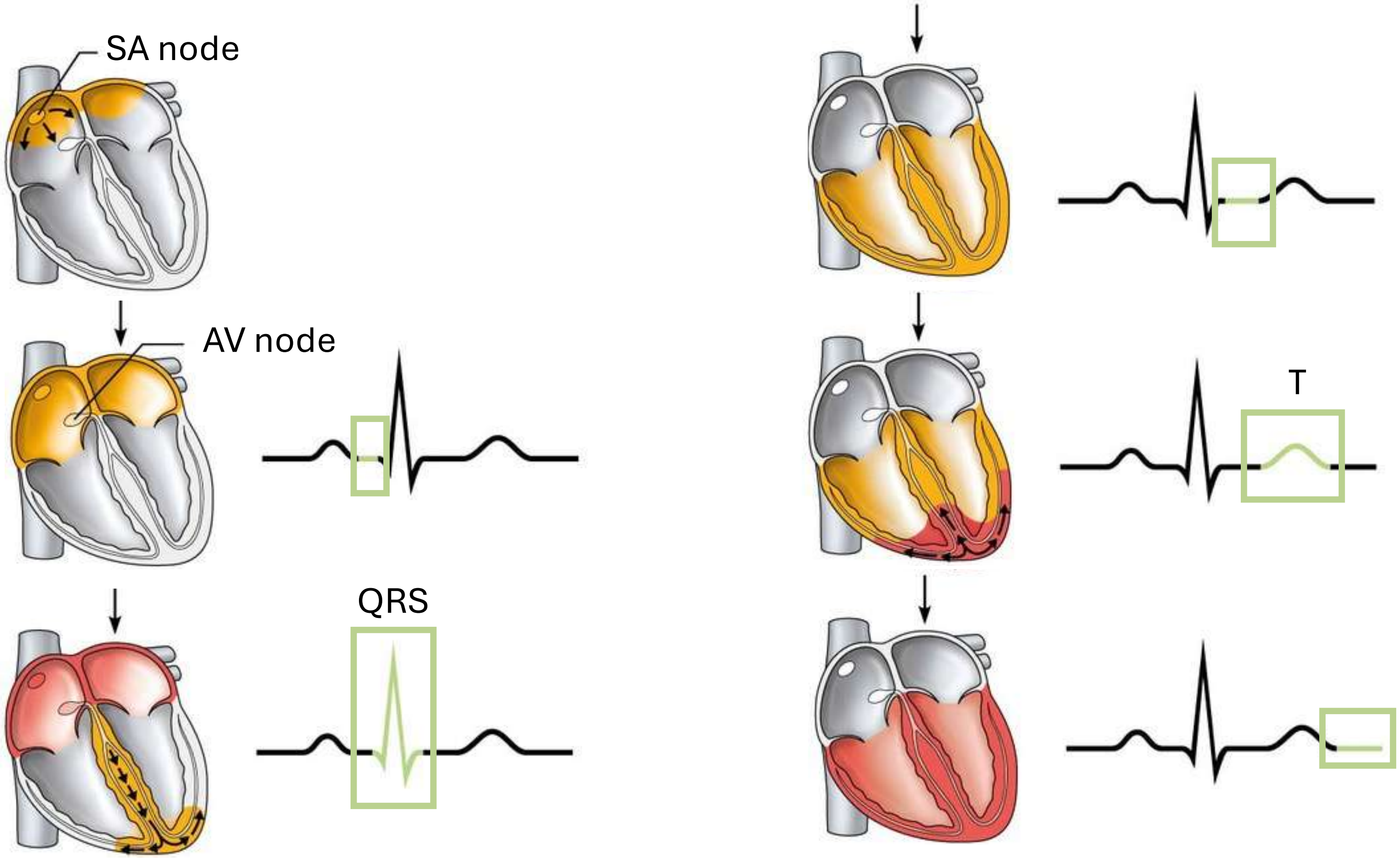
Electrocardiogram (ECG)



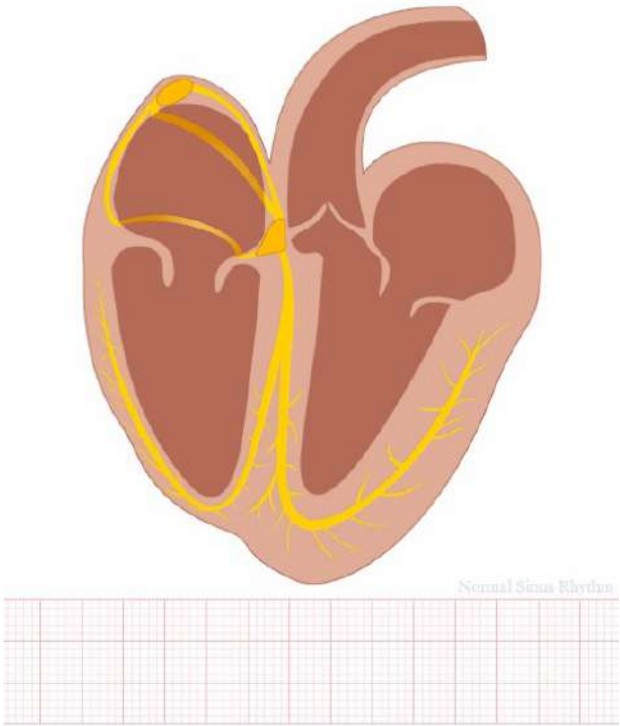
Holter monitor

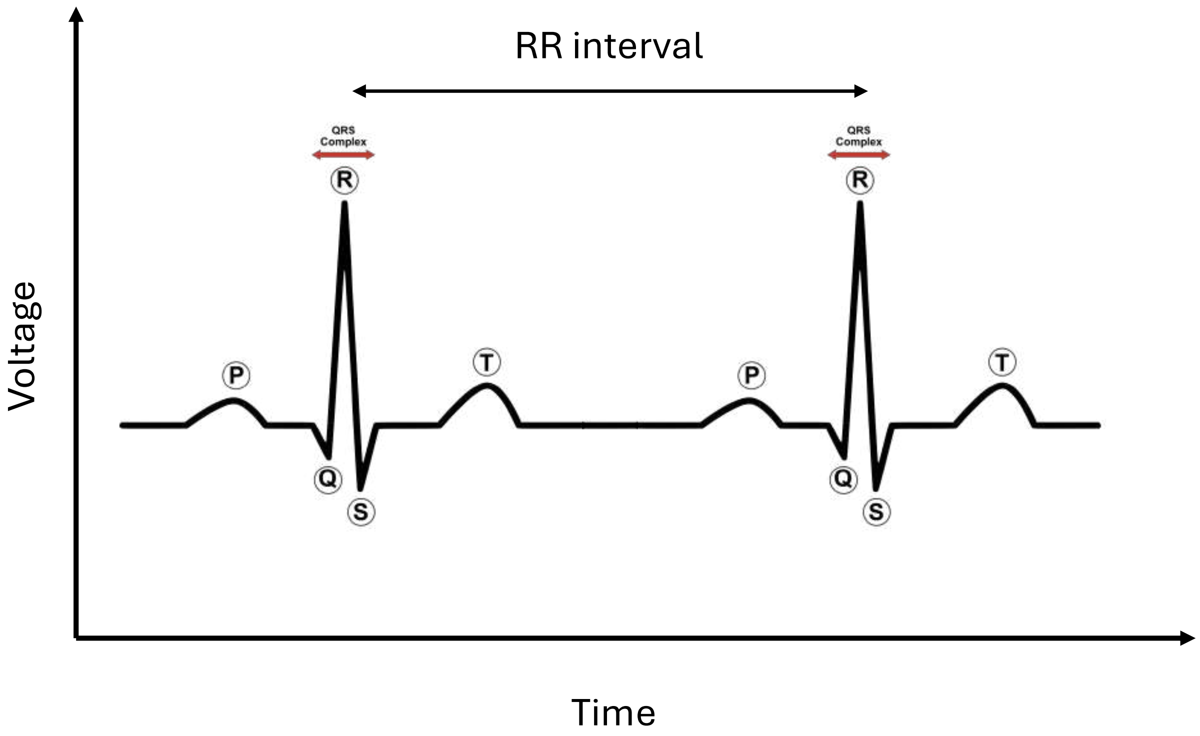


Cardiac cycle

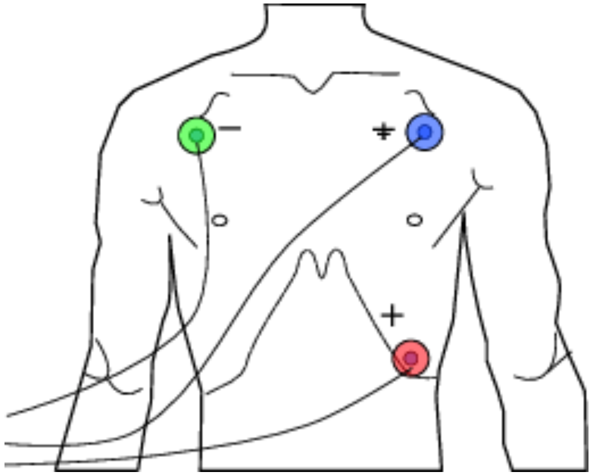


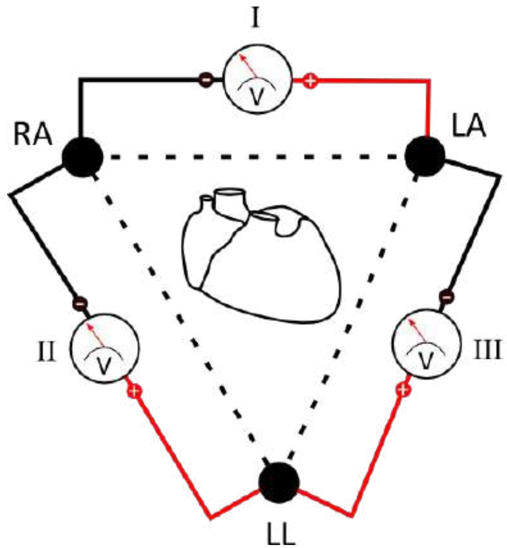
Cardiac cycle

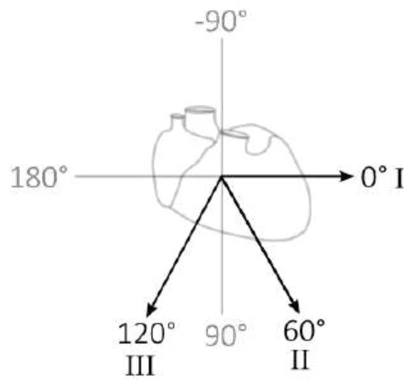




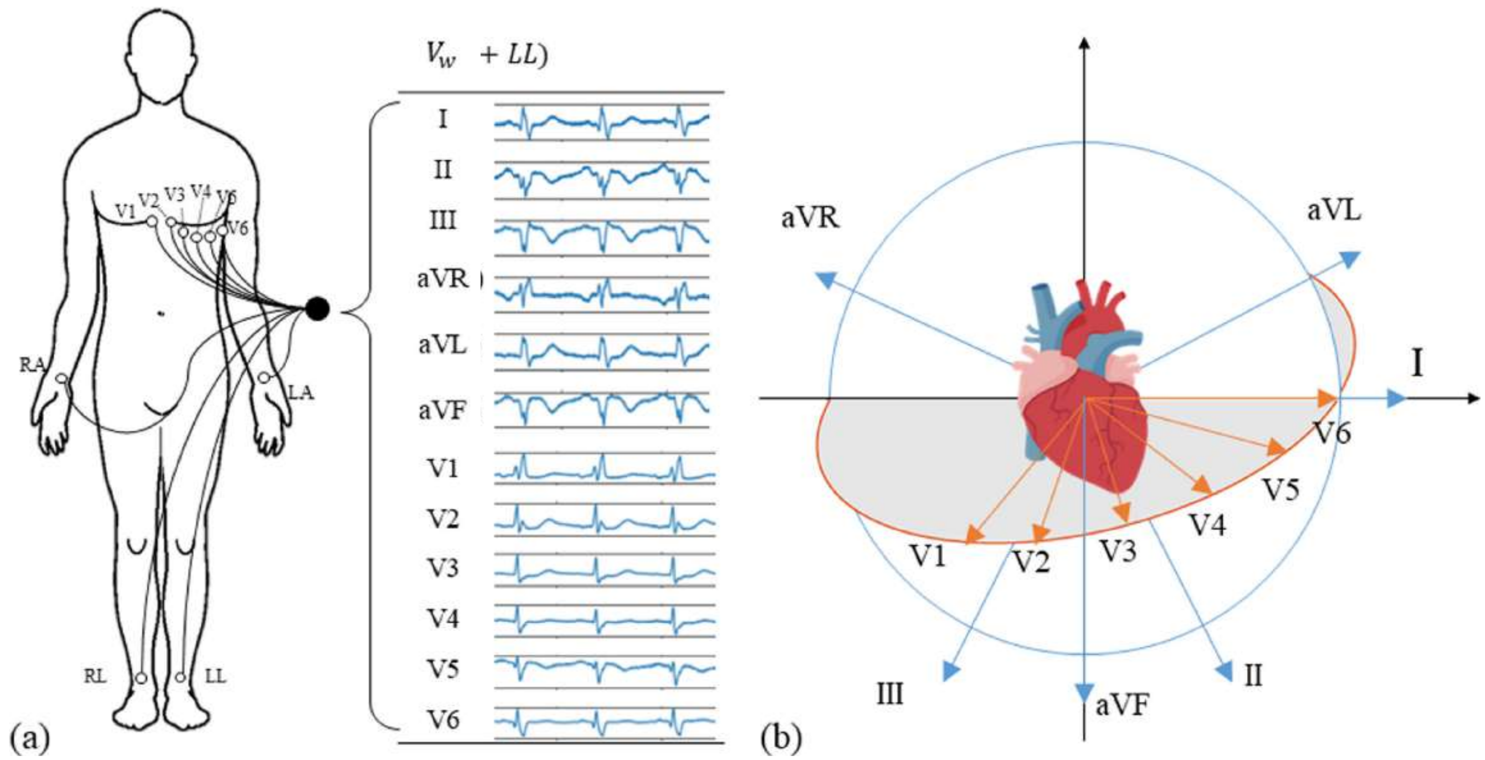
ECG 2-lead vs 12-lead







ECG 2-lead vs 12-lead



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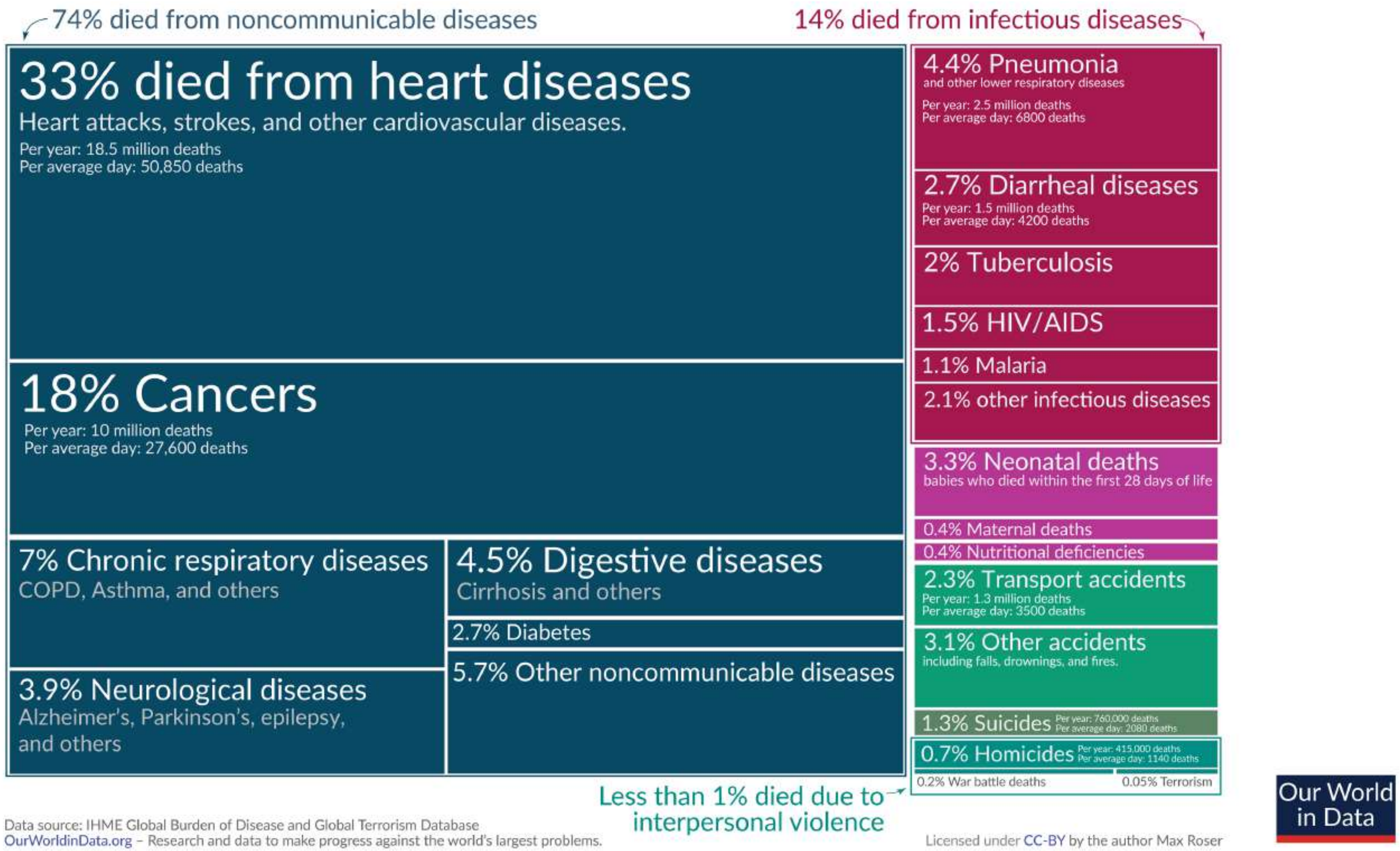
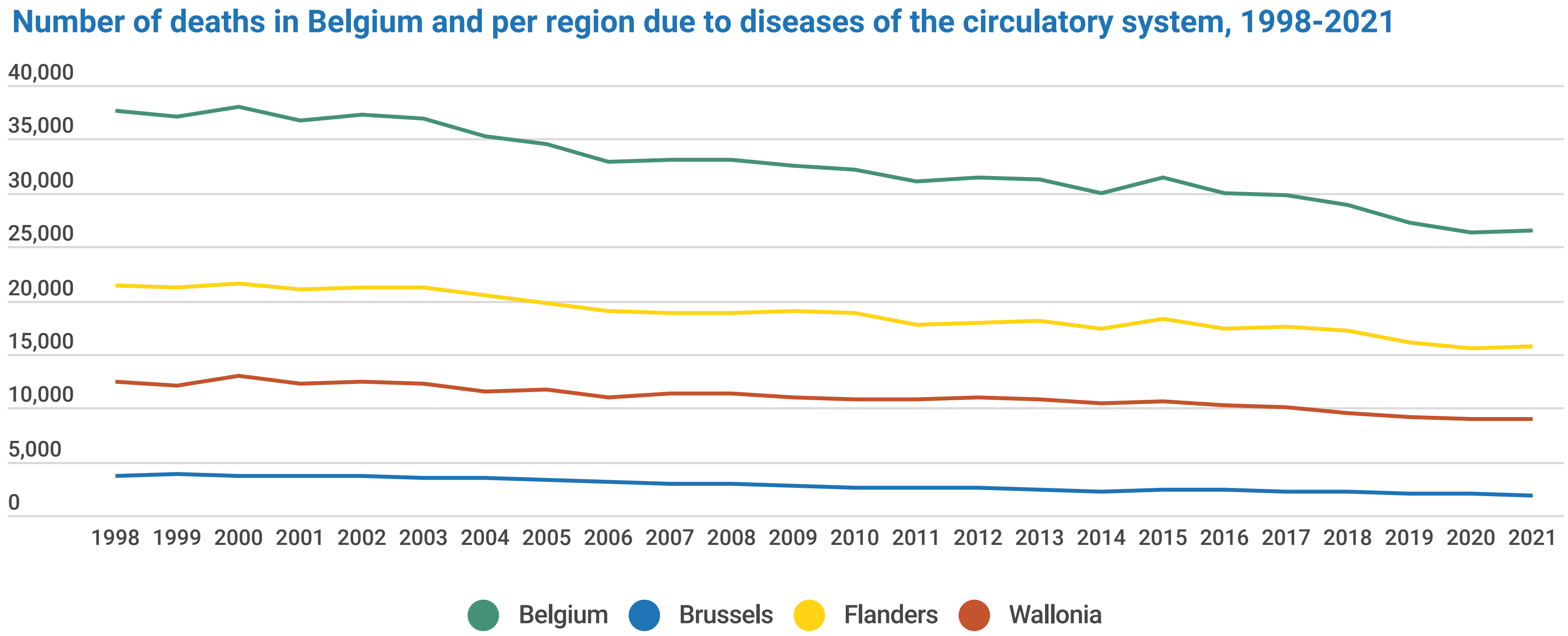
Causes of death globally in 2019



Cardiovascular diseases in Belgium

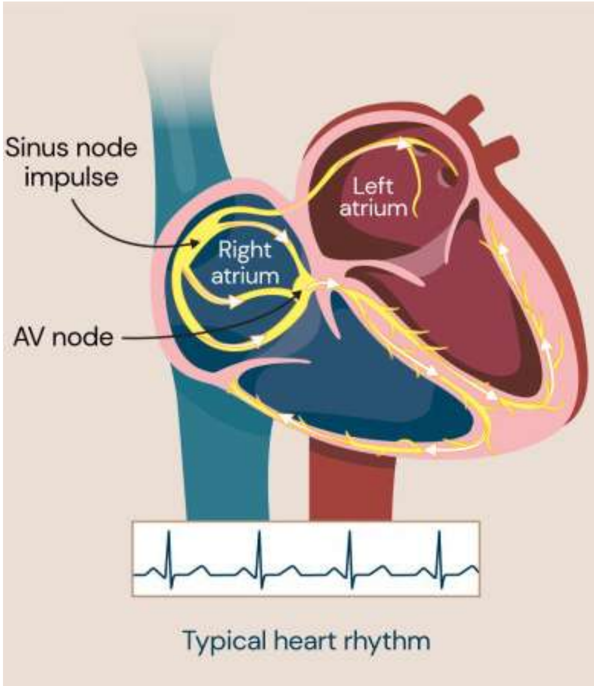


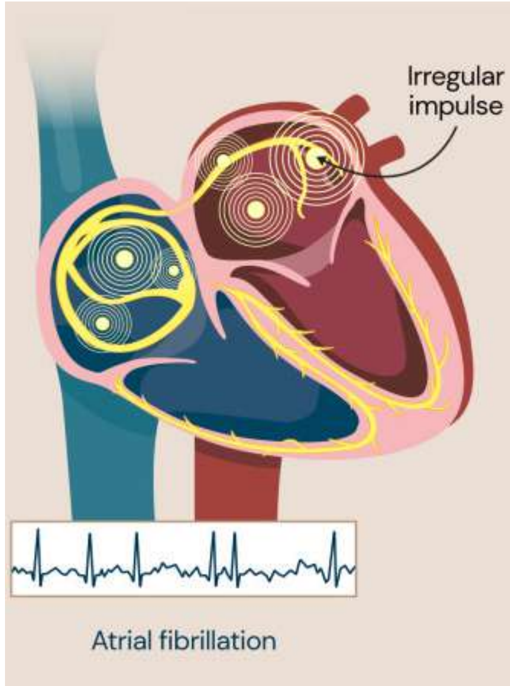

NORMAL
HEARTBEAT


ATRIAL
FIBRILLATION

Atrial Fibrillation (AF)

- Cardiovascular disease
- 2% of the world population
  - 8% (>55)
  - 20% (>80)
- Risk
  - 5x stroke
  - 2x death
- Belgium
  - 10 000 strokes / year
  - 150 000 AF





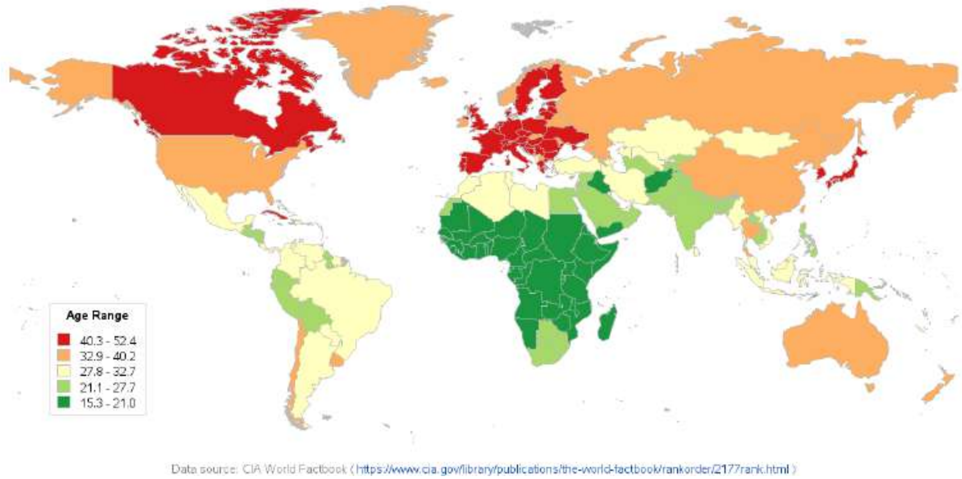
Global prevalence of AF

2020 ESC Guidelines for the diagnosis and management of atrial fibrillation (European Heart Journal 2020-doi/10.1093/eurheart/ehaa612)

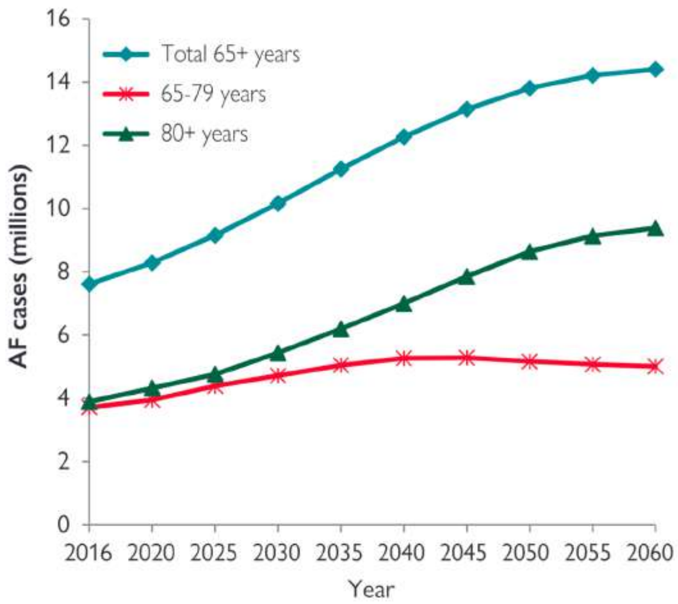
Global prevalence of AF – relation with age

Global AF prevalence

Mean age

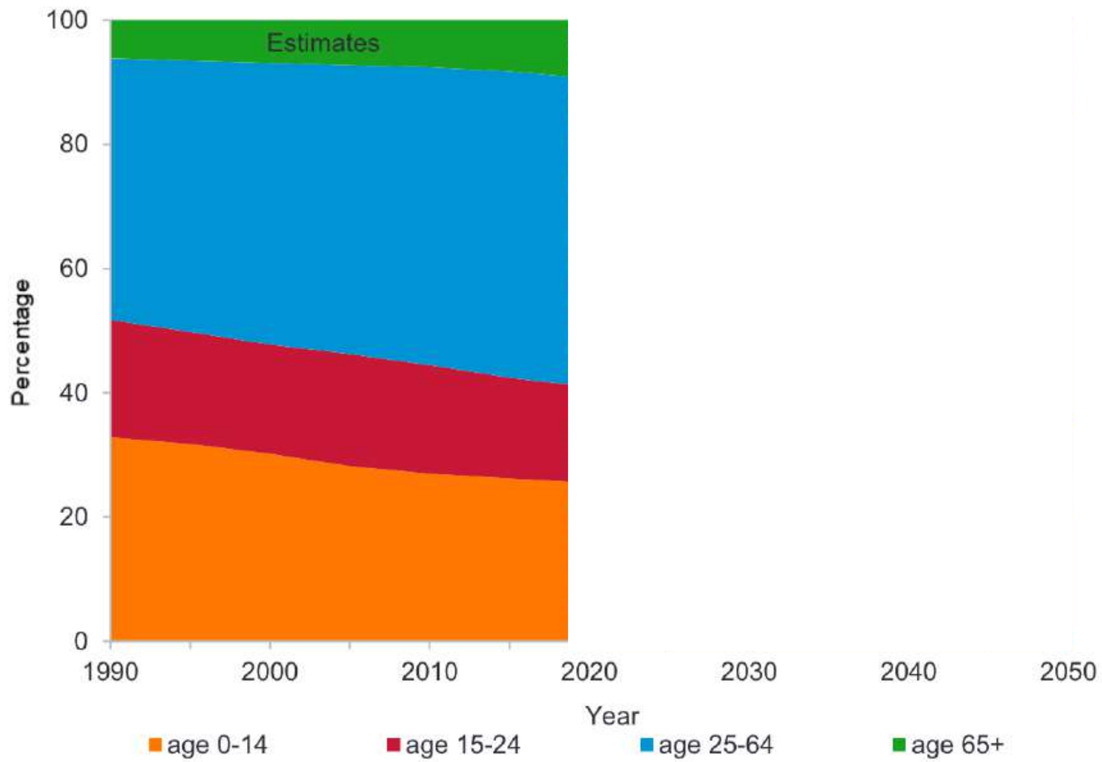


Projection of AF prevalence increase



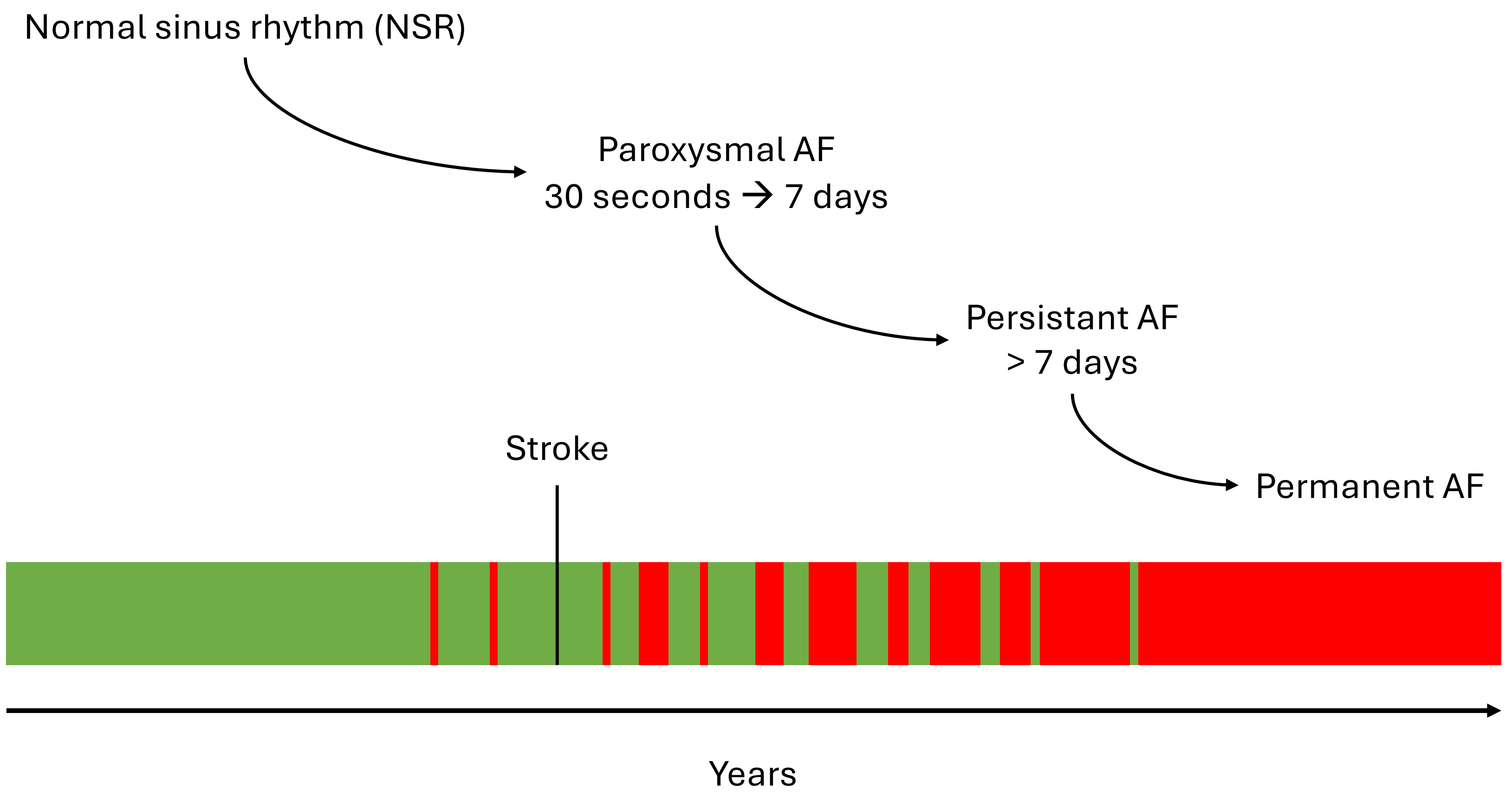
2020 ESC Guidelines for the diagnosis and management of atrial fibrill
(European Heart Journal 2020-doi/10.1093/eurheart/ehaa612)

Global population by broad age groups, 1990-2050 (percentage)



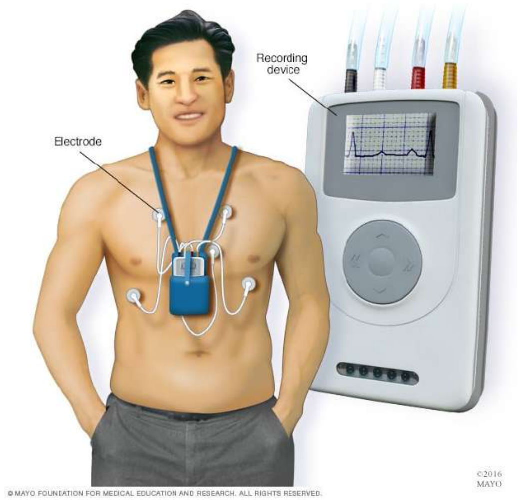
Source: United Nations, Department of Economic and Social Affairs, Population Division (2019). *World Population Prospects 2019.*

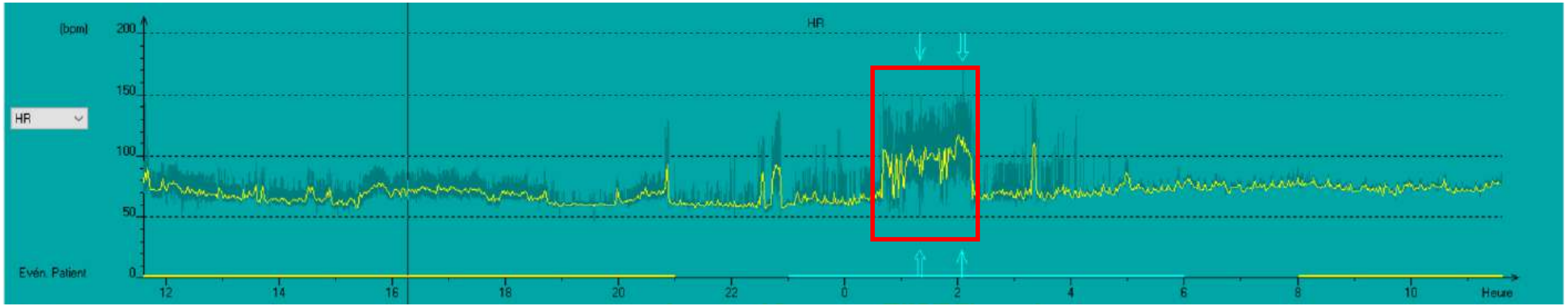
AF evolution



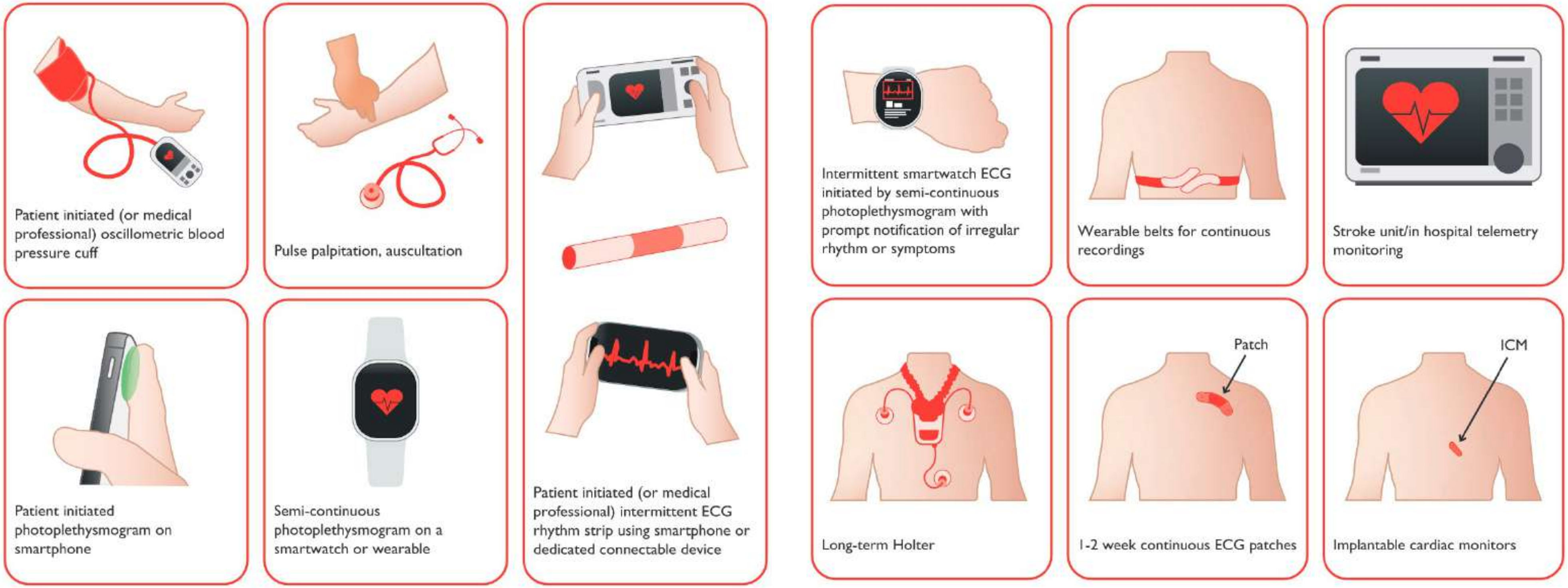
AF screening

- Holter monitor
- 24-hour recordings



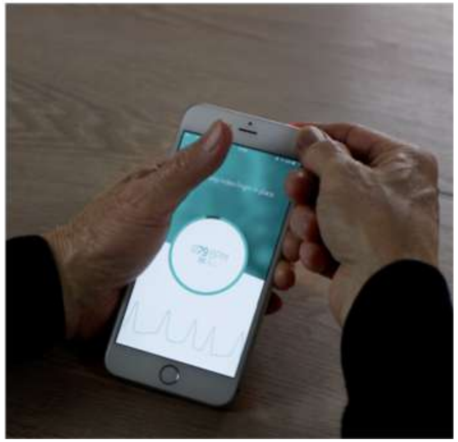


Systems for AF screening

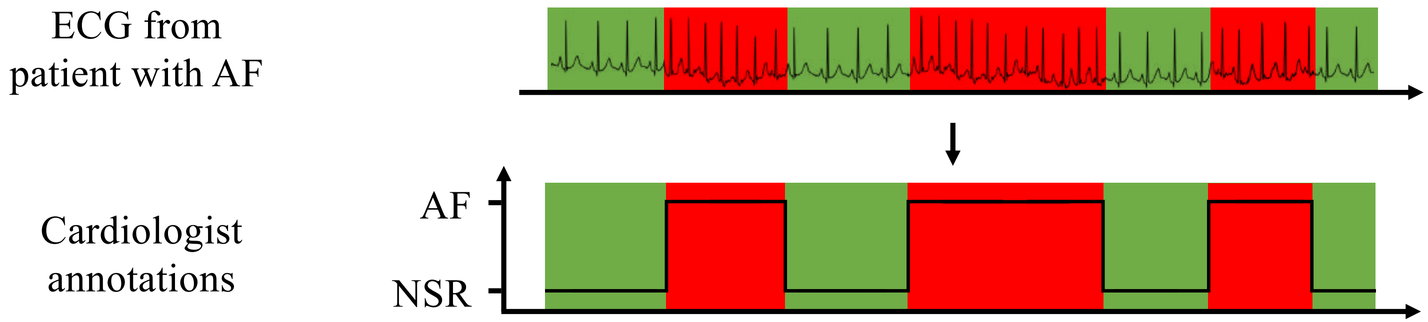


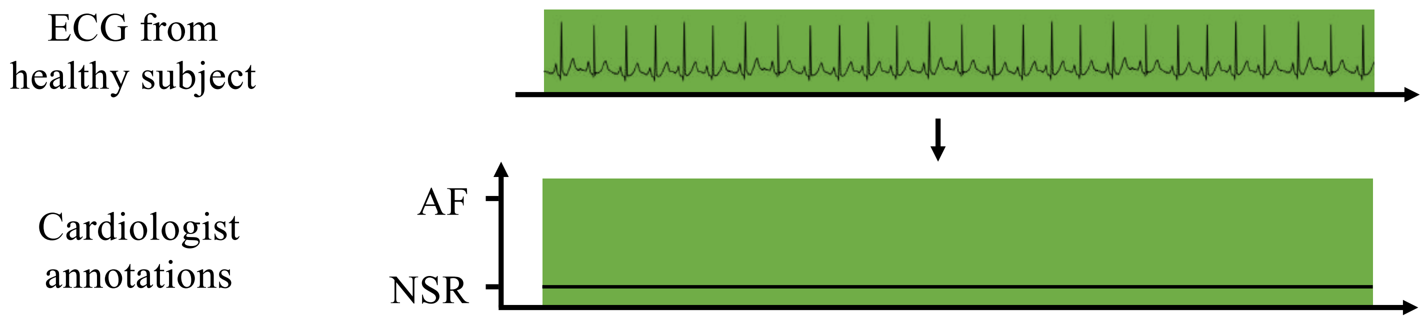
Systems for AF screening

- Compagnies
  - Apple Watch
  - KardiaMobile
  - Fibricheck



AF detection in ECG





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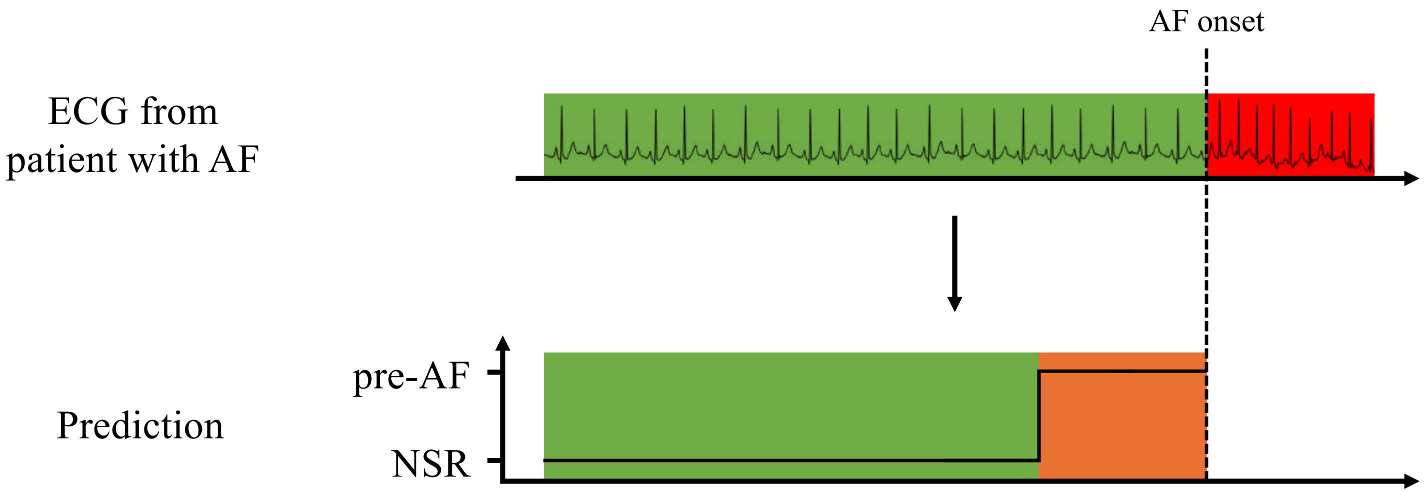
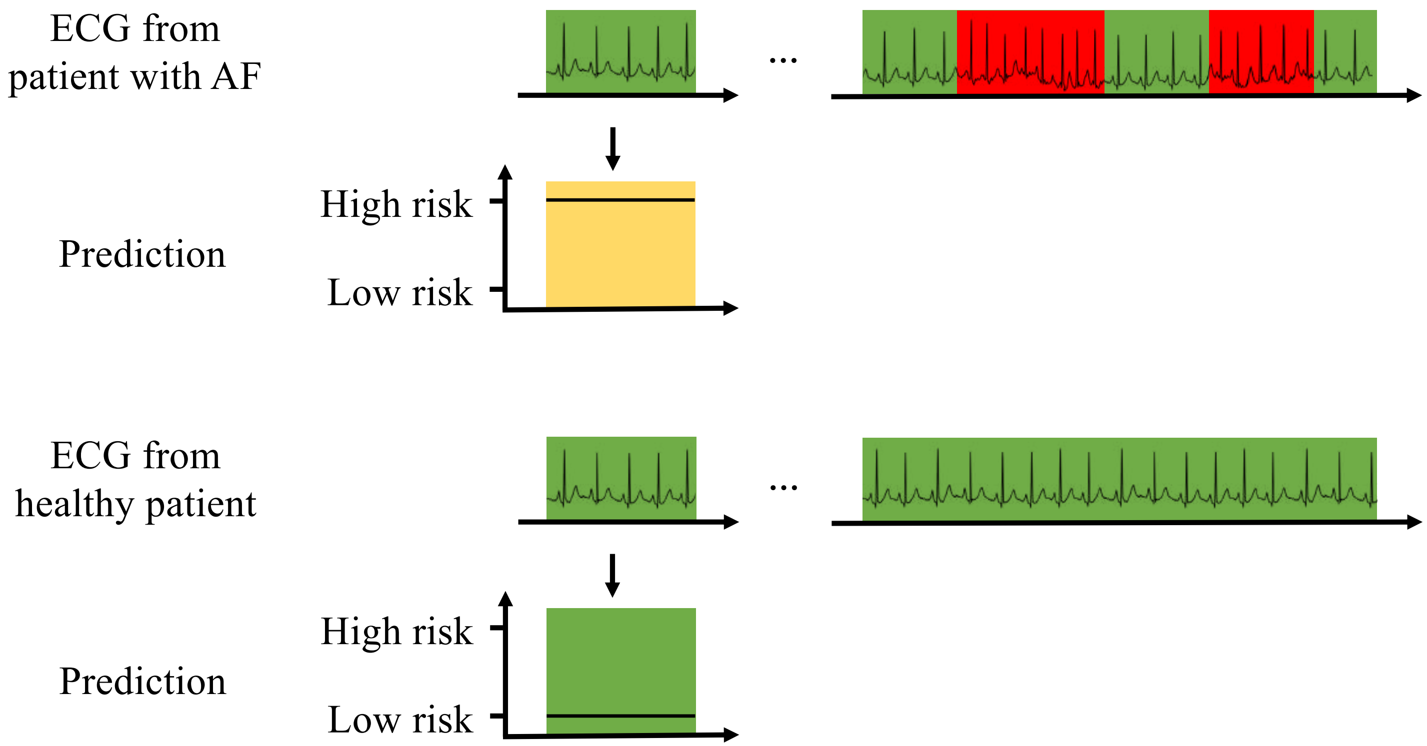
AF onset forecast

Find AF signature before the AF onset



AF risk identification

Find AF signature during Normal Sinus Rhythm



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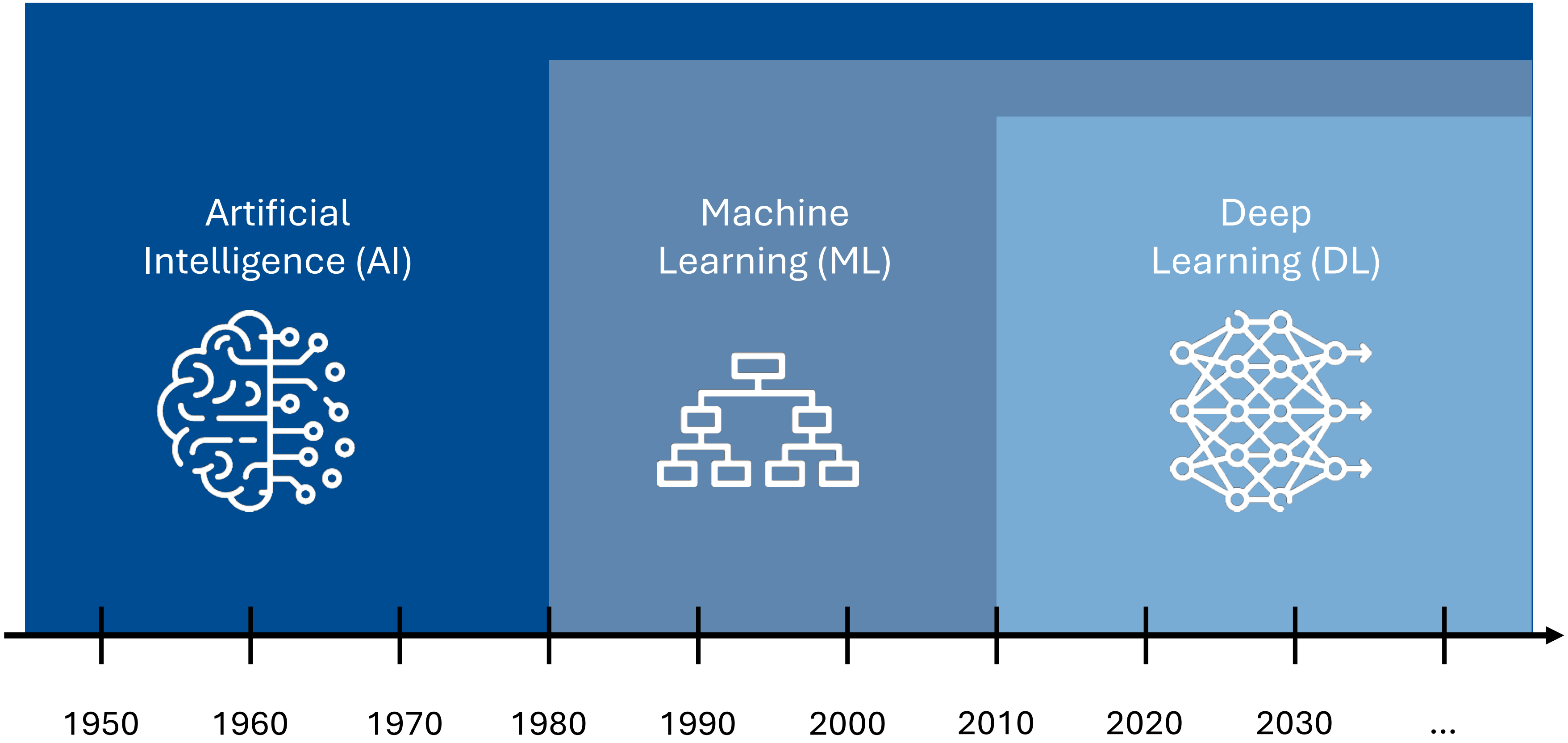
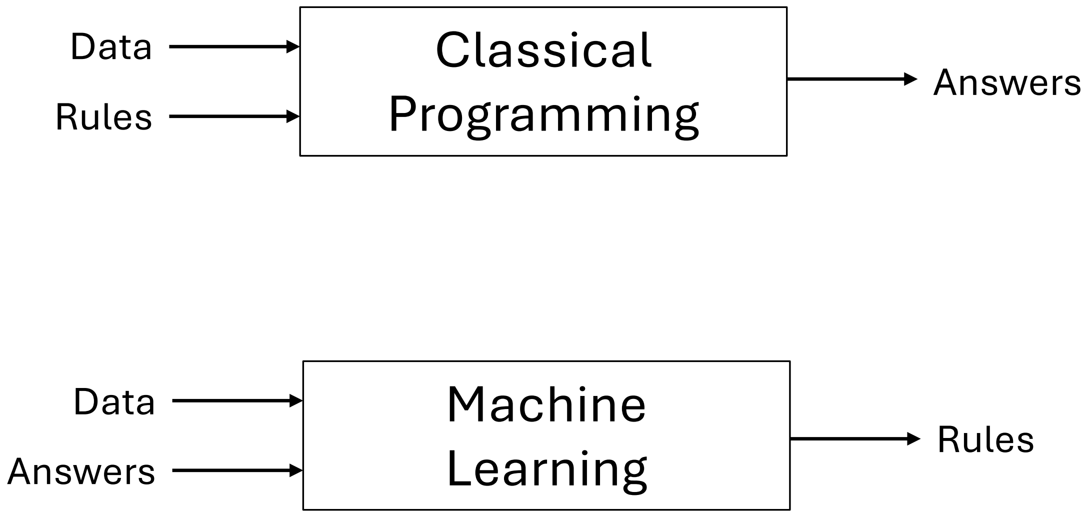
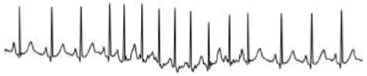
Machine Learning (ML)



Machine Learning (ML) paradigm

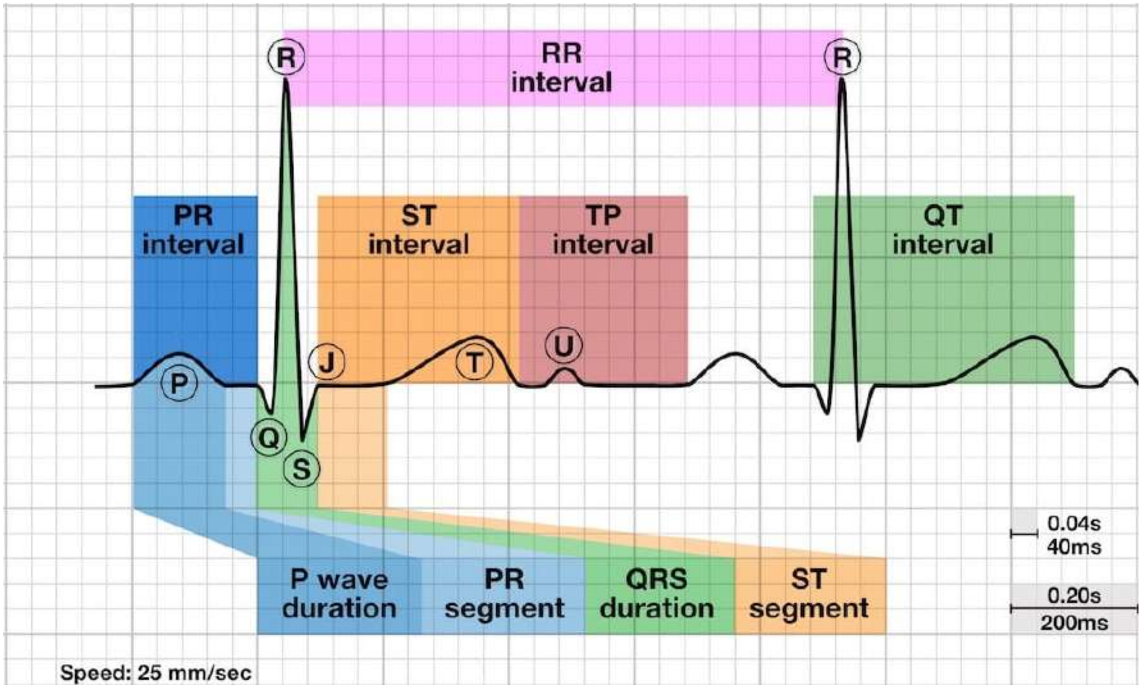


Machine Learning vs Deep Learning

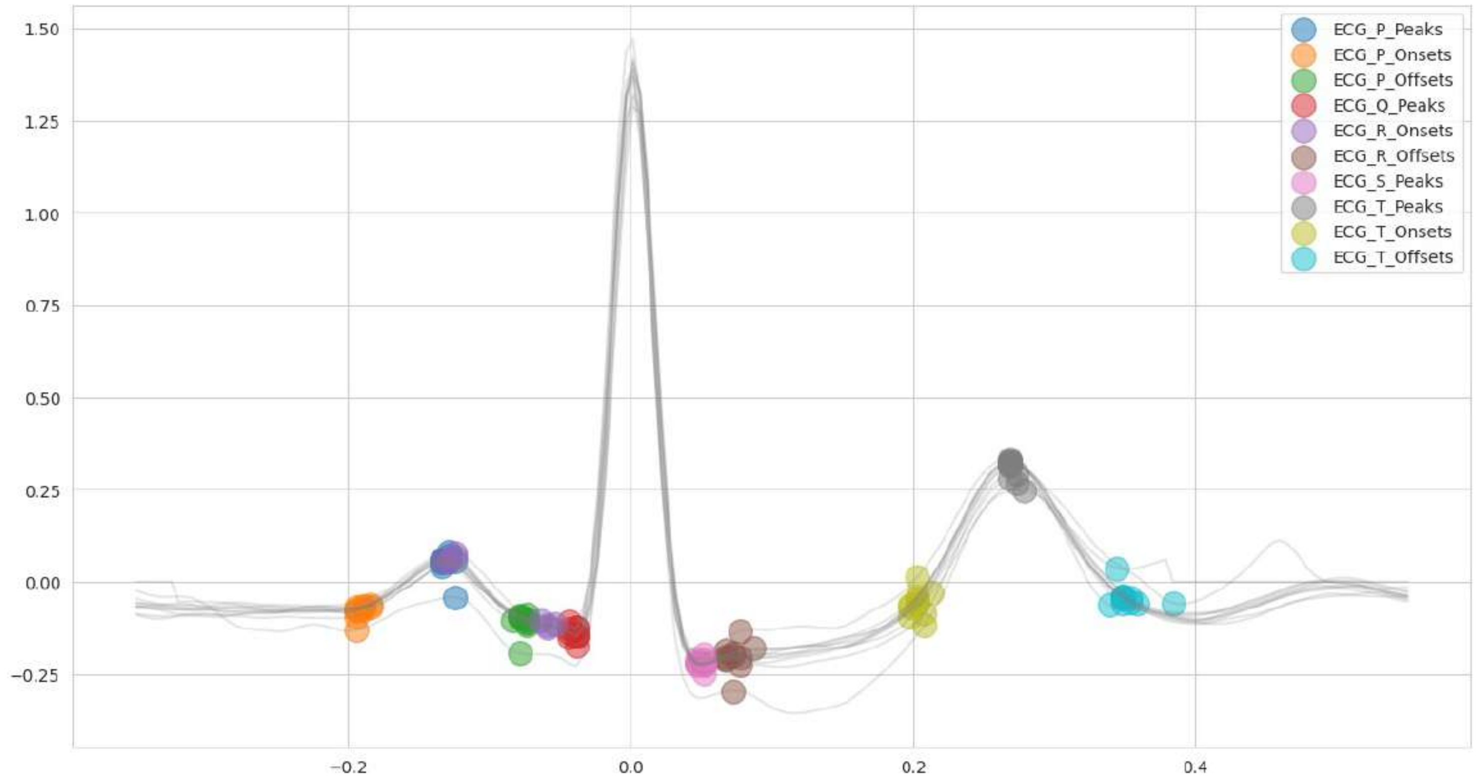
	Input						Output
Machine Learning		→	Features	→	Model	→	Prediction

Features from ECG Morphology

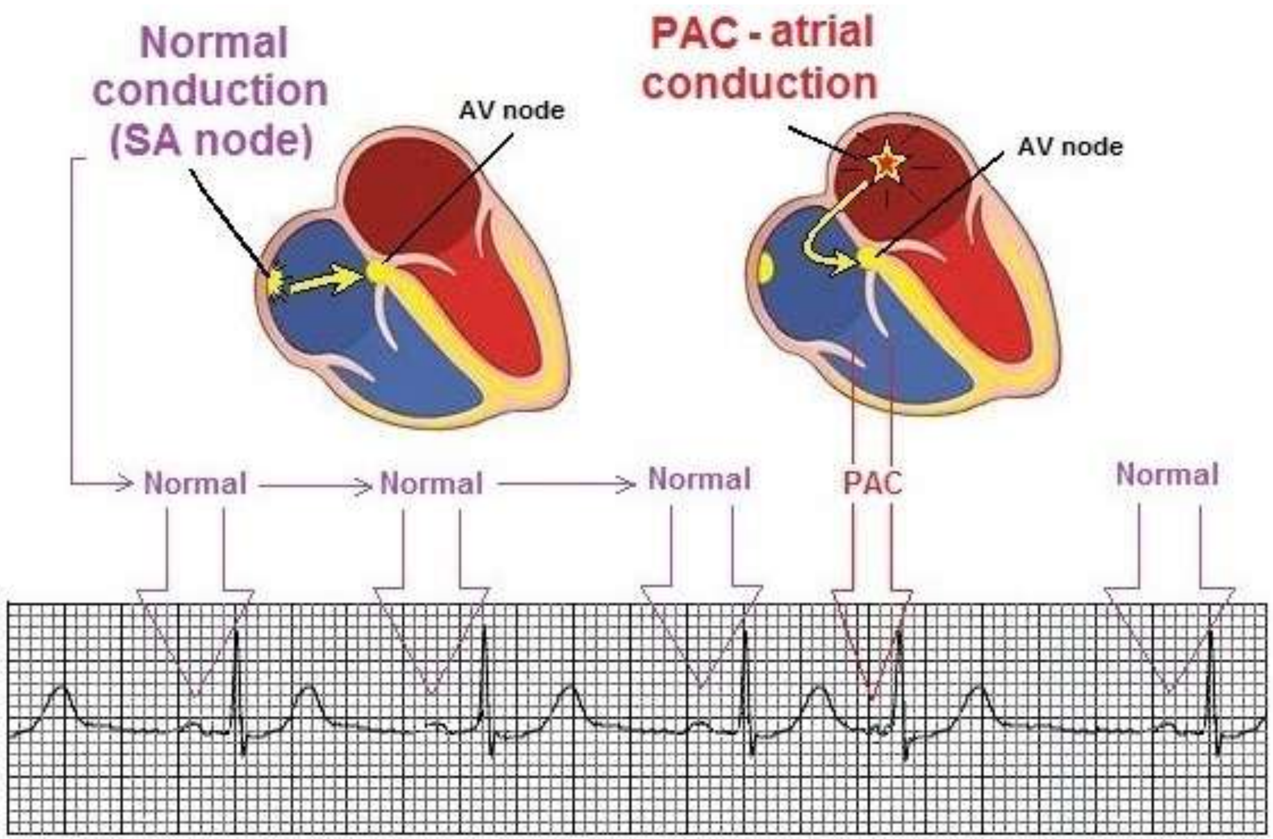
- Waves
  - Duration
  - Amplitude
  - Area
- Intervals
- Segments



ECG delienation



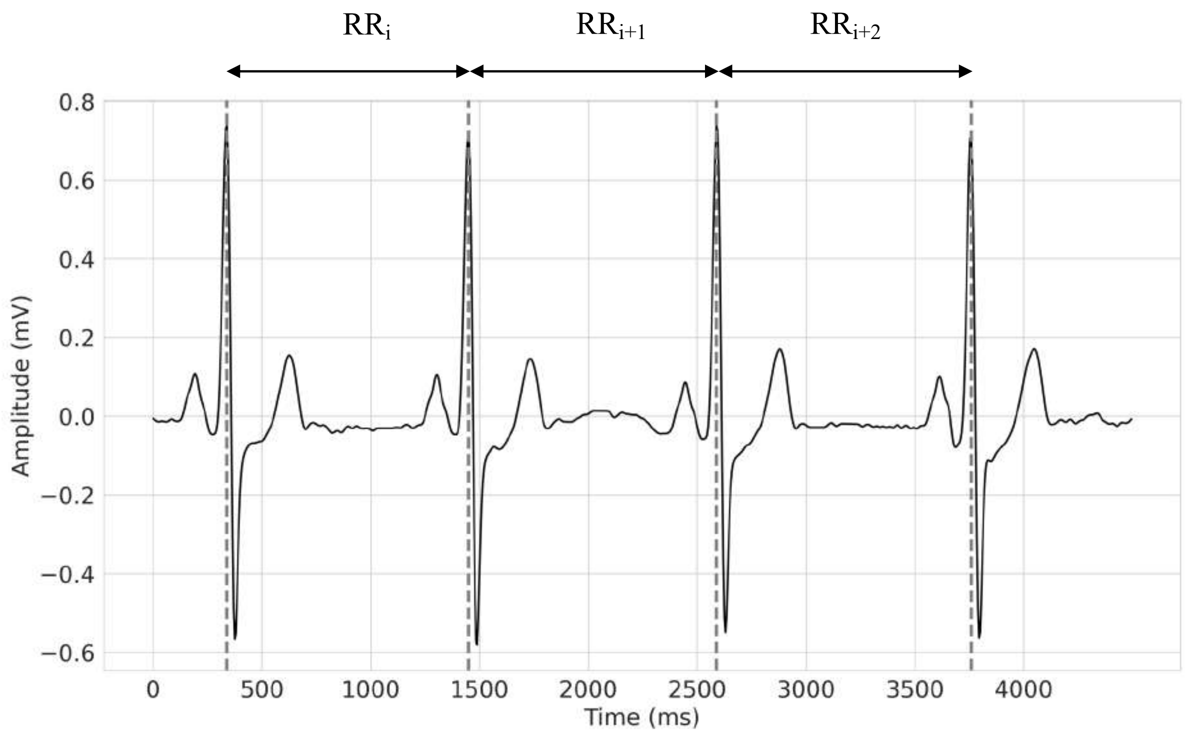
Premature Atrial Contractions (PAC)



https://ekgstripsearch.com/PAC.htm

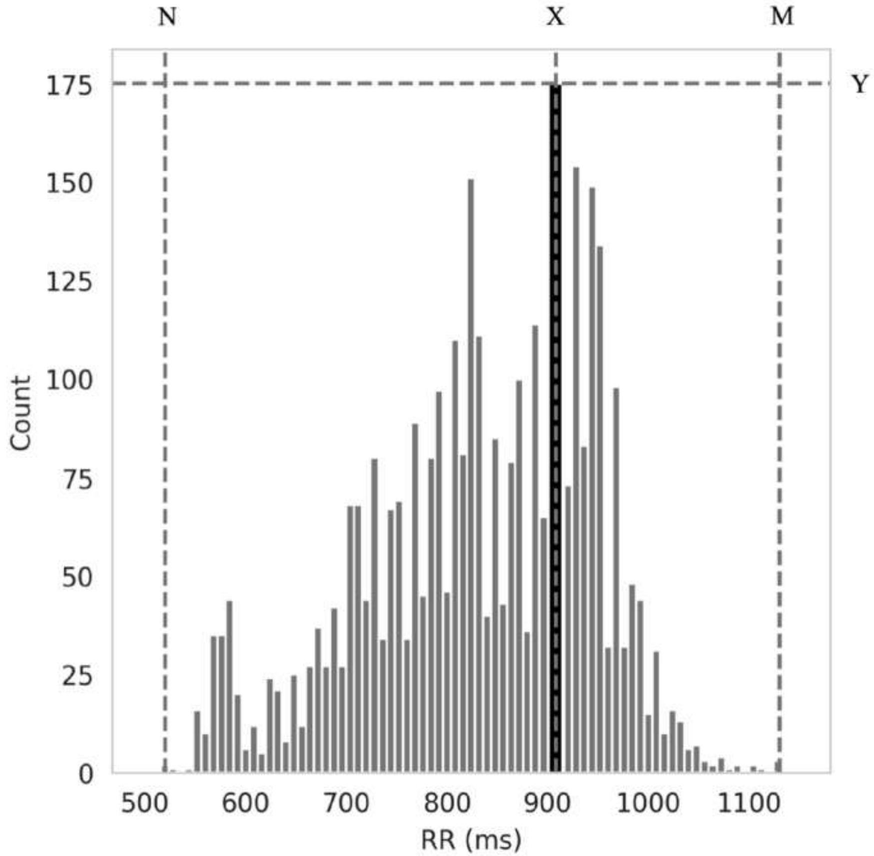
Features from HRV

- RR intervals
- Temporal
  - Value: mean, min, max
  - Deviation: sd
  - Difference: pNN50



Features from HRV

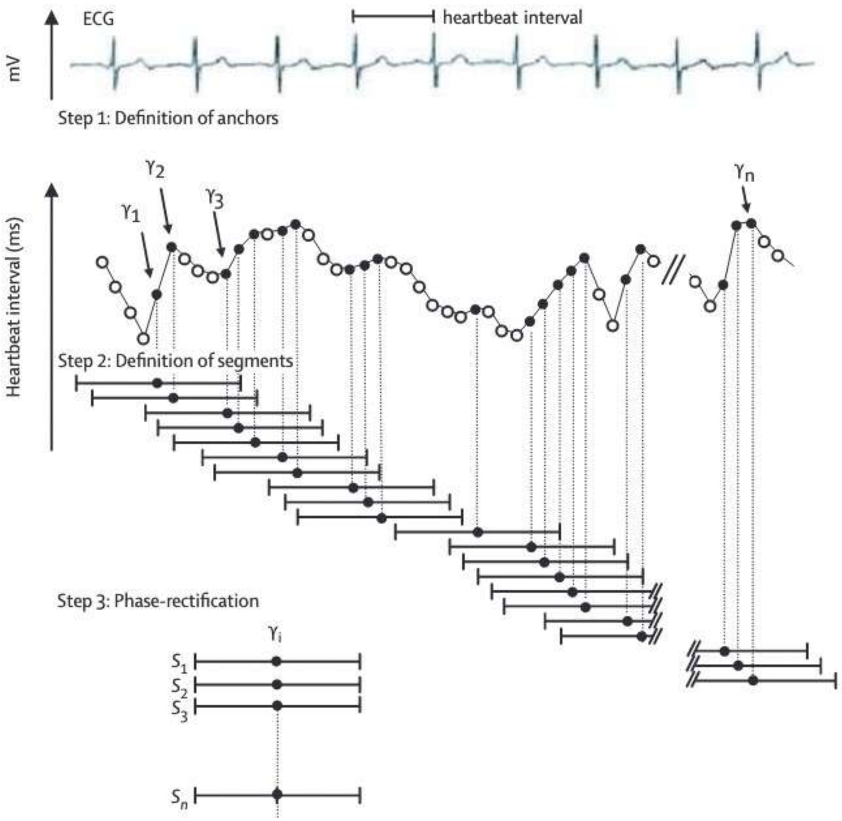
- RR intervals
- Temporal
  - Value: mean, min, max
  - Deviation: sd
  - Difference: pNN50
  - RR distribution

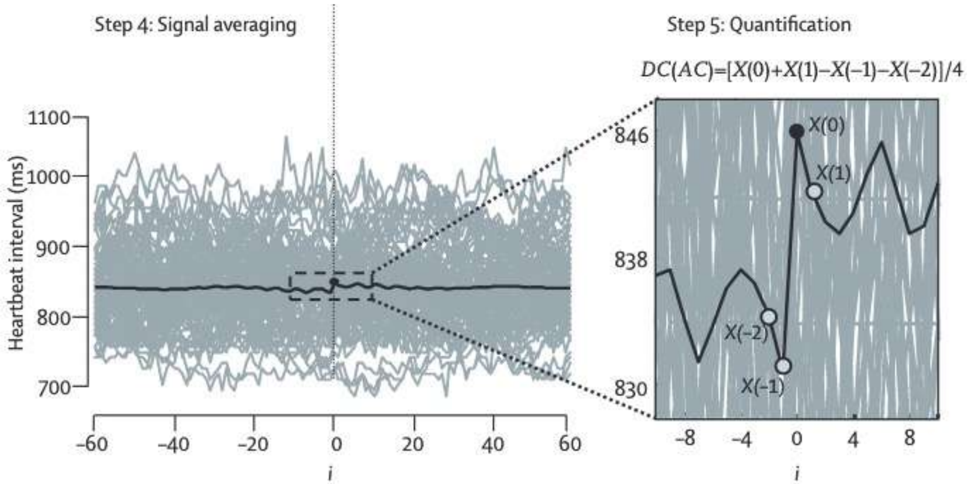


Features from HRV

- RR intervals
- Temporal
  - Value: mean, min, max
  - Deviation: sd
  - Difference: pNN50
  - RR distribution
  - AC DC

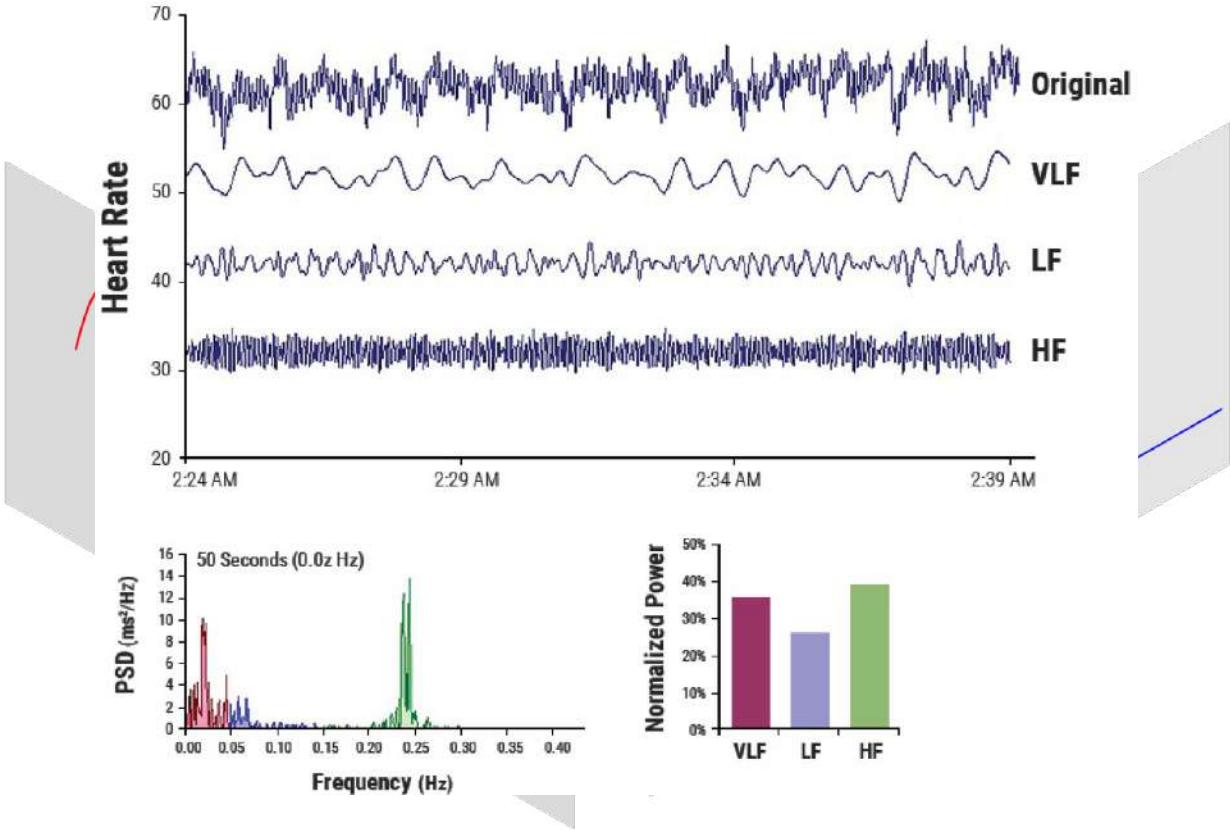
AC and DC


ECG
heartbeat interval
mV
Step 1: Definition of anchors
Heartbeat interval (ms)
Step 2: Definition of segments
Step 3: Phase-rectification

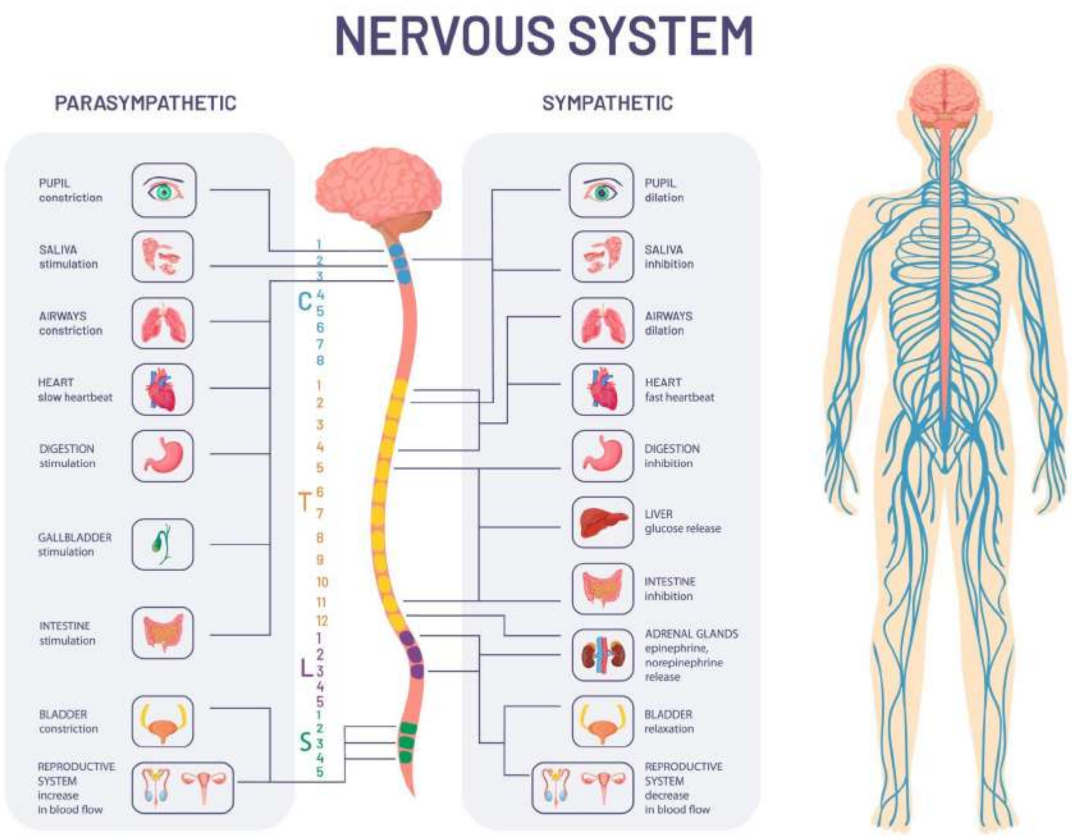

Step 4: Signal averaging
Step 5: Quantification
DC(AC)=[X(0)+X(1)–X(–1)–X(–2)]/4
Heartbeat interval (ms)
1100
1000
900
800
700
–60
–40
–20
0
20
40
60
i
846
838
830
X(0)
X(1)
X(–2)
X(–1)
–8
–4
0
4
8
i

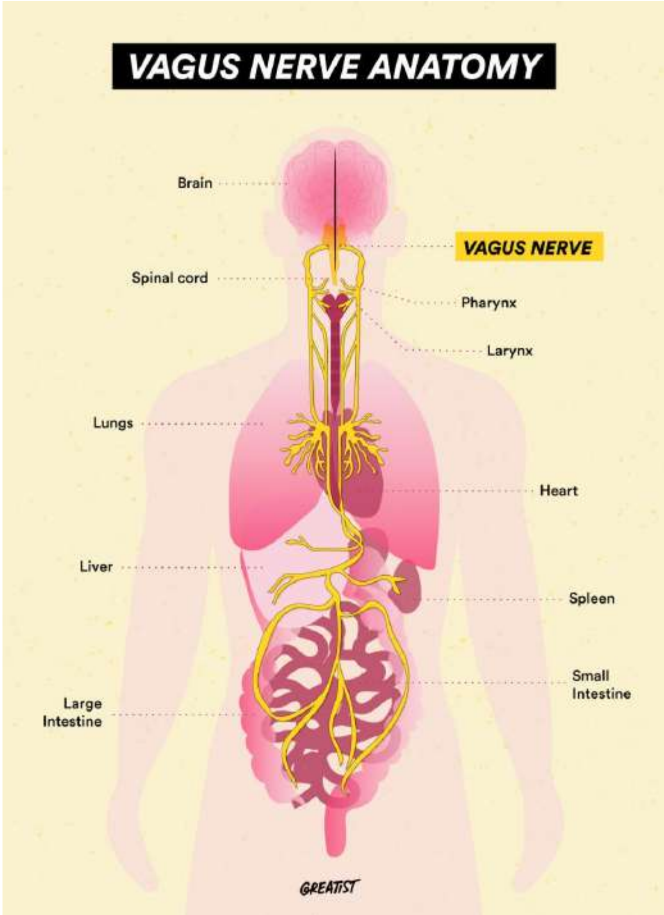
Features from HRV

- RR intervals
- Temporal
- Frequential
  - Low frequency
  - High frequency
- Geometric
  - Poincare
  - SODP



Autonomous nervous system

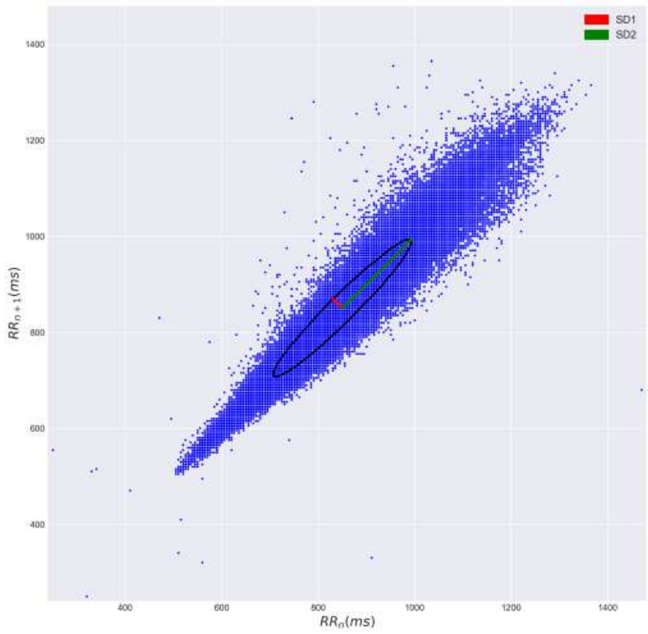




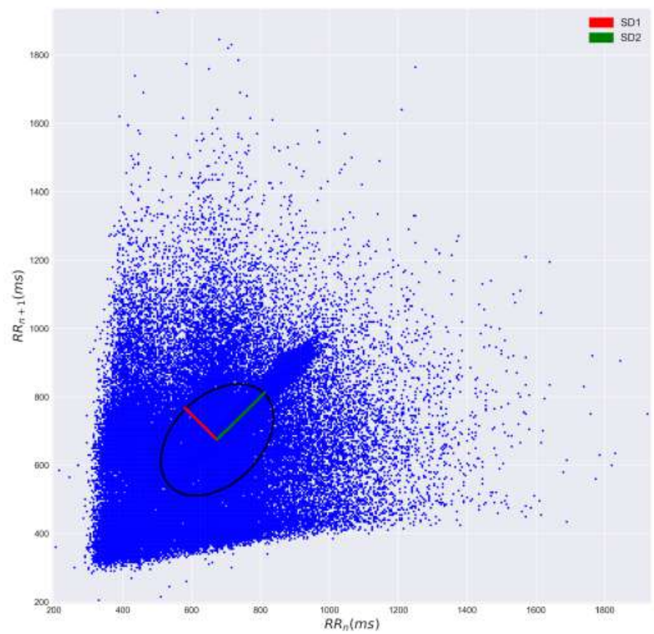
Poincaré plot

- RR intervals = (1015,1030,1030,1030,1060 … 1085,1100,1095,1080)
- X = RR_i
- Y = RR_{i+1}

Normal Sinus Rhythm



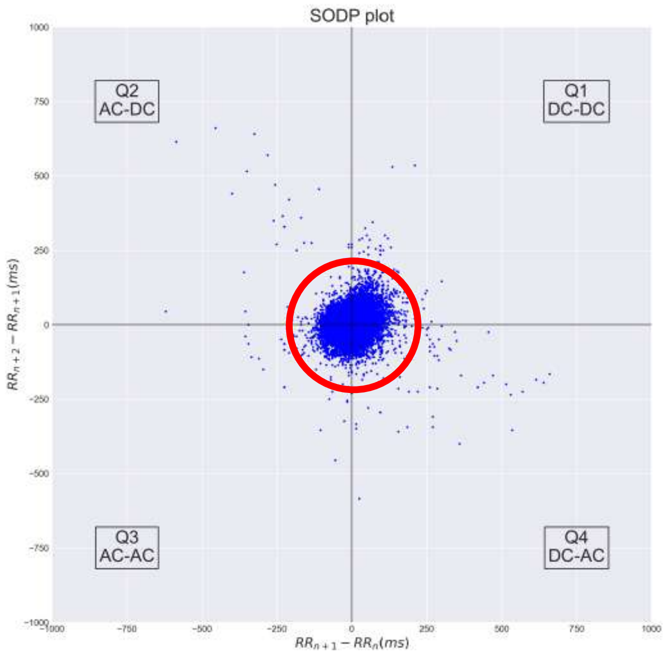
Atrial Fibrillation



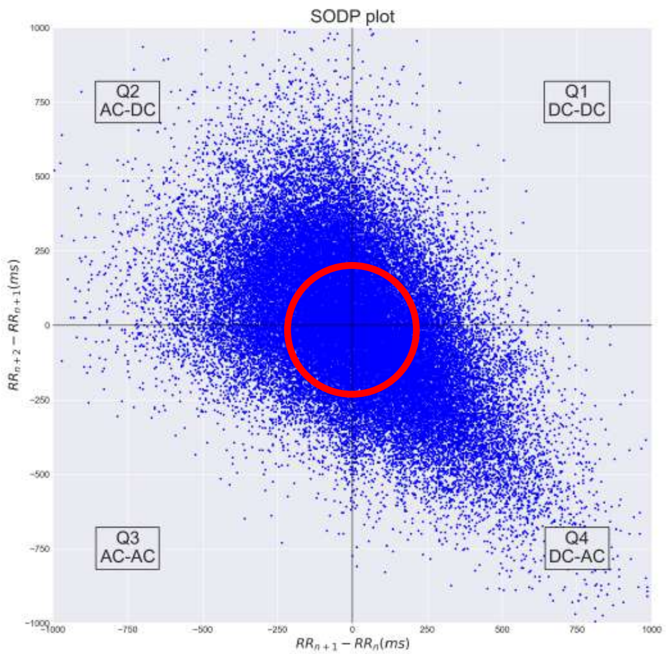
SODP plot

- RR intervals = (1015,1030,1030,1030,1060 … 1085,1100,1095,1080)
- $X = RR_{i+1} - RR_i$
- $Y = RR_{i+2} – RR_{i+1}$

Normal Sinus Rhythm

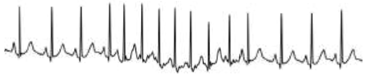


Atrial Fibrillation

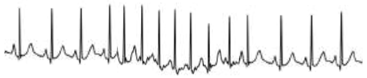


Machine Learning vs Deep Learning

Input				Output

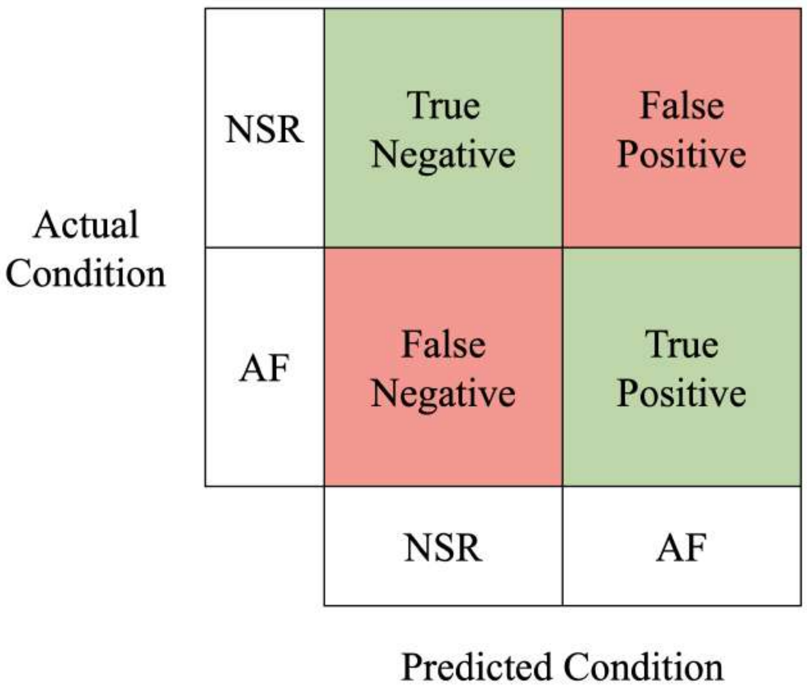
Machine Learning  → Features → Model → Prediction

Input			Output

Deep Learning  → Model → Prediction

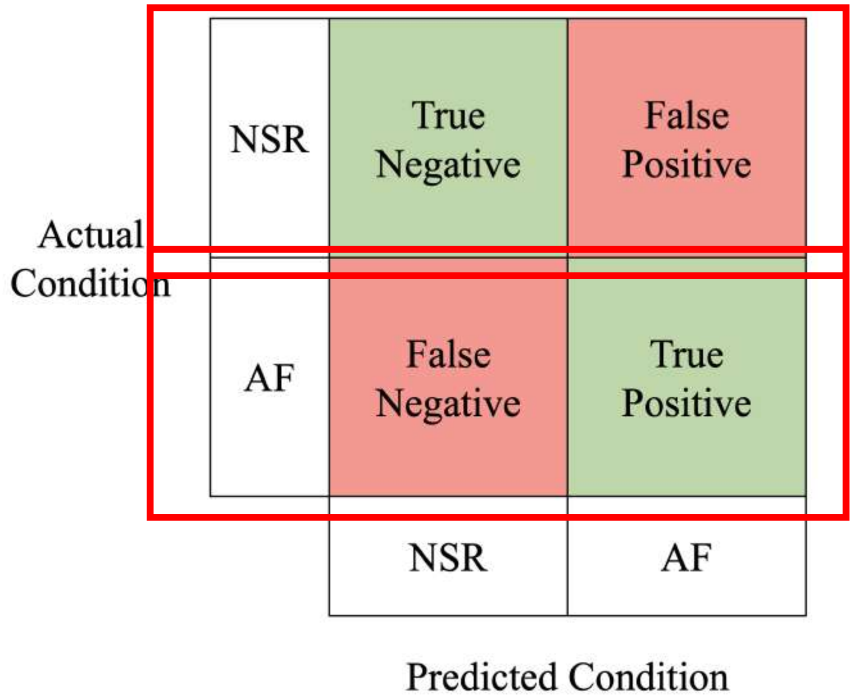
Confusion matrix

- Binary classification
  - AF vs NSR
  - pre-AF vs NSR
  - Low risk vs high risk
- Prediction score 0 → 1
  - score > 0.5 → AF
  - score ≤ 0.5 → NSR



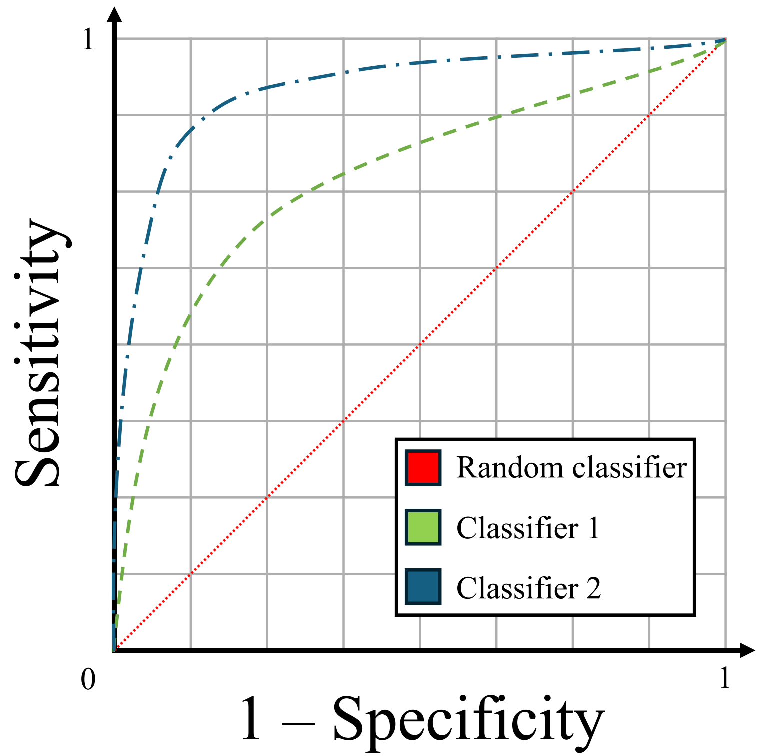
Confusion matrix

- Binary classification
- Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$
- Sensitivity: $\frac{TP}{TP+FN}$
- Specificity: $\frac{TN}{TN+FP}$

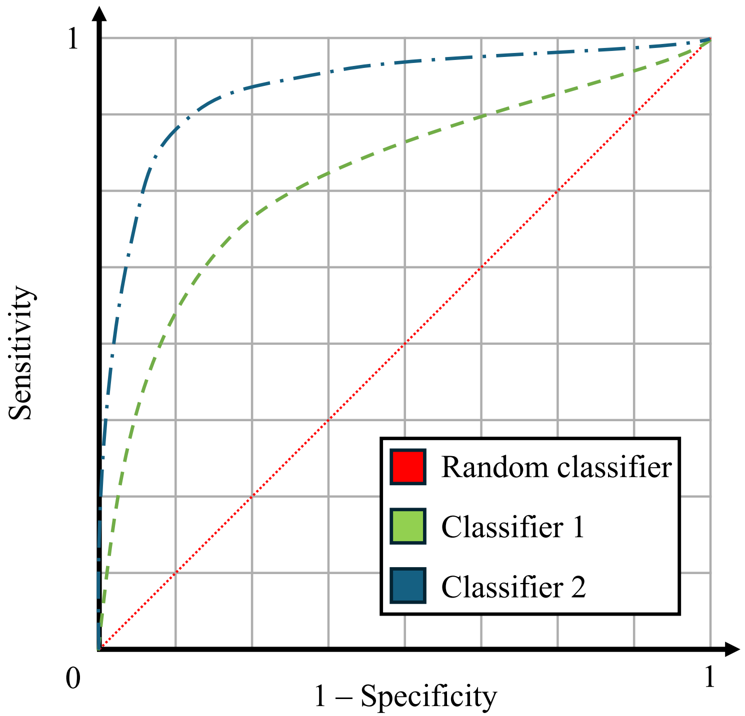


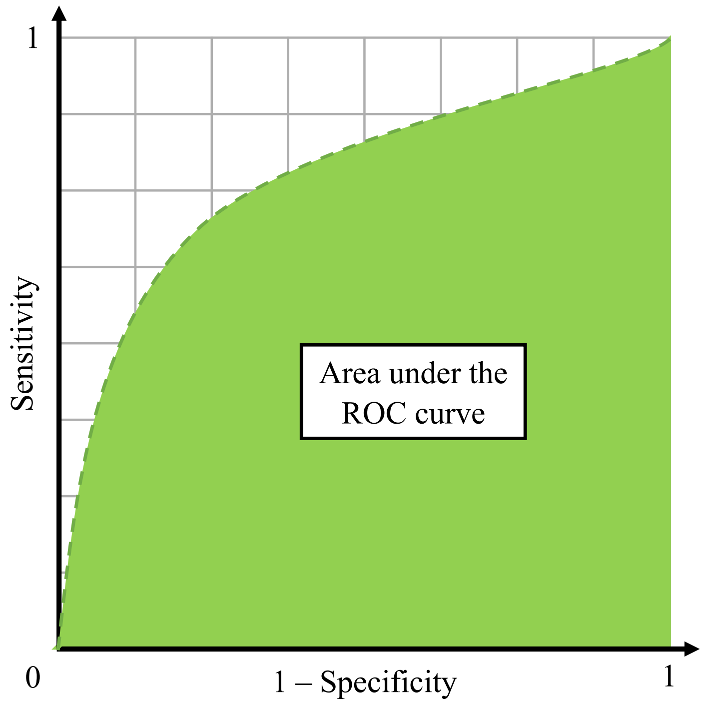
Area under the curve

- All thresholds between 0 and 1
  - 0.001
  - 0.002
  - 0.003
  - …
  - 0.997
  - 0.998
  - 0.999

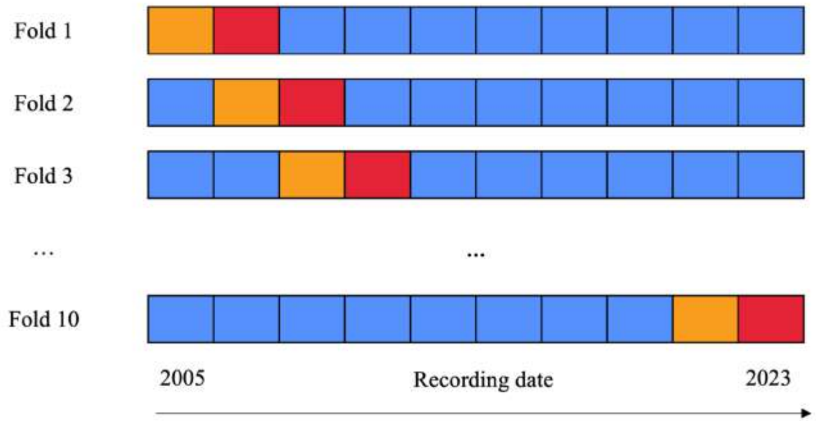


Area under the curve

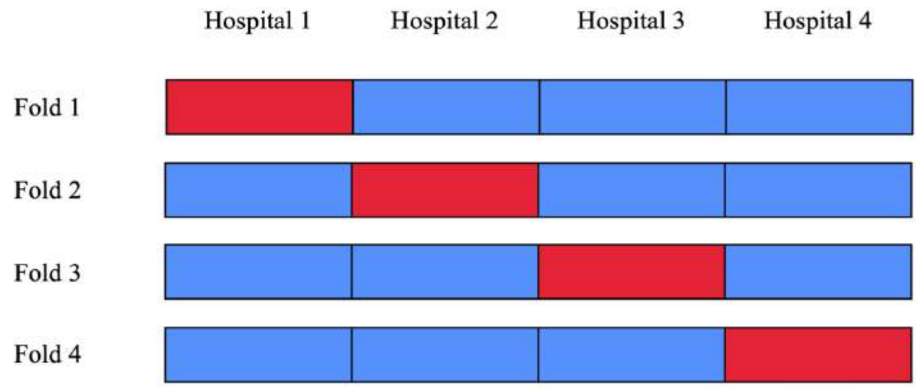




Train split and test split



Temporal cross-validation



Spacial cross-validation

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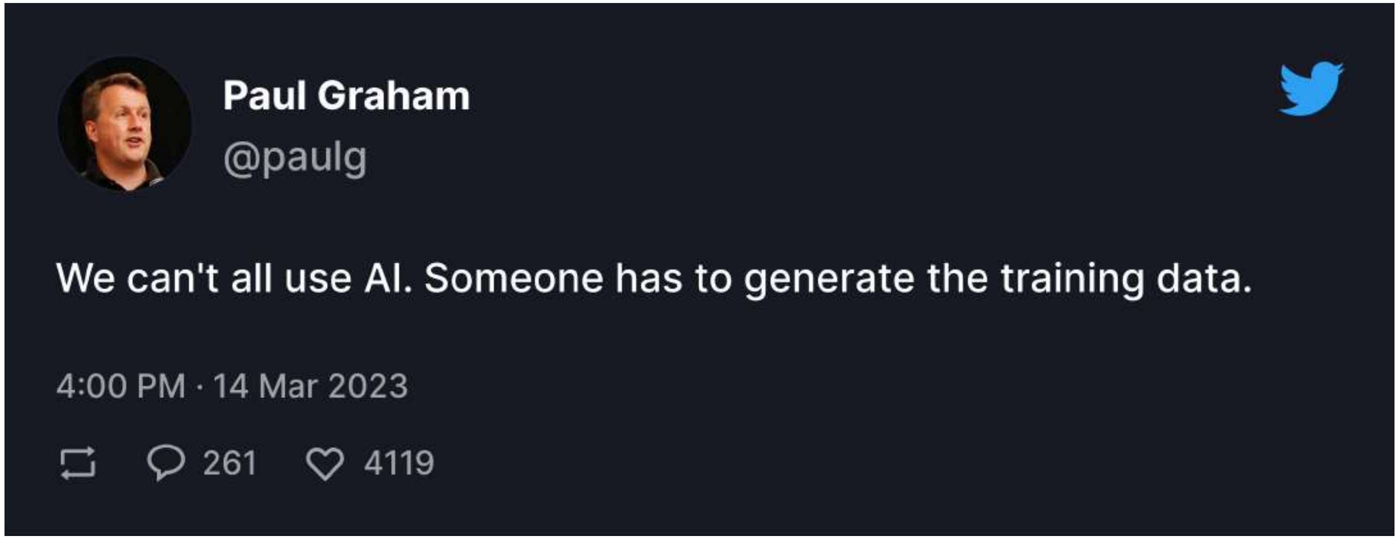

Paul Graham
@paulg
We can't all use AI. Someone has to generate the training data.
4:00 PM · 14 Mar 2023
261
4119

1

AF long-term Holter ECG Database

2

AF onset forecast

3

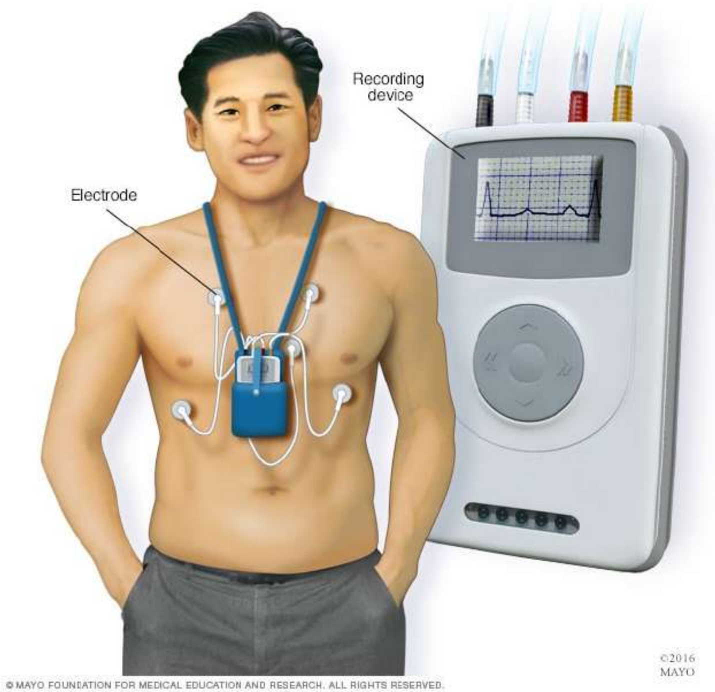
AF risk identification during sinus rhythm

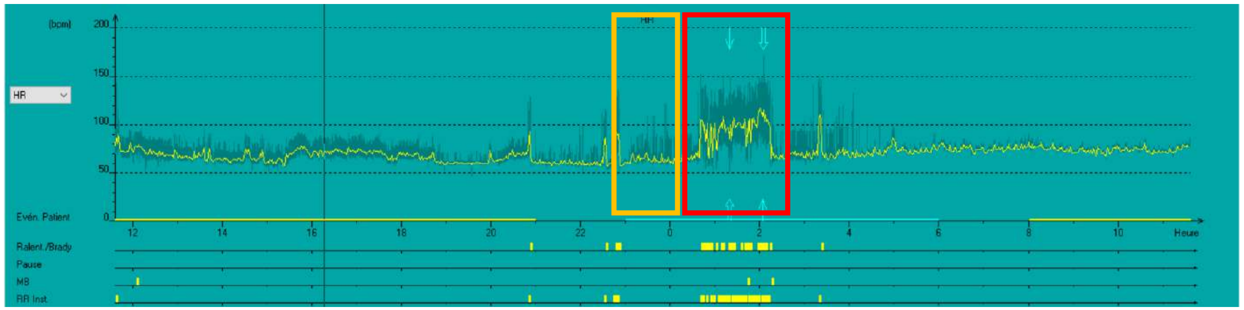
4

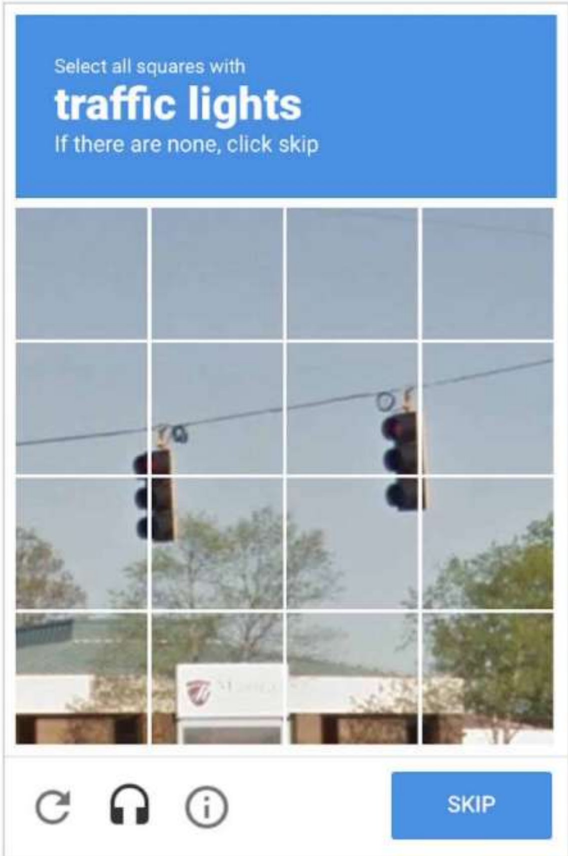
Conclusions and perspectives

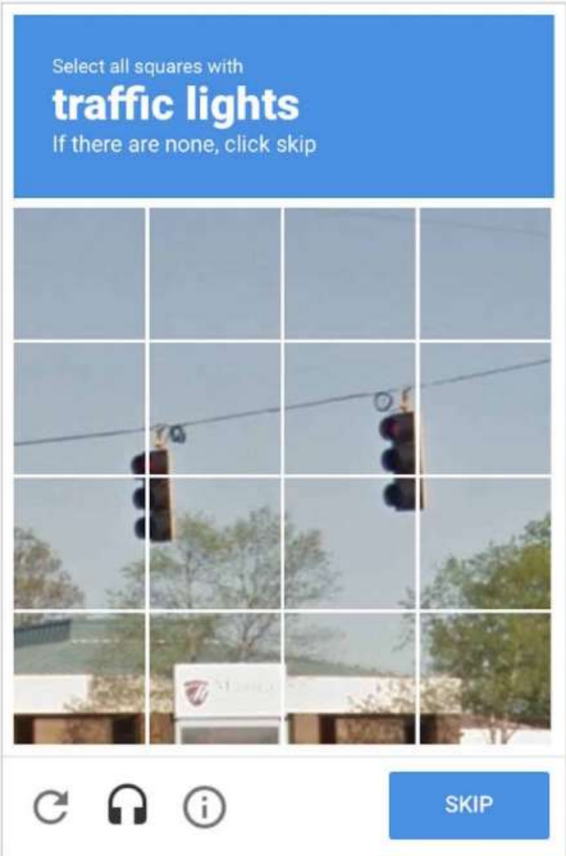
1	2	3	4
AF long-term Holter ECG Database	AF onset forecast	AF risk identification during sinus rhythm	Conclusions and perspectives

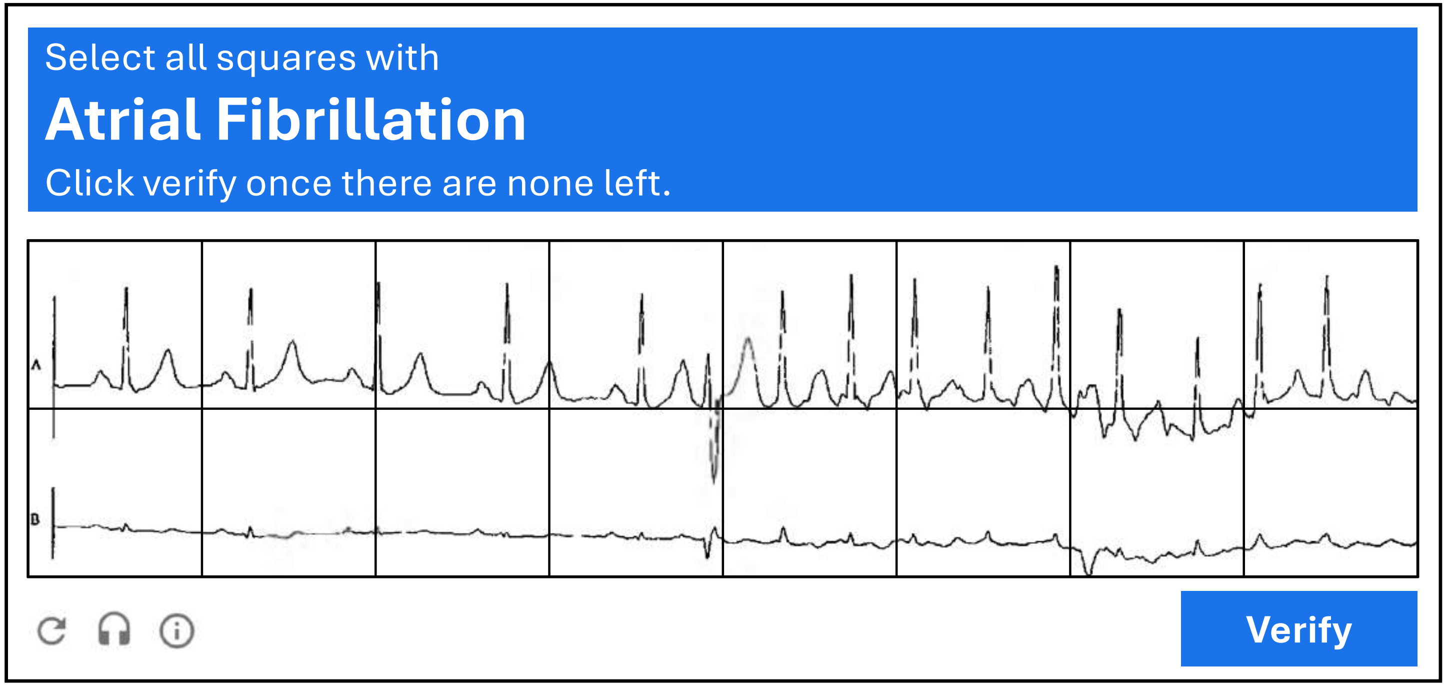
Holter monitoring



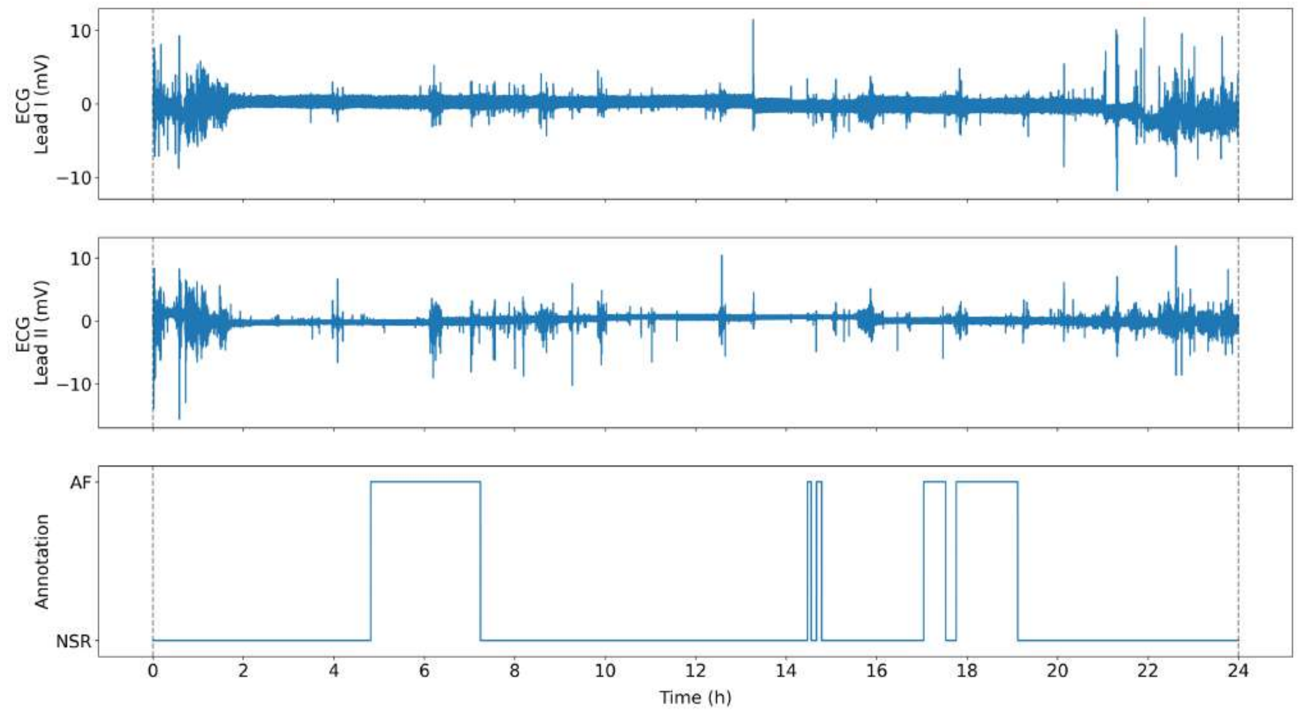



Select all squares with
traffic lights
If there are none, click skip
SKIP


Select all squares with
traffic lights
If there are none, click skip
SKIP

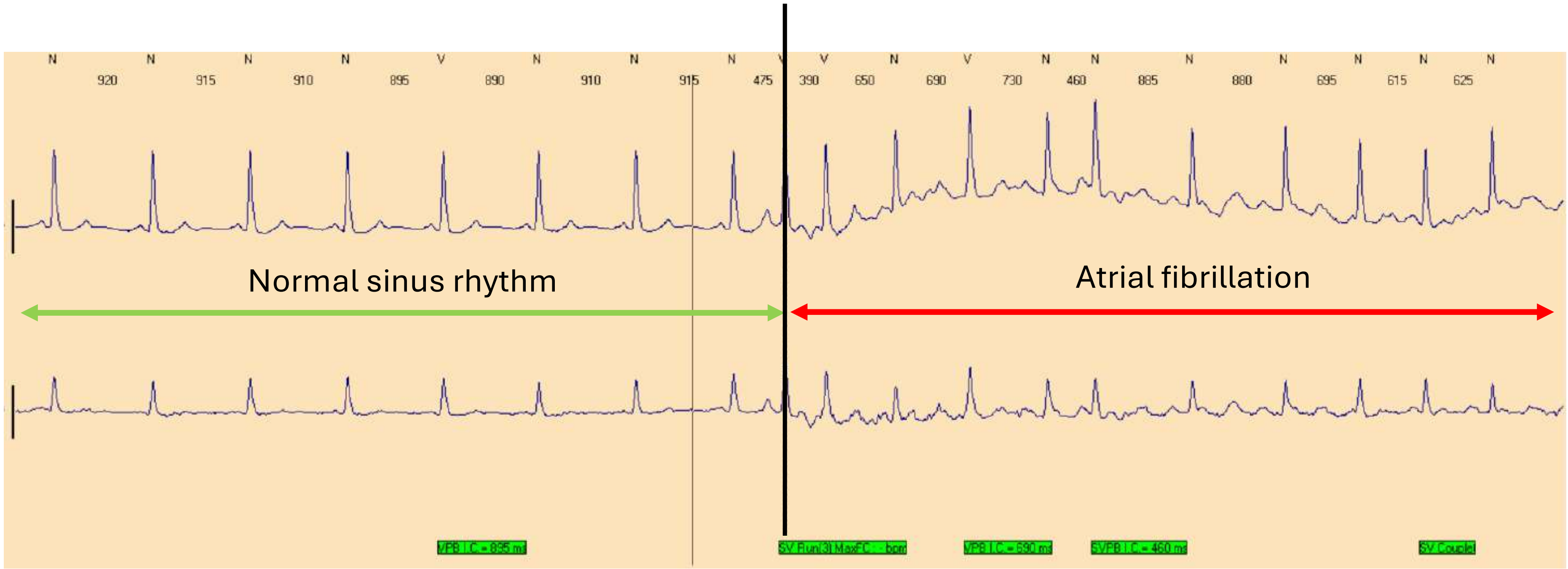

Select all squares with
Atrial Fibrillation
Click verify once there are none left.
Verify

Recording with annotations



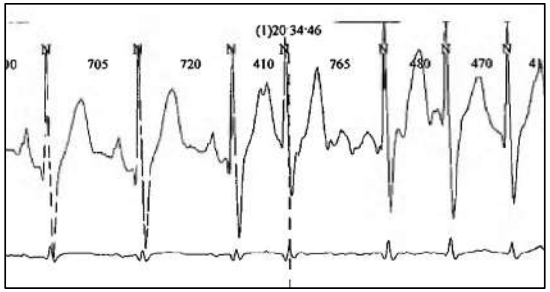
Cardiologist annotation

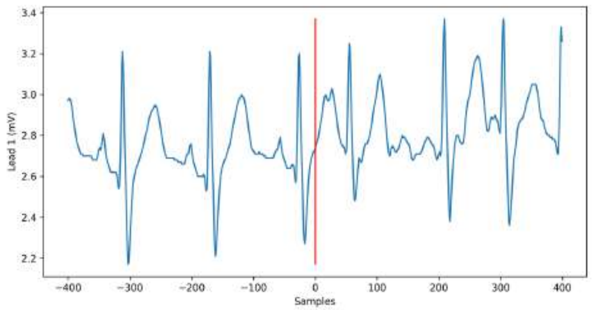
Atrial fibrillation onset

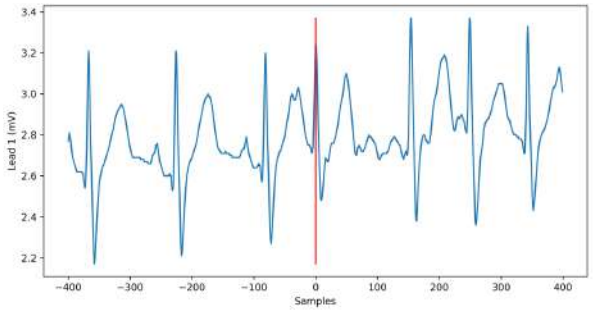


Annotation proces

Realign annotations and time series







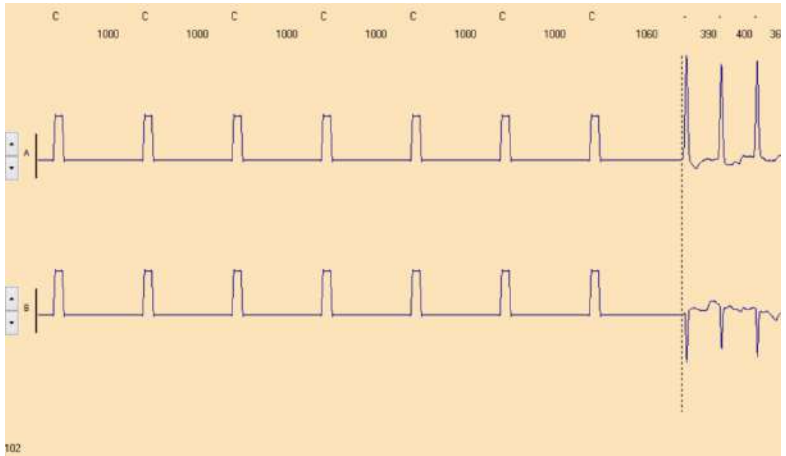
Cardiologist annotation

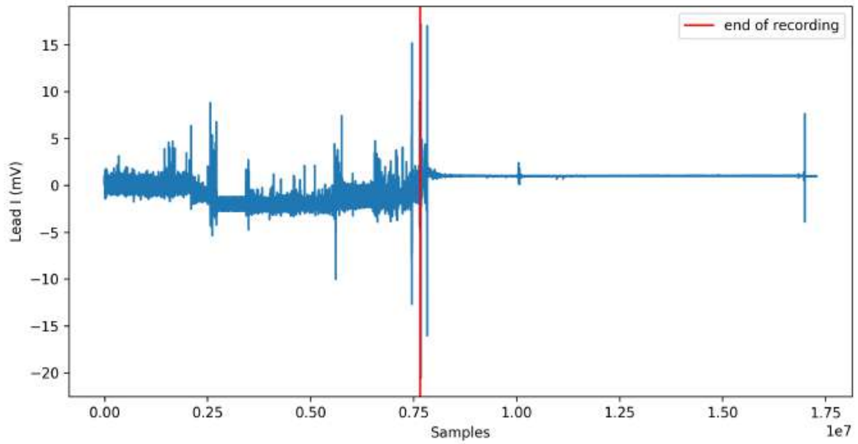
Converted annotation

Time (h:m:s) → sample (200 Hz)

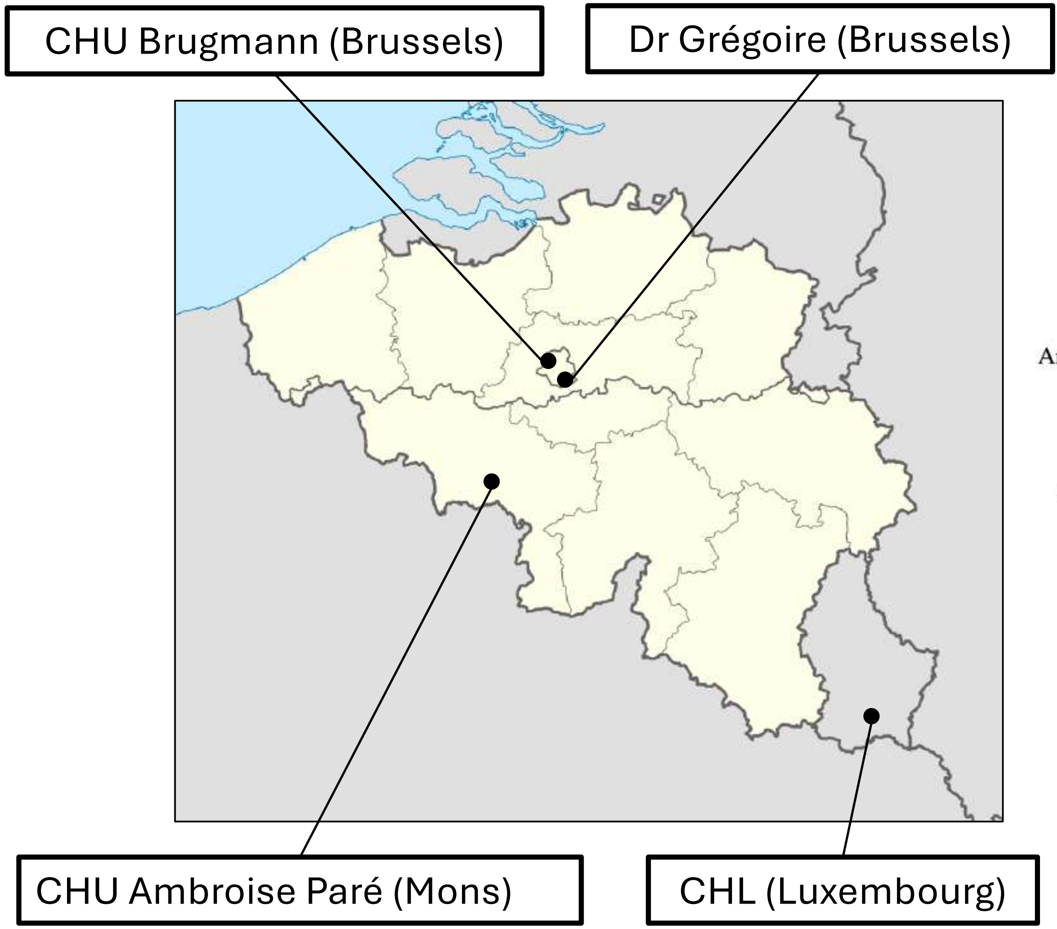
Mannually corrected annotation

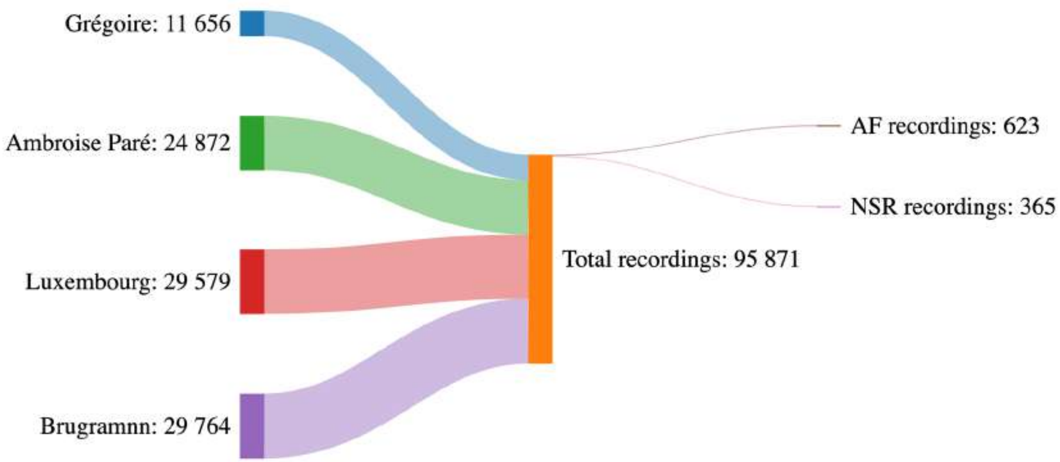
Recording cleaning



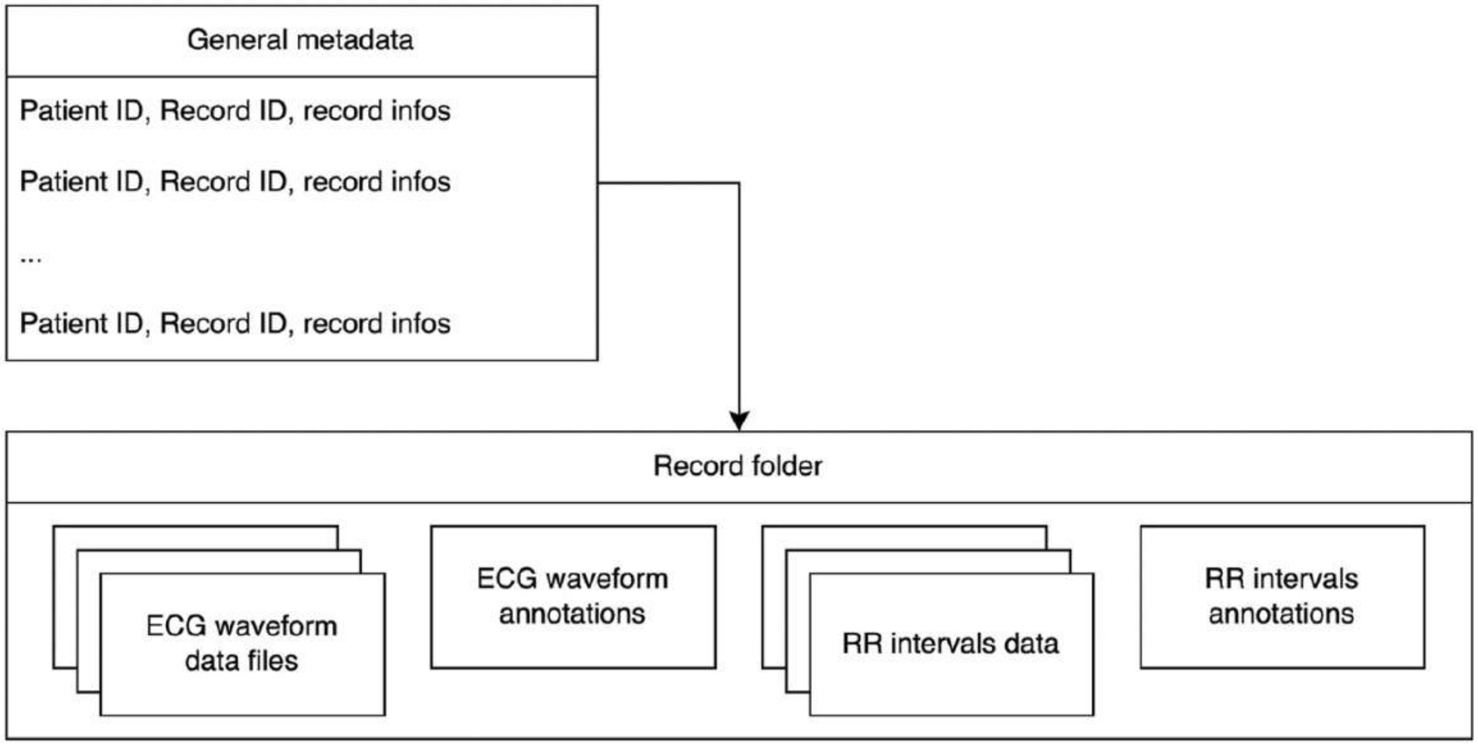


4 centres


CHU Brugmann (Brussels)
Dr Grégoire (Brussels)
CHU Ambroise Paré (Mons)
CHL (Luxembourg)


Grégoire: 11 656
Ambroise Paré: 24 872
Luxembourg: 29 579
Brugramnn: 29 764
Total recordings: 95 871
AF recordings: 623
NSR recordings: 365

Database structure



Database structure

Patients

```
patient_id,patient_sex,patient_age,record_id,record_date,record_start_time,record_end_time,record_timedelta,record_files,record_seconds,record_samples
patient_000,female,86,record_000,2012-10-02,2012-10-02T10:50:11,2012-10-03T10:50:02,86391,1,86391,17278200
patient_001,female,72,record_001,2011-08-19,2011-08-19T11:19:55,2011-08-21T11:19:54,172799,2,172798,34559600
patient_002,male,73,record_002,2012-01-16,2012-01-16T11:29:38,2012-01-17T09:34:22,79484,1,79484,15896800
...
patient_149,female,75,record_164,2010-11-03,2010-11-03T14:11:05,2010-11-04T14:10:56,86391,1,86391,17278200
patient_150,male,82,record_165,2010-09-11,2010-09-11T11:20:54,2010-09-13T11:20:53,172799,2,172798,34559600
patient_151,male,43,record_166,2009-10-19,2009-10-19T13:27:13,2009-10-21T08:08:12,153659,2,153390,30678001
```

ECG

```
start_datetime,start_file_index,start_qrs_index,end_datetime,end_file_index,end_qrs_index,af_duration,nsr_before_duration
2011-08-19T18:31:39,0,5180959,2011-08-20T02:32:02,0,10945498,28823,25904
2011-08-20T06:25:17,0,13744484,2011-08-20T07:33:47,0,14566492,4110,13995
2011-08-20T14:47:37,1,2492420,2011-08-20T17:26:09,1,4394883,9512,26030
2011-08-21T00:07:07,1,9206585,2011-08-21T03:59:56,1,12000242,13969,24058
```

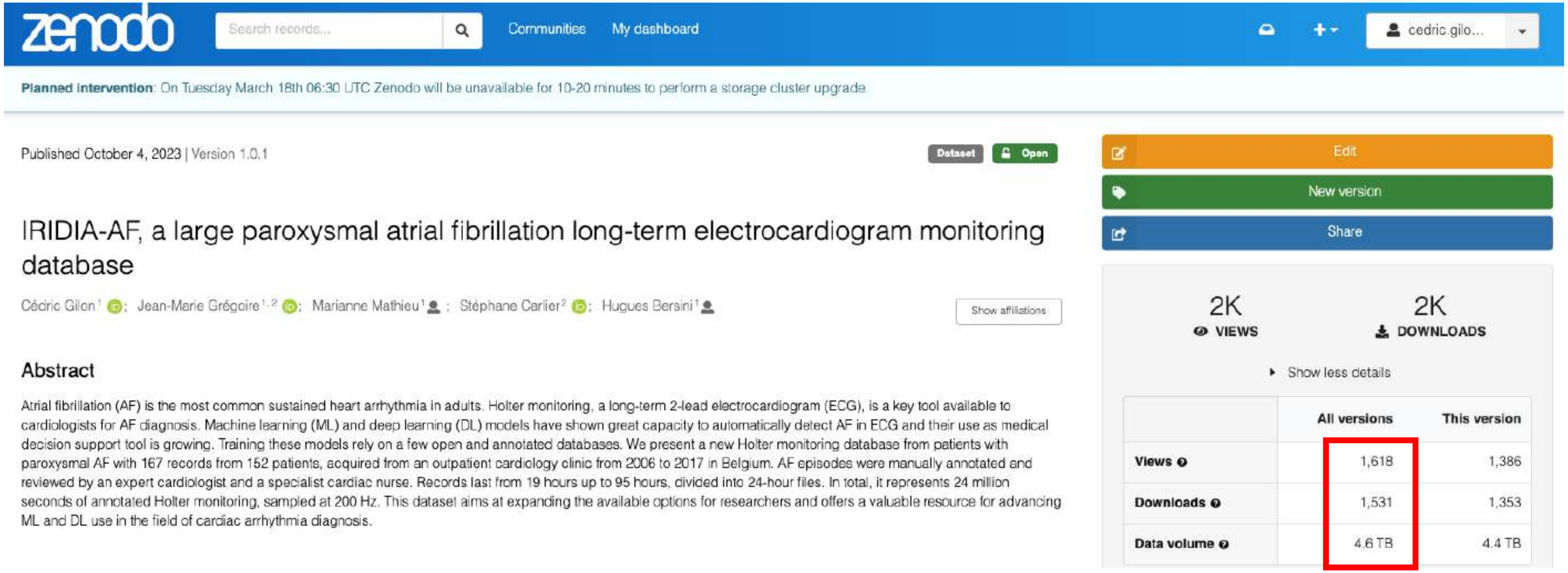
RR

```
start_file_index,start_rr_index,end_file_index,end_rr_index
0,36077,0,99785
0,115995,0,124148
1,16508,1,37229
1,69828,1,99795
```

Comparison with existing databases

Database name	Total duration (seconds)	Sampling rate (Hz) (Hz)	Total samples (Samples per lead)
MIT-BIH Arrhythmia (Moody et al. 2001b)	86 400	360	31 104 000
AF classification challenge 2017(Clifford et al. 2017)	277 138	300	83 141 400
SPH dataset (Liu et al. 2022)	281 109	500	140 554 500
CU-SPH dataset (Zheng et al. 2020)	106 460	500	53 230 000
PTB-XL 100 Hz (Wagner et al. 2020)	218 370	100	21 837 000
PTB-XL 500 Hz (Wagner et al. 2020)	218 370	500	109 185 000
IRIDIA-AF v1 (Gilon et al. 2023b)	24 085 688	200	4 817 137 600
IRIDIA-AF v2	100 655 332	200	20 131 094 524

IRIDIA-AF v1

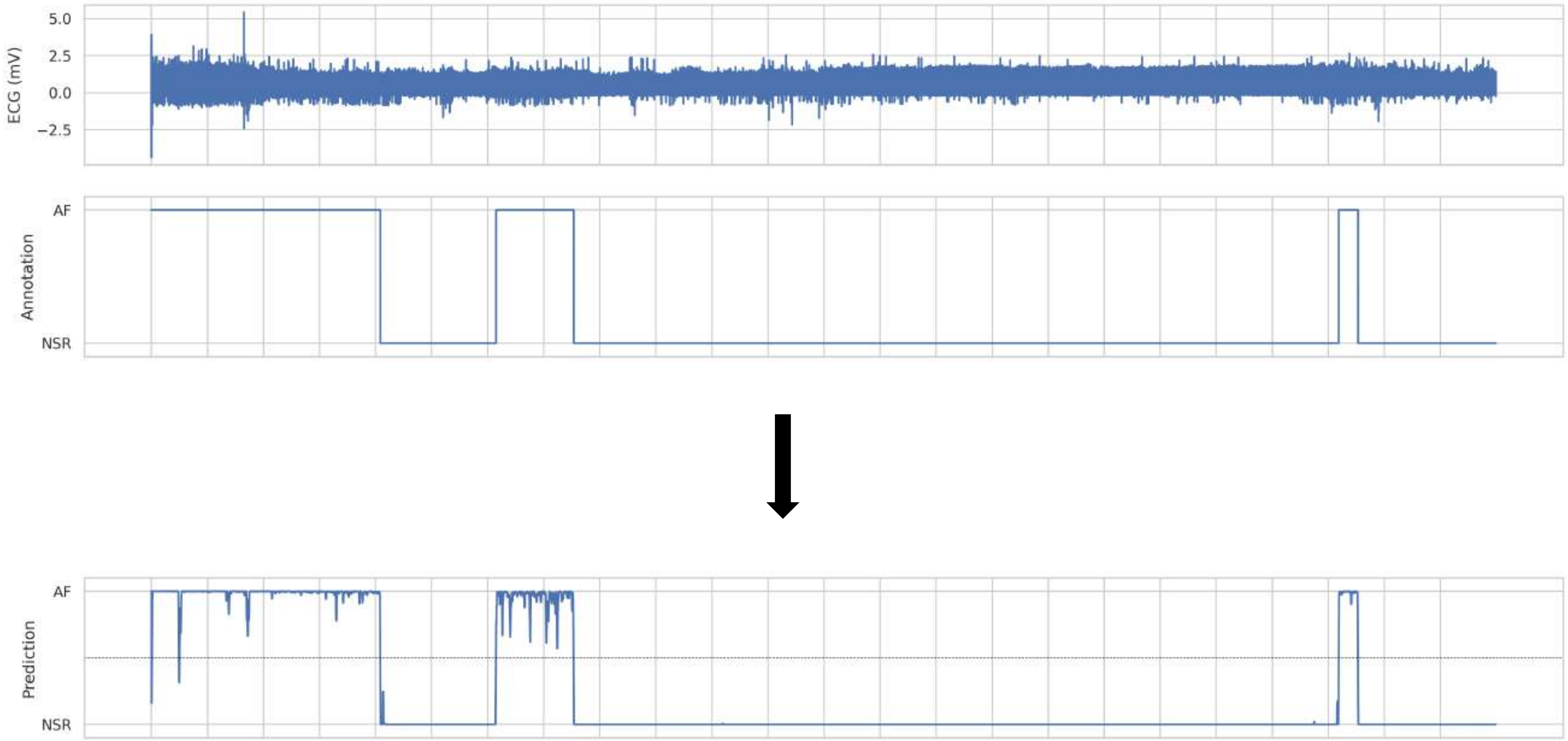

zenodo
Search records...
Communities
My dashboard
cedric.gilo...
Planned intervention: On Tuesday March 18th 06:30 UTC Zenodo will be unavailable for 10-20 minutes to perform a storage cluster upgrade.
Published October 4, 2023 | Version 1.0.1
Dataset
Open
IRIDIA-AF, a large paroxysmal atrial fibrillation long-term electrocardiogram monitoring database
Cédric Gilon[1]; Jean-Marie Grégoire[1,2]; Marianne Mathieu[1]; Stéphane Carlier[2]; Hugues Bersini[1]
Show affiliations
Abstract
Atrial fibrillation (AF) is the most common sustained heart arrhythmia in adults. Holter monitoring, a long-term 2-lead electrocardiogram (ECG), is a key tool available to cardiologists for AF diagnosis. Machine learning (ML) and deep learning (DL) models have shown great capacity to automatically detect AF in ECG and their use as medical decision support tool is growing. Training these models rely on a few open and annotated databases. We present a new Holter monitoring database from patients with paroxysmal AF with 167 records from 152 patients, acquired from an outpatient cardiology clinic from 2006 to 2017 in Belgium. AF episodes were manually annotated and reviewed by an expert cardiologist and a specialist cardiac nurse. Records last from 19 hours up to 95 hours, divided into 24-hour files. In total, it represents 24 million seconds of annotated Holter monitoring, sampled at 200 Hz. This dataset aims at expanding the available options for researchers and offers a valuable resource for advancing ML and DL use in the field of cardiac arrhythmia diagnosis.
Edit
New version
Share
2K VIEWS
2K DOWNLOADS
Show less details
All versions
This version
Views 1,618 1,386
Downloads 1,531 1,353
Data volume 4.6 TB 4.4 TB

AF detection using Machine Learning

ECG

Cardiologist annotations

Machine Learning predictions



AF detection

HRV + ML models
Temporal split

Model	AUROC	AUPRC
Logistic Regression	0.957 (0.943–0.971)	0.772 (0.726–0.818)
Decision Tree	0.947 (0.937–0.957)	0.926 (0.911–0.942)
Random Forest	0.990 (0.984–0.997)	0.963 (0.937–0.989)
XGBoost	0.990 (0.983–0.996)	0.960 (0.936–0.984)

HRV + ML models
Spacial split

	XGBoost		Random Forest	
Hospital	AUROC	AUPRC	AUROC	AUPRC
Dr Grégoire	0.999	0.998	0.996	0.964
CHU Ambroise Paré	0.956	0.960	0.953	0.958
CHL Luxembourg	0.976	0.844	0.974	0.865
CHU Brugmann	0.983	0.980	0.980	0.979

1

AF long-term Holter ECG Database

2

AF onset forecast

3

AF risk identification during sinus rhythm

4

Conclusions and perspectives

1

AF long-term Holter ECG Database

2

AF onset forecast

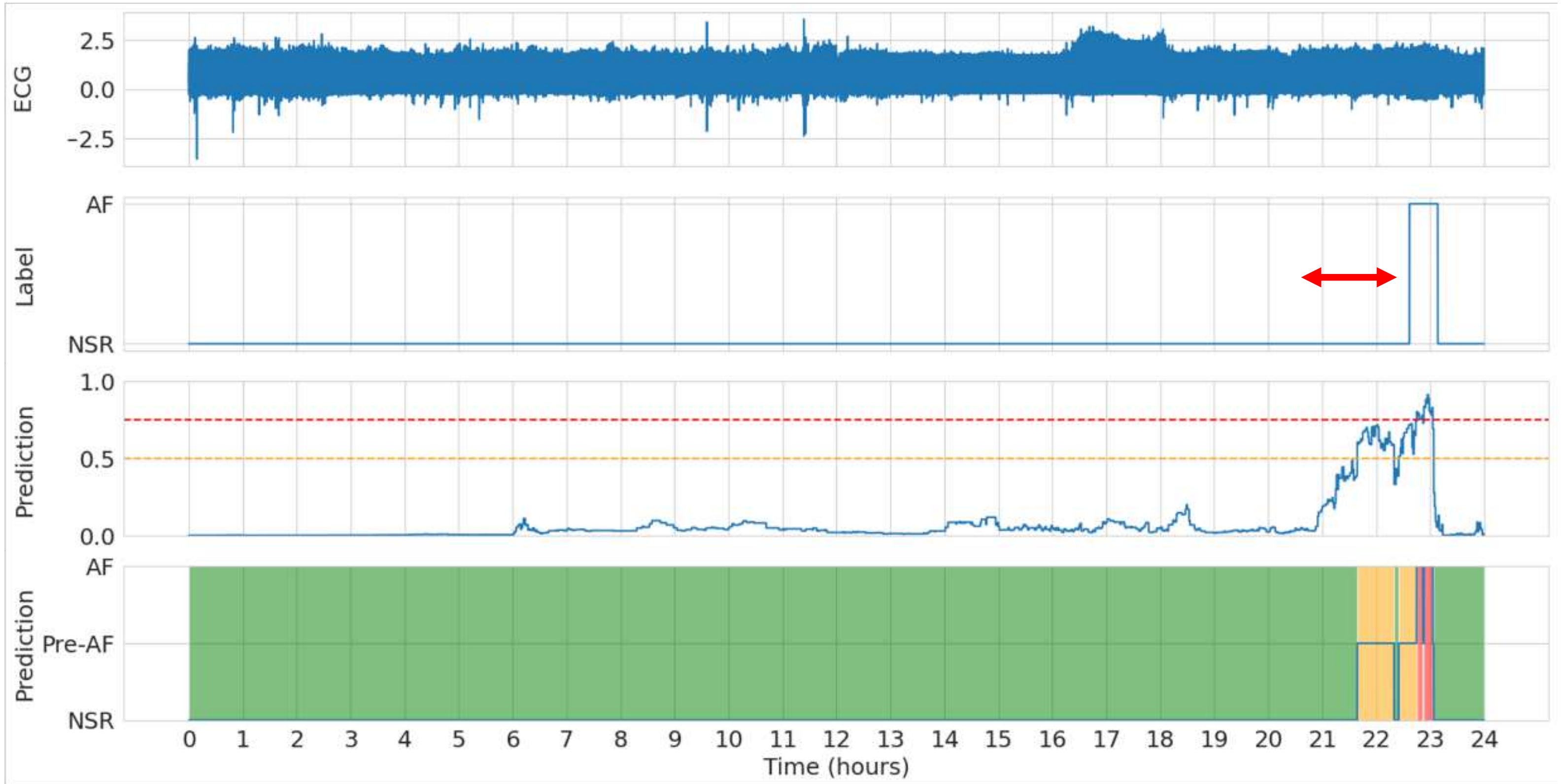
3

AF risk identification during sinus rhythm

4

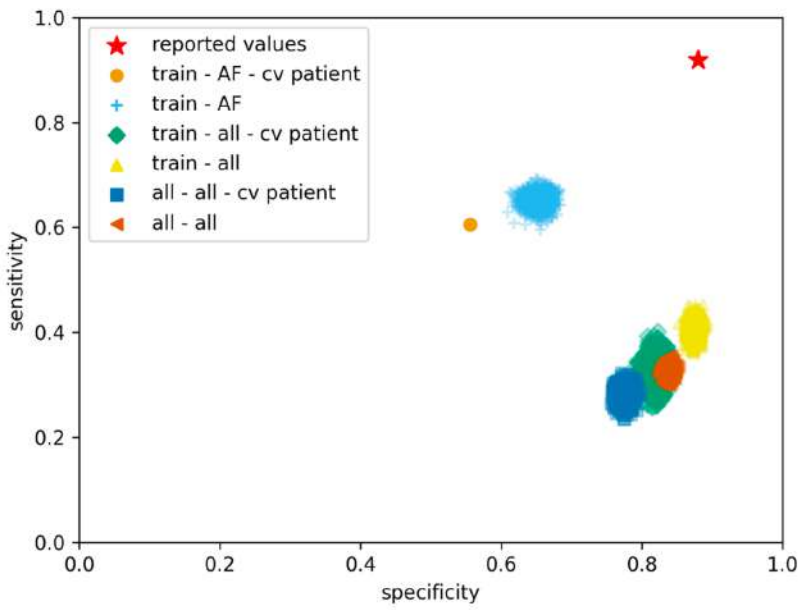
Conclusions and perspectives

AF onset forecast



State-of-the-art reproducibility

- Reproduction of 3 models and methodologies from literature
- MIT-BIH AF Pred. DB (2001)
  - 200 recordings
  - 53 pre-AF recordings
- HRV + ML models
- Conclusion
  - Unreproducible results
  - Unanswered methodology questions



State-of-the-art reproducibility

- Reproduction of 3 models and methodologies from literature
- Conclusion
  - Unreproducible results
  - Unanswered methodology questions

Authors	Reported Sensitivity	Reported Specificity	Reproduced Sensitivity	Reproduced Specificity
Mohebbi et al. (2012)	96.30%	93.10%	59.28%	36.56%
Boon et al. (2018)	86.8%	88.7%	61.33%	64.39%
Narin et al. (2018)	92.0%	88.0%	65.12%	65.21%

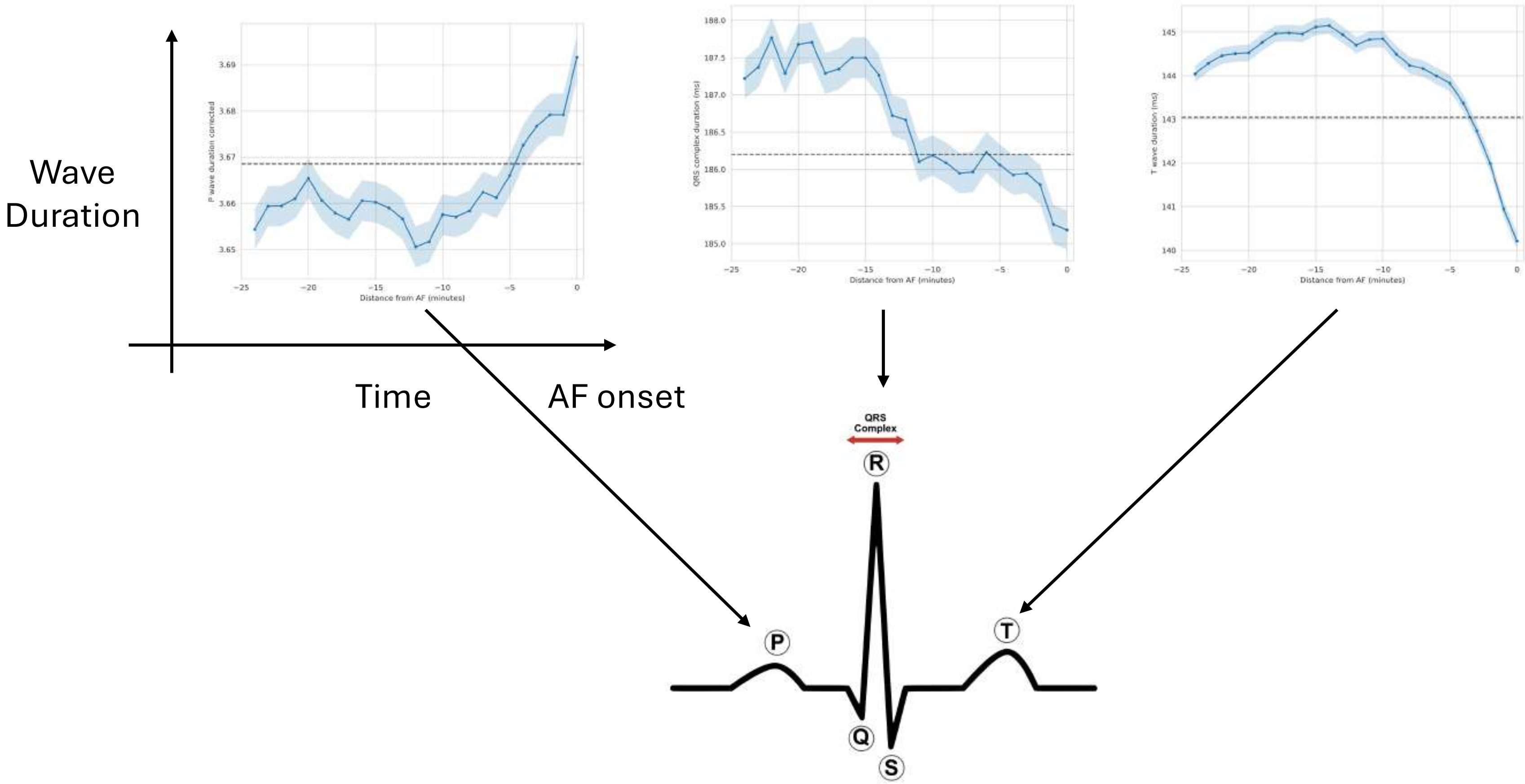
State-of-the-art databases

Database name	Year	Patients	Recordings	Duration	Sample Rate	Leads	AF episodes
MIT-BIH AFDB (Moody et al. 1983)	1983	25	25	30 min	250 Hz	2	11
AFPDB (Moody et al. 2001a)	2001	100	200	30 min	128 Hz	2	53
LTAFDB (Petrutiu et al. 2007)	2007	84	84	24 h	128 Hz	2	2
IRIDIA-AF v1	2023	152	167	24 - 96 h	200 Hz	2	261
IRIDIA-AF v2	2023	928	988	24 - 96 h	200 Hz	2	964

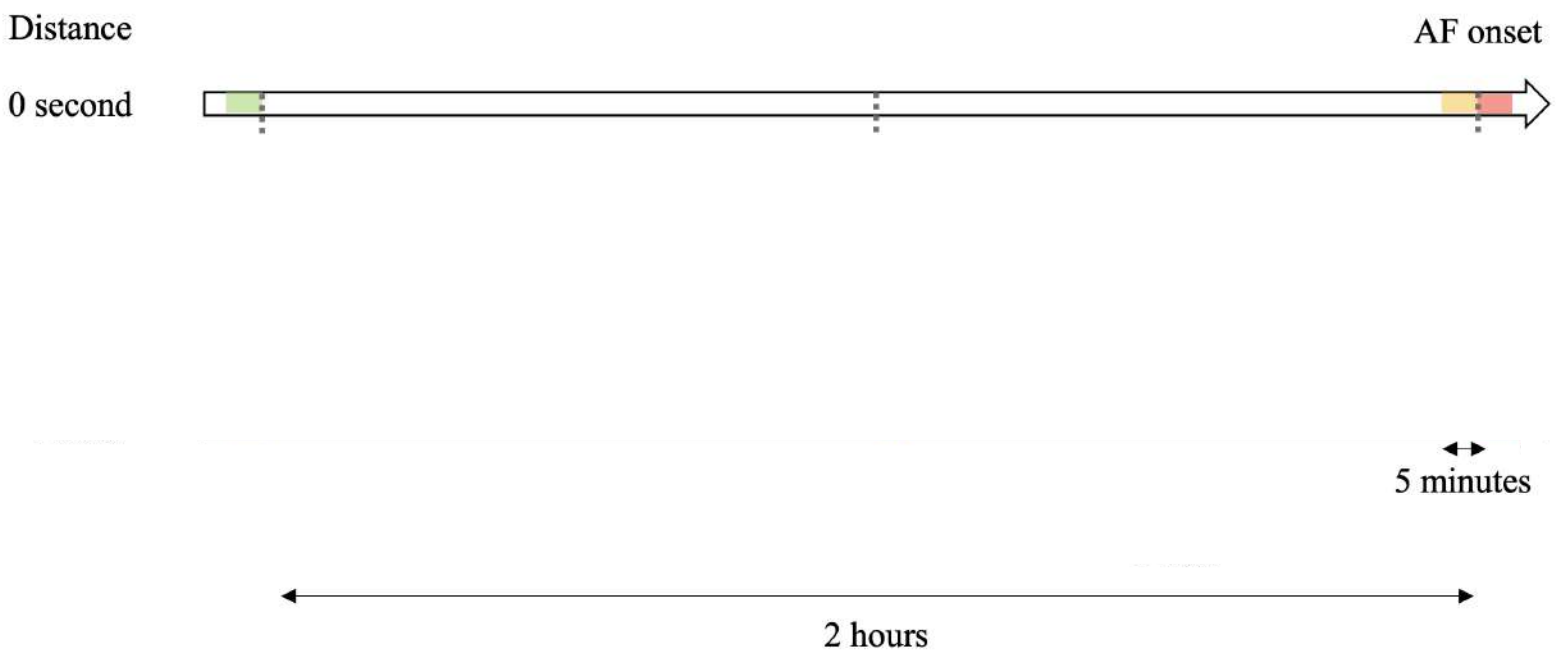
Selection criteria:

1. > 30 min NSR
2. > 5 min AF

ECG evolution



Prediction evolution before AF onset

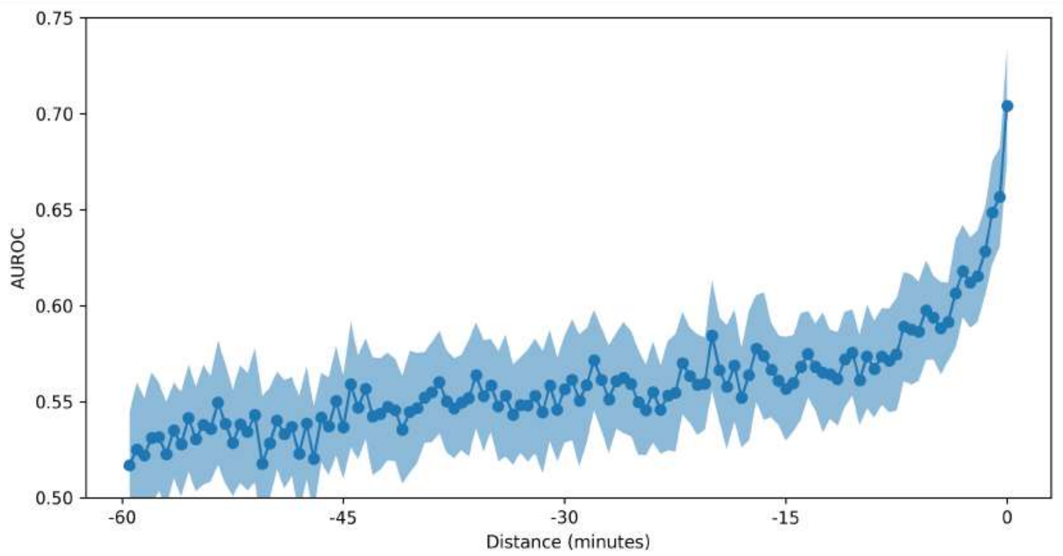


Prediction evolution before AF onset

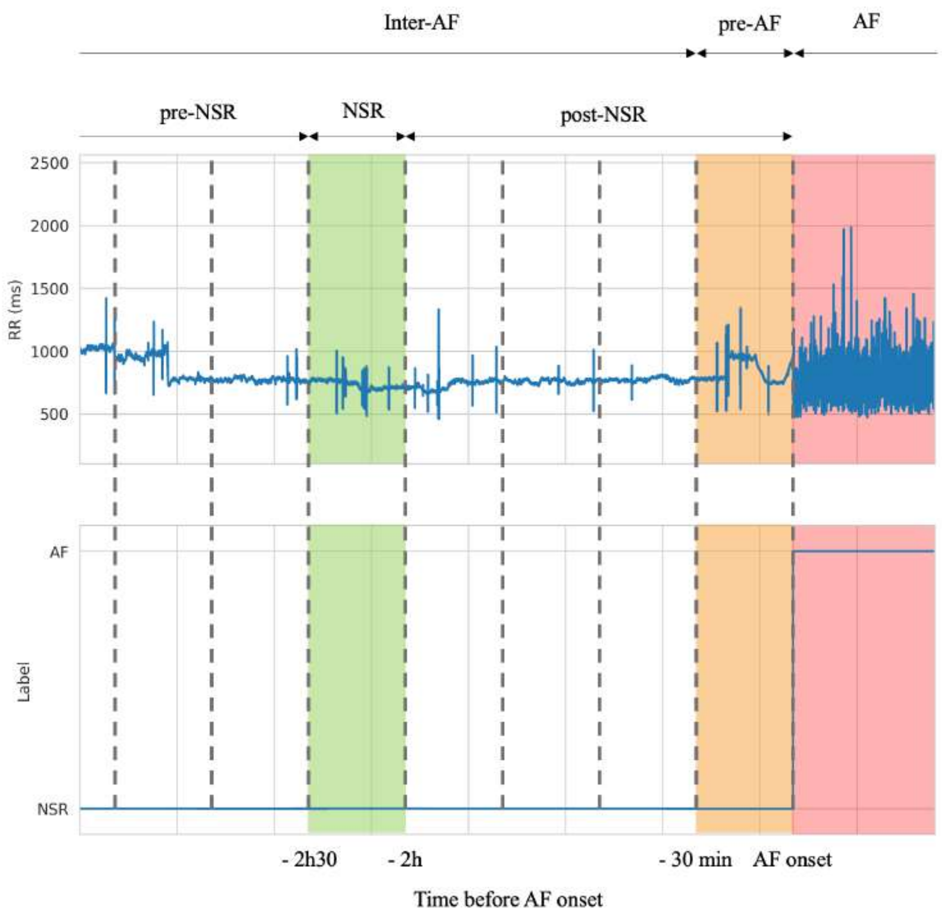
- For each distance
  - 10x 10-fold
  - HRV features
  - Random forest model

- AUROC
  - 0.562 (95% CI 0.539–0.586)

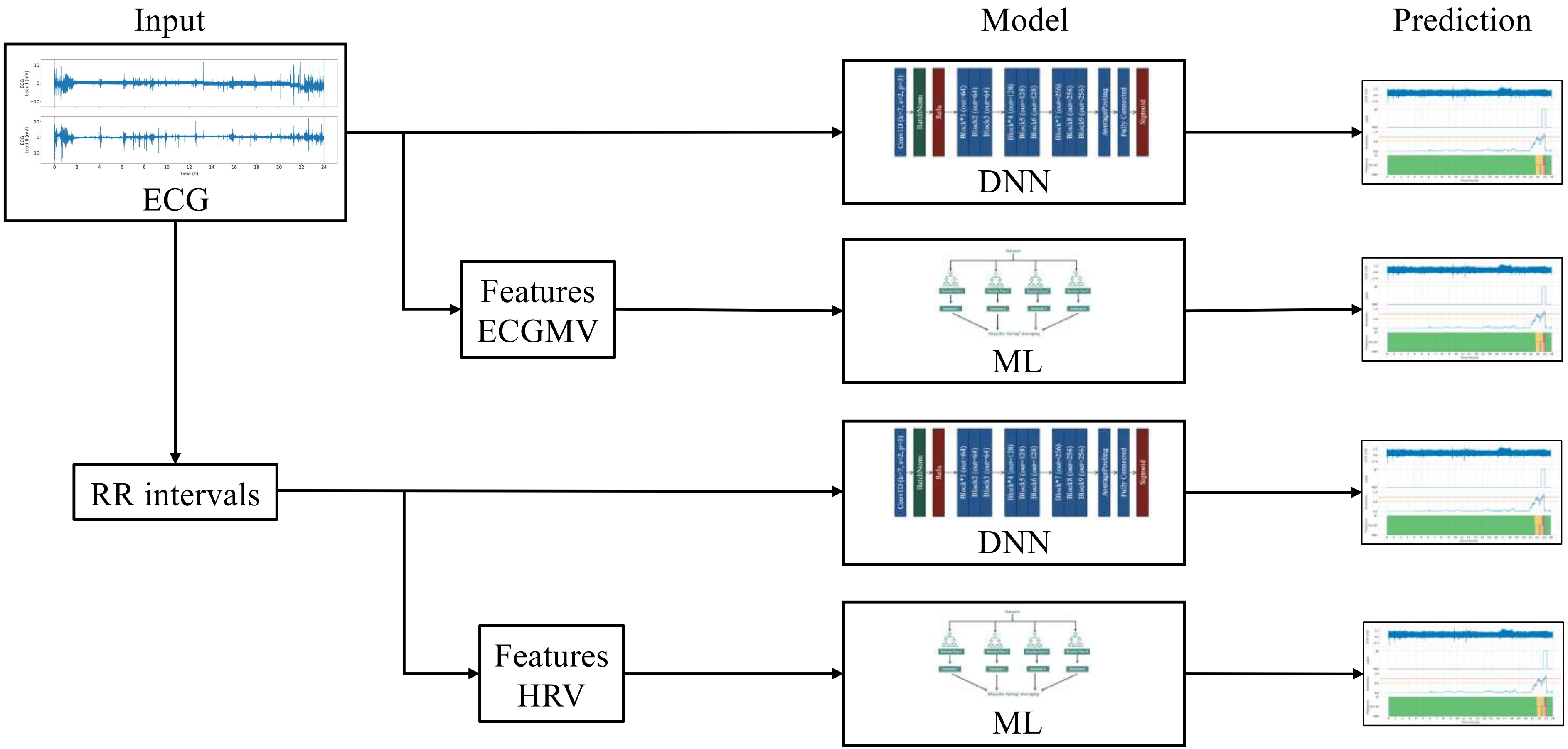
    ⬇
  - 0.714 (95% CI 0.692–0.735)



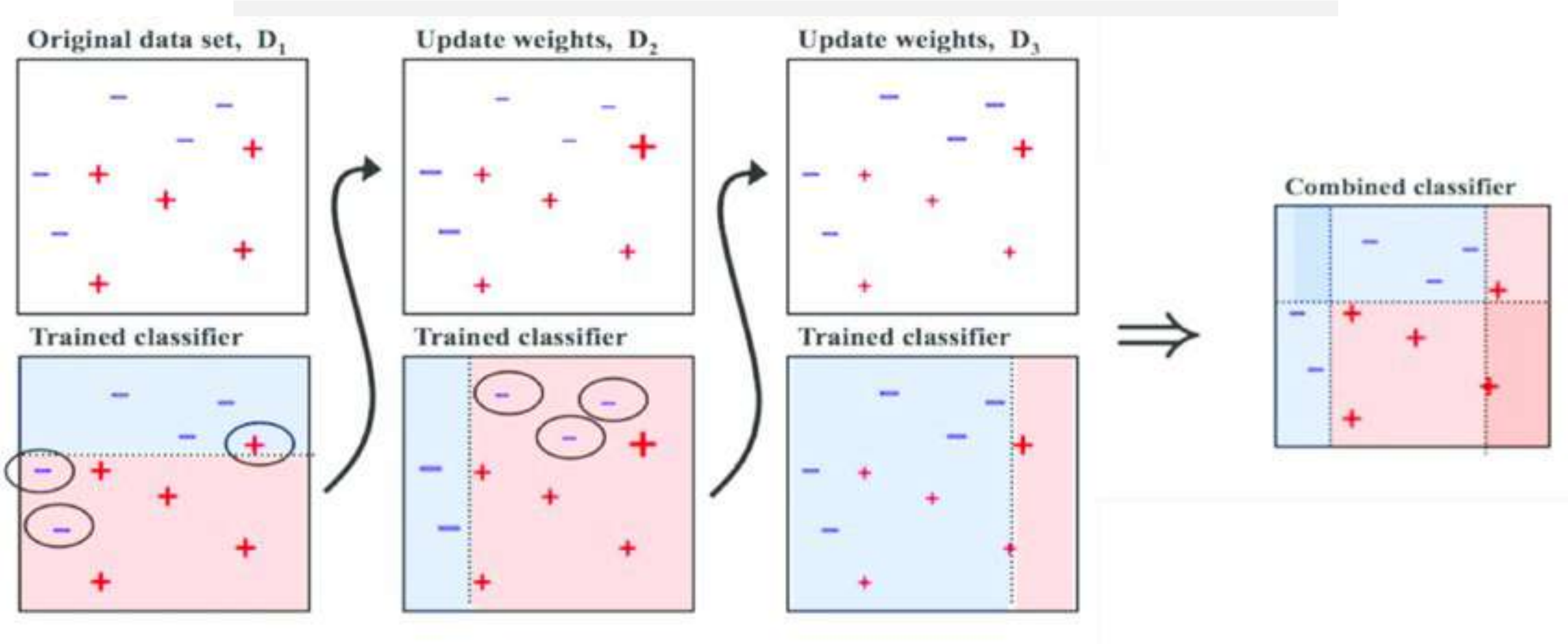
Model comparison for AF onset forecast



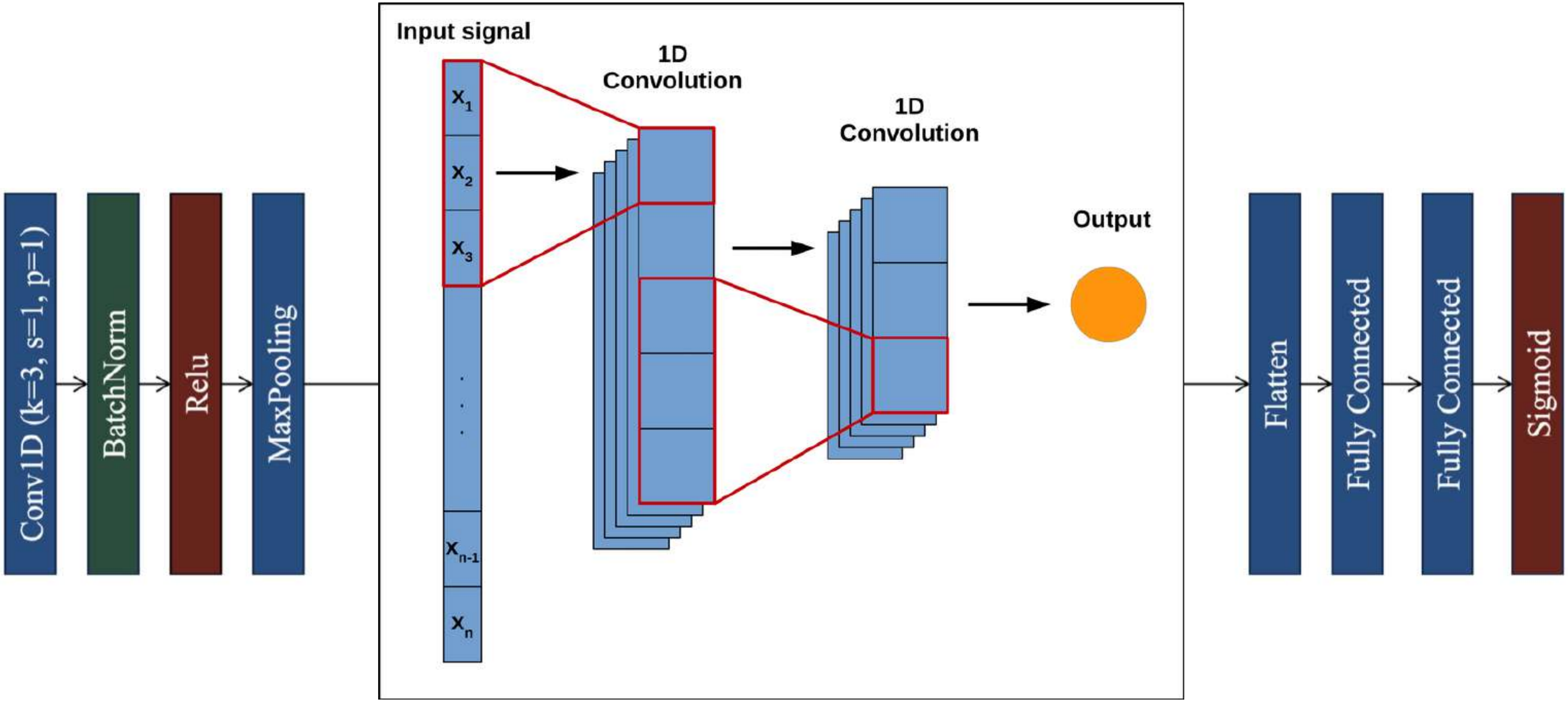
Model comparison for AF onset forecast



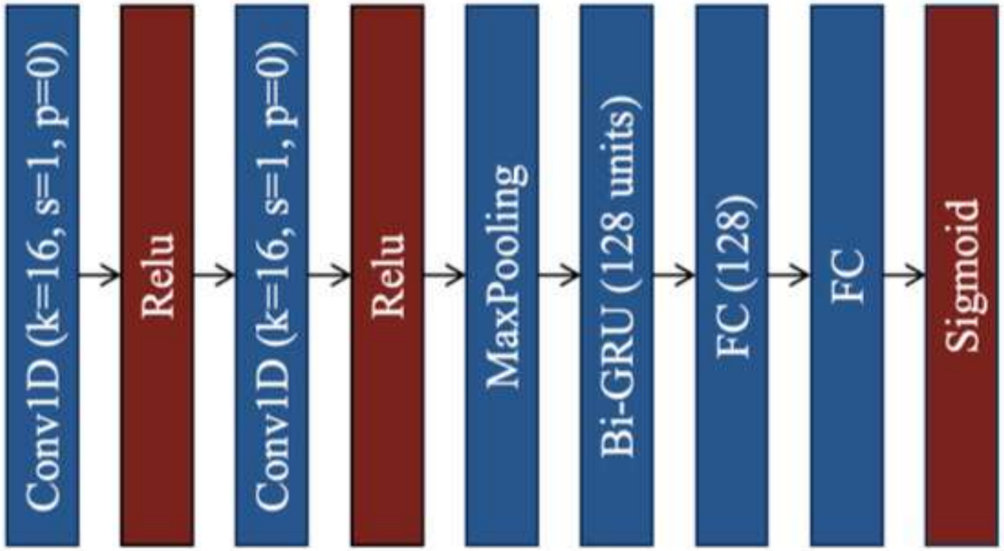
Random Forest vs XGB



CNN

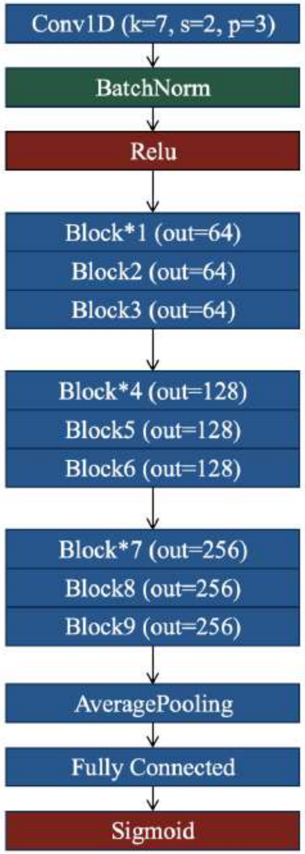

Conv1D (k=3, s=1, p=1)
BatchNorm
Relu
MaxPooling
Input signal
1D Convolution
1D Convolution
Output
x1
x2
x3
xn-1
xn
Flatten
Fully Connected
Fully Connected
Sigmoid

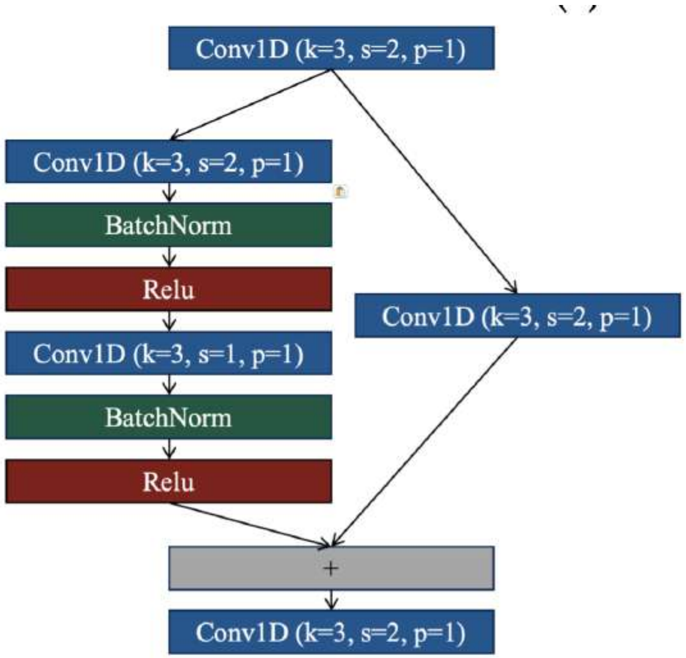
CNN-RNN

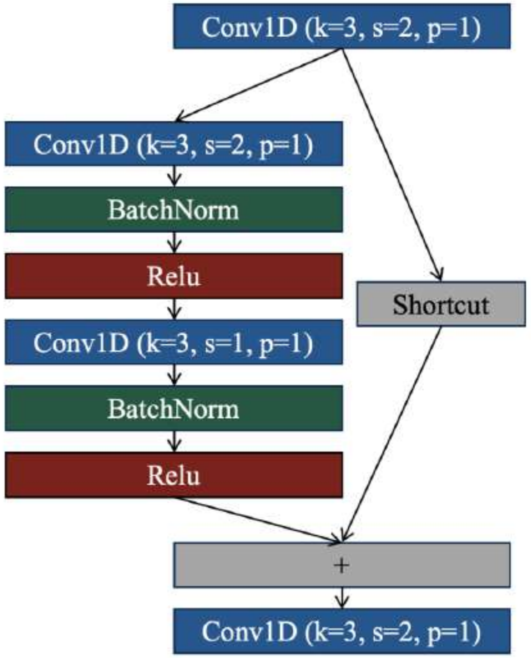


Conv1D (k=16, s=1, p=0)
Relu
Conv1D (k=16, s=1, p=0)
Relu
MaxPooling
Bi-GRU (128 units)
FC (128)
FC
Sigmoid

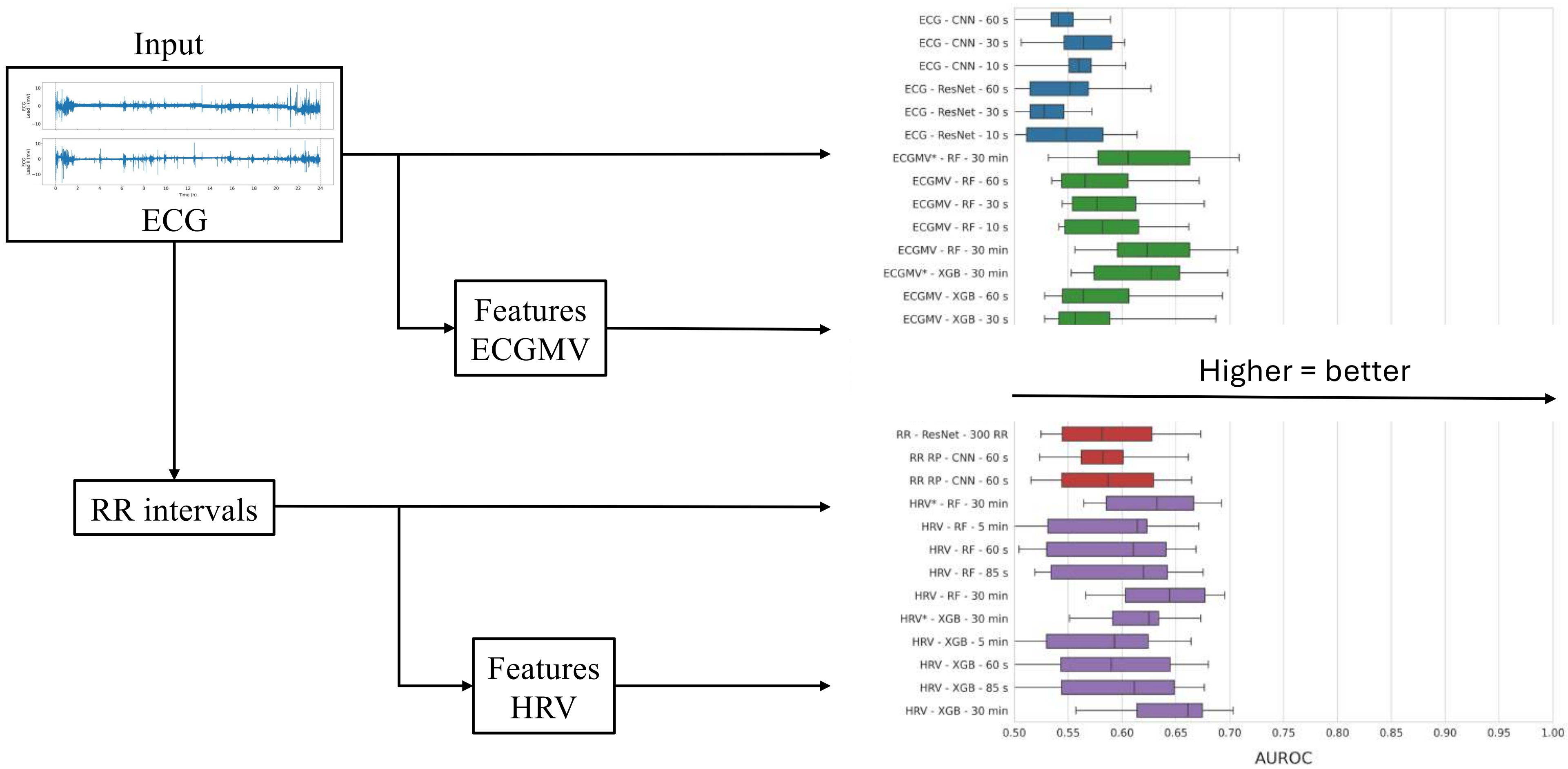
ResNet


Conv1D (k=7, s=2, p=3)
BatchNorm
Relu
Block*1 (out=64)
Block2 (out=64)
Block3 (out=64)
Block*4 (out=128)
Block5 (out=128)
Block6 (out=128)
Block*7 (out=256)
Block8 (out=256)
Block9 (out=256)
AveragePooling
Fully Connected
Sigmoid


Conv1D (k=3, s=2, p=1)
Conv1D (k=3, s=2, p=1)
BatchNorm
Relu
Conv1D (k=3, s=1, p=1)
BatchNorm
Relu
Conv1D (k=3, s=2, p=1)
+
Conv1D (k=3, s=2, p=1)


Conv1D (k=3, s=2, p=1)
Conv1D (k=3, s=2, p=1)
BatchNorm
Relu
Conv1D (k=3, s=1, p=1)
BatchNorm
Relu
Shortcut
+
Conv1D (k=3, s=2, p=1)

Model comparison for AF onset forecast



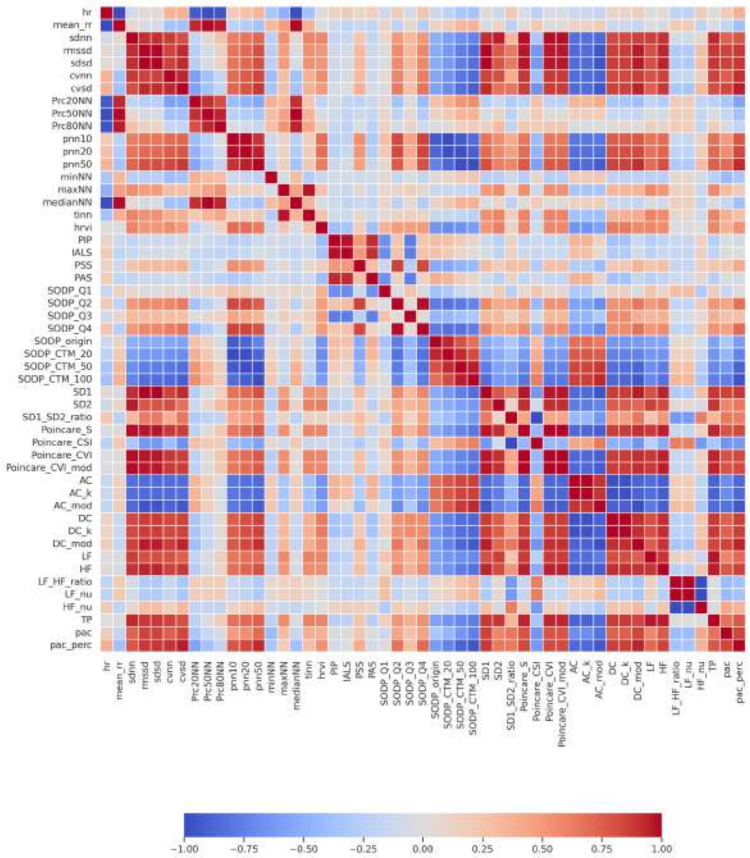
Metrics

Table A.4: Metrics for the XGB model using HRV features computed from the 30-minute window. Evaluation is at episode level.

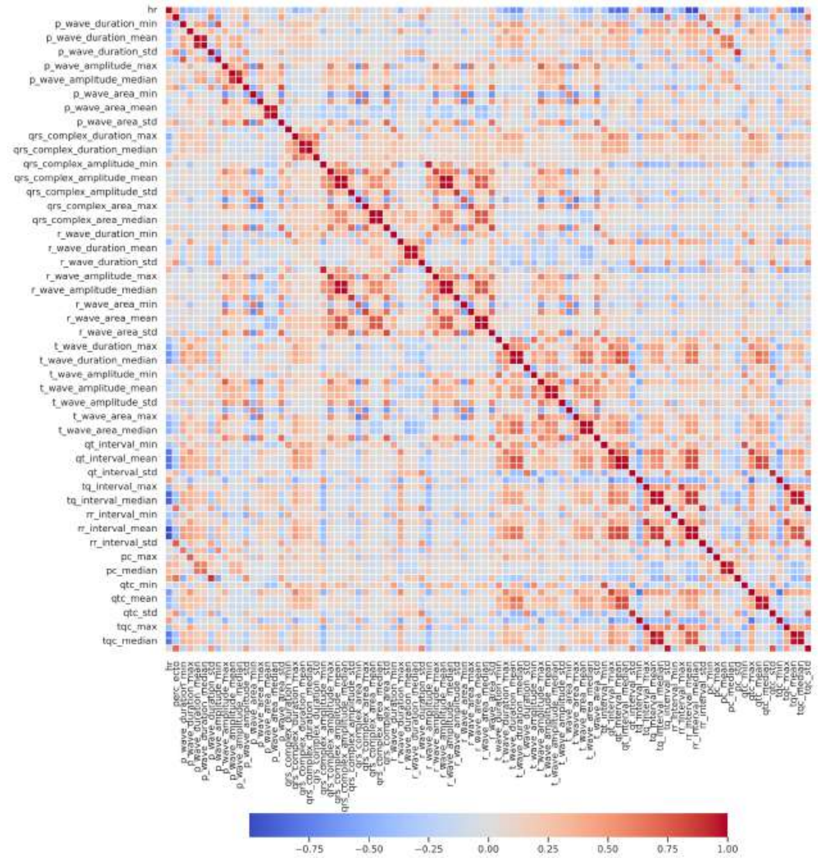
Threshold	Accuracy	Sensitivity	Specificity	PPV	NPV	F1-score
0.1	0.518	1.000	0.000	0.518	nan	0.682
0.2	0.531	0.987	0.043	0.525	0.750	0.685
0.3	0.568	0.933	0.175	0.548	0.710	0.691
0.4	0.606	0.846	0.349	0.582	0.678	0.690
0.5	0.608	0.706	0.504	0.604	0.615	0.651
0.6	0.587	0.466	0.716	0.638	0.555	0.538
0.7	0.524	0.167	0.907	0.658	0.504	0.266
0.8	0.486	0.016	0.992	0.667	0.484	0.030
0.9	0.482	0.000	1.000	nan	0.482	nan

Features correlation

HRV



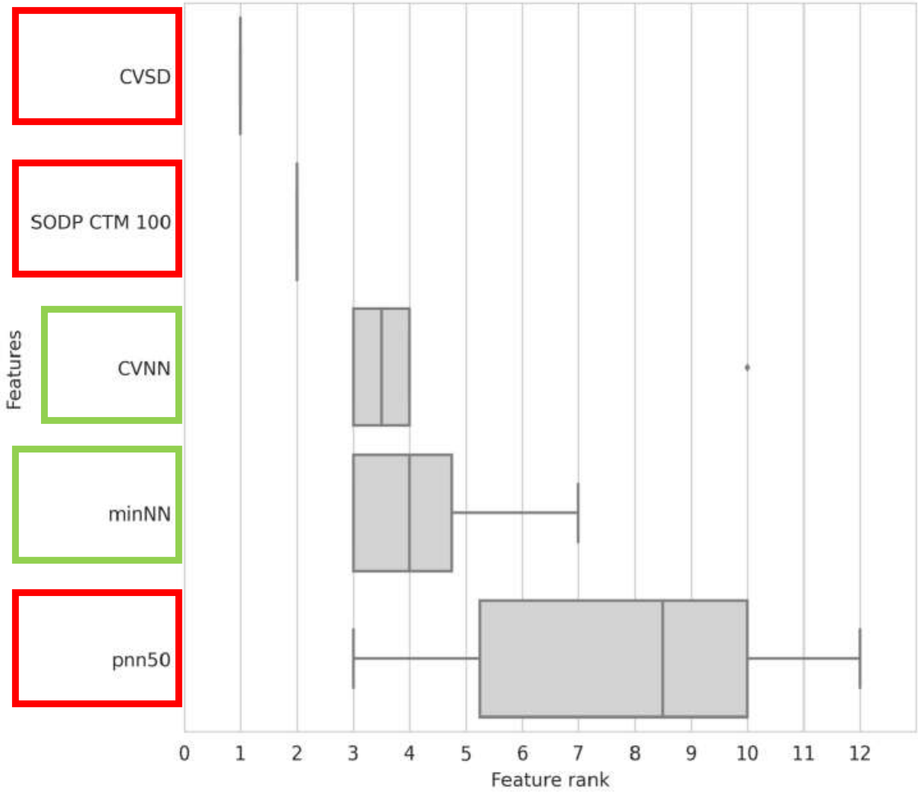
ECGMV



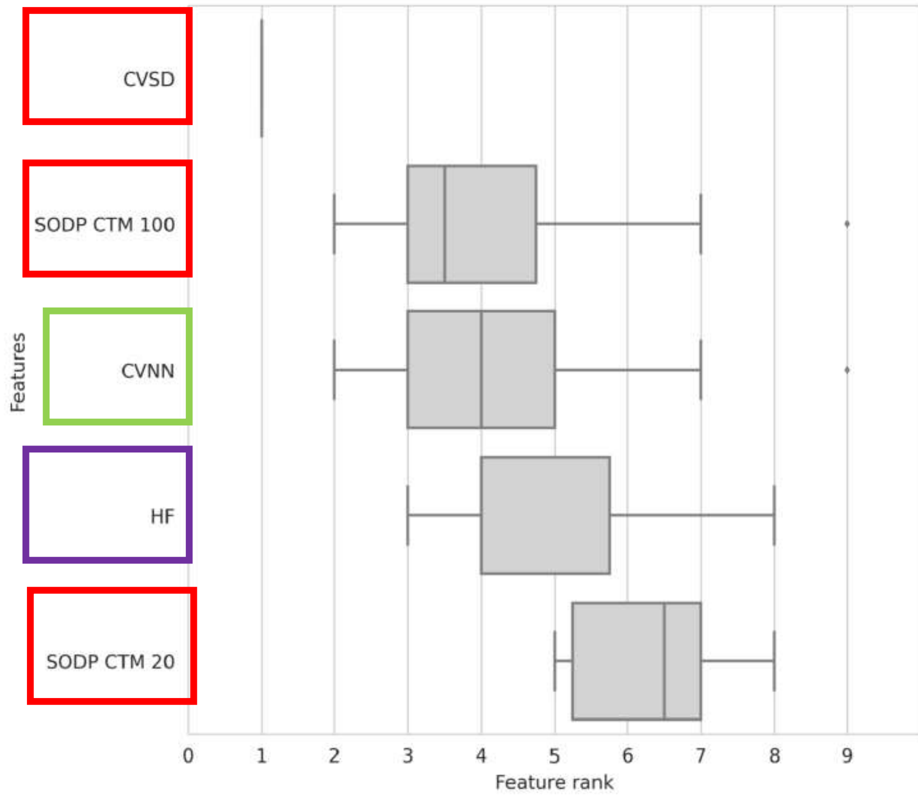
Features selected

Input	Model	Input size	Features	AUROC	AUPRC
HRV	RF	30 min	all	0.640 (0.608-0.671)	0.631 (0.599-0.662)
	RF	30 min	selected	0.627 (0.595-0.659)	0.615 (0.579-0.652)
	XGB	30 min	all	**0.643 (0.609-0.677)**	**0.634 (0.594-0.674)**
	XGB	30 min	selected	0.617 (0.589-0.645)	0.610 (0.575-0.646)
ECGMV	RF	30 min	all	0.627 (0.591-0.663)	0.600 (0.565-0.635)
	RF	30 min	selected	0.616 (0.576-0.656)	0.603 (0.559-0.646)
	XGB	30 min	all	0.625 (0.591-0.659)	0.603 (0.562-0.643)
	XGB	30 min	selected	0.621 (0.584-0.659)	0.606 (0.565-0.647)

Features importance: HRV

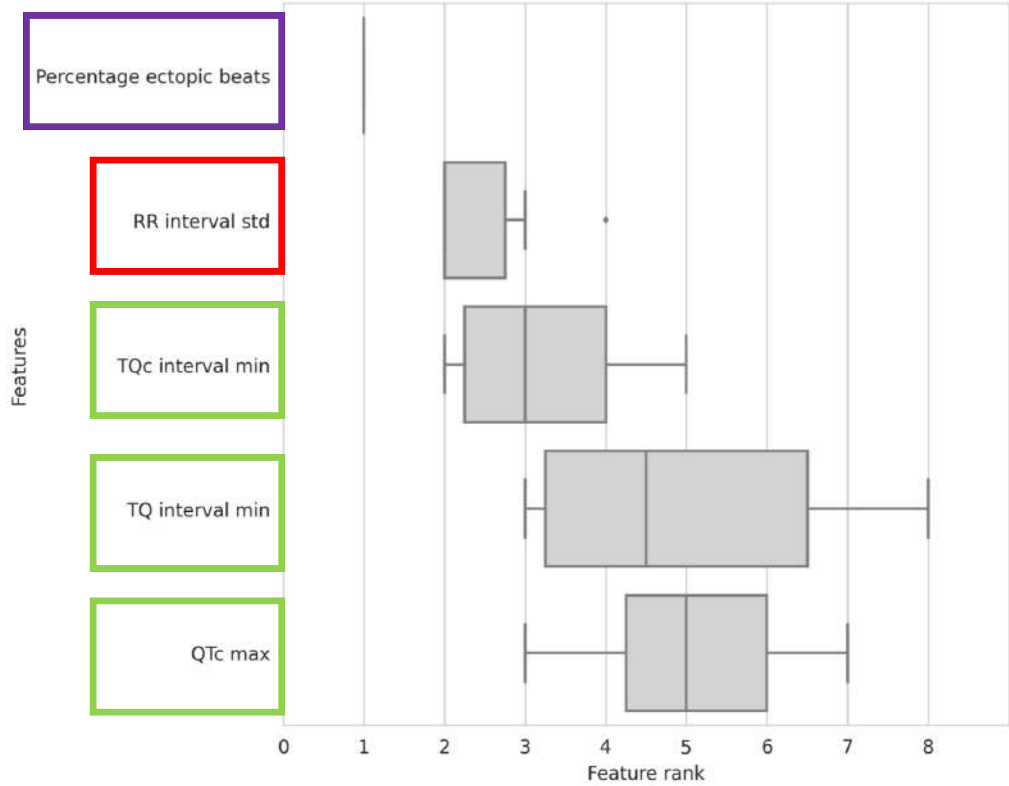


Random forest

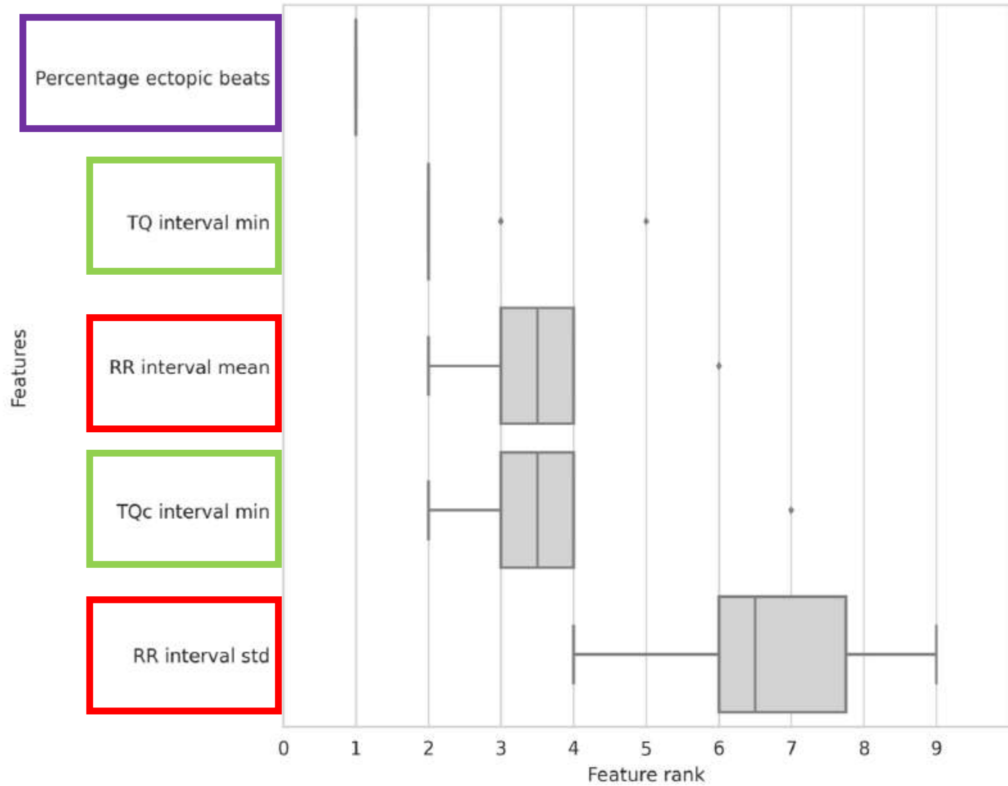


XGBoost

Features importance: ECGMV



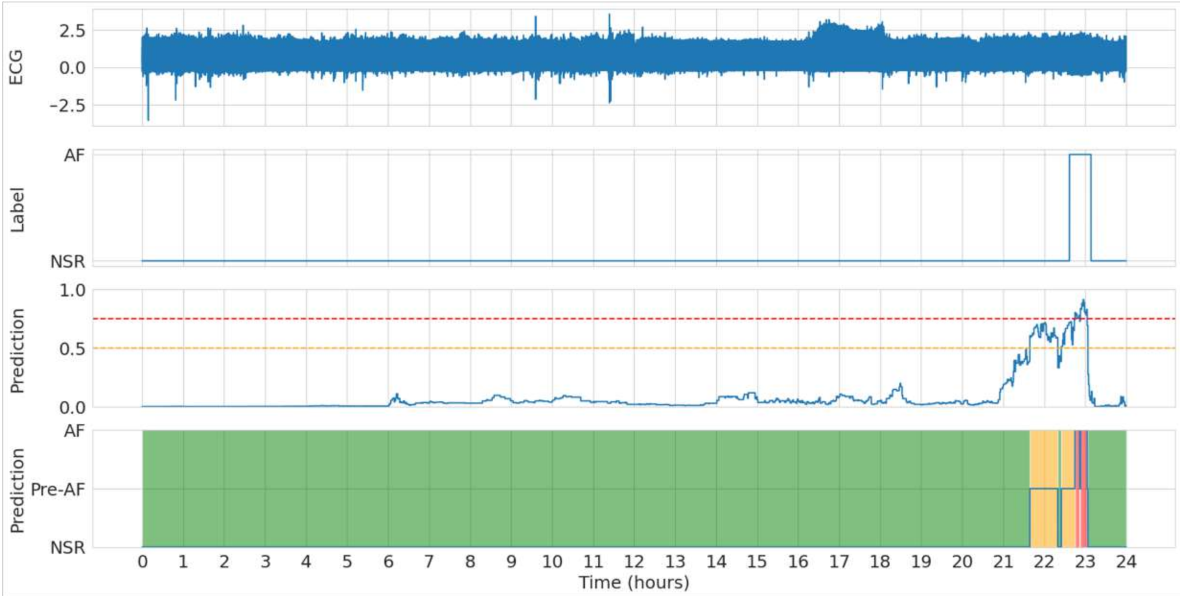
Random forest



XGBoost

Summary

- 0.70 AUROC
  - 5 minutes before AF
  - ML model
  - HRV parameters
- Features importance
  - Short-term variability
- AF to NSR conversion
  - Wearables and CIED
  - Pill in the pocket



1	2	3	4
AF long-term Holter ECG Database	AF onset forecast	AF risk identification during sinus rhythm	Conclusions and perspectives

1

AF long-term Holter ECG Database

2

AF onset forecast

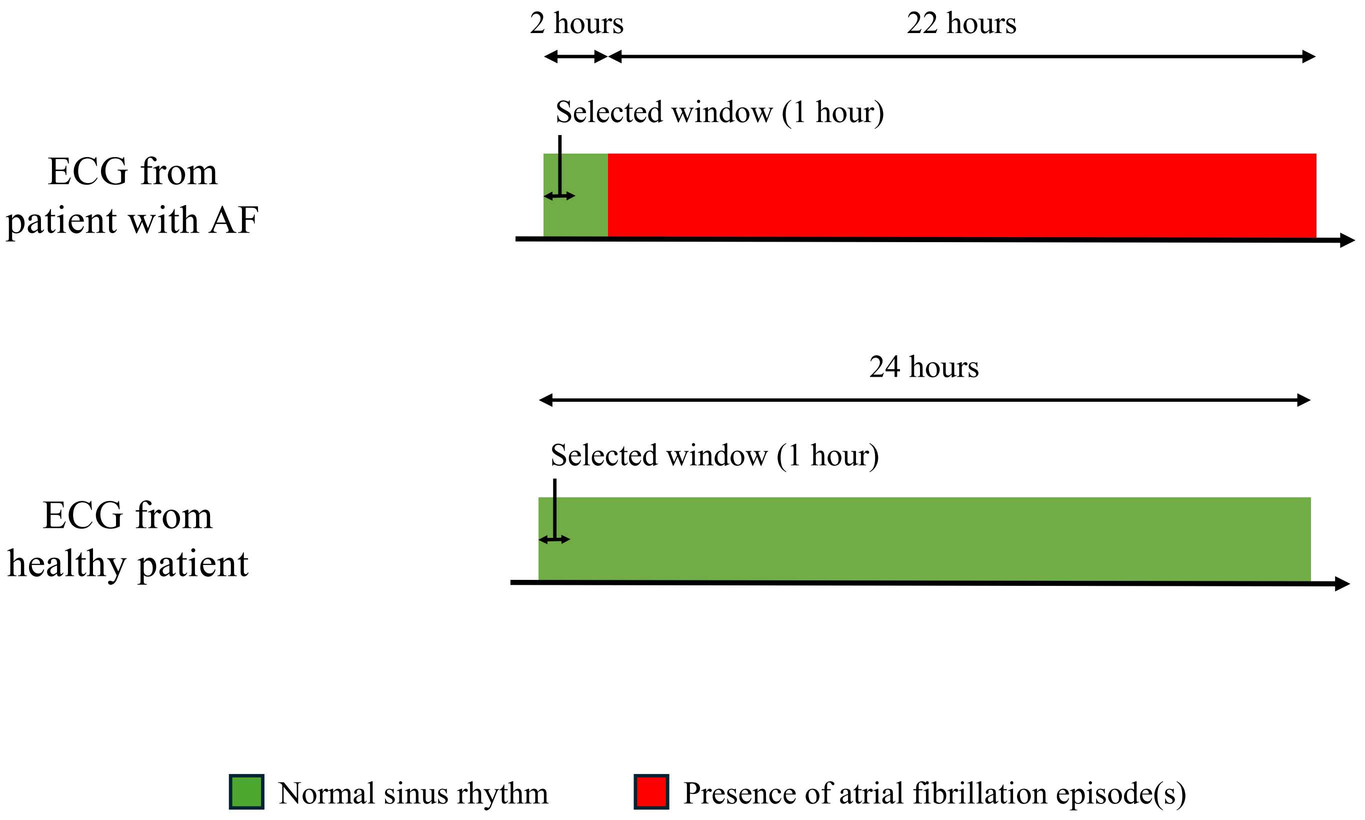
3

AF risk identification during sinus rhythm

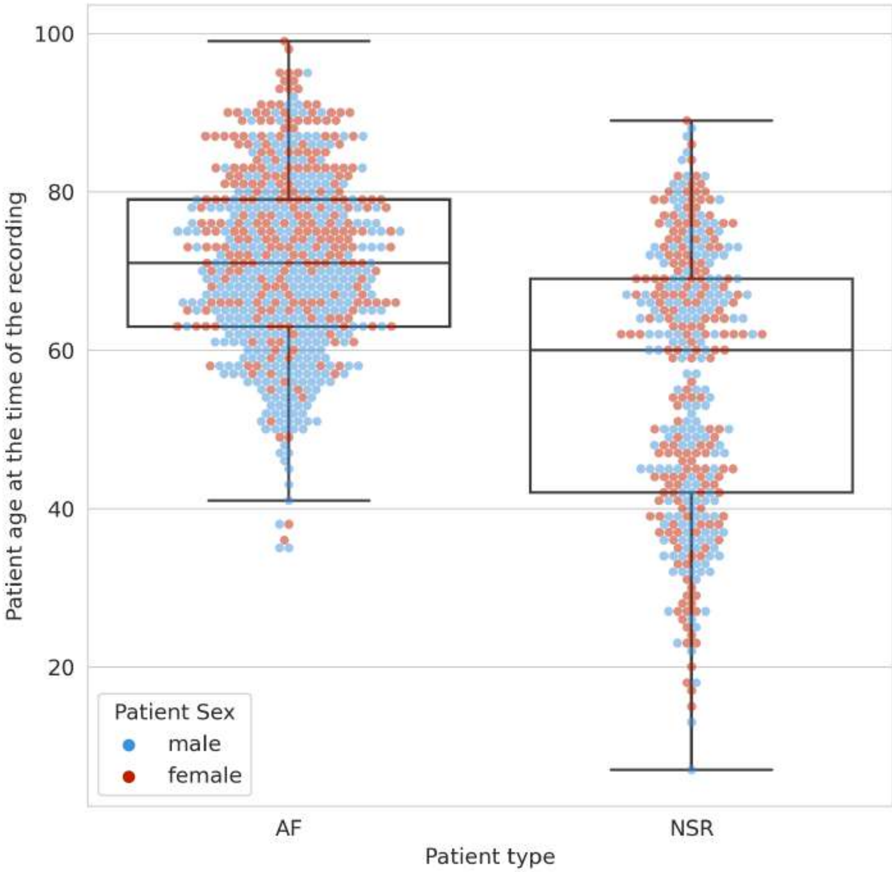
4

Conclusions and perspectives

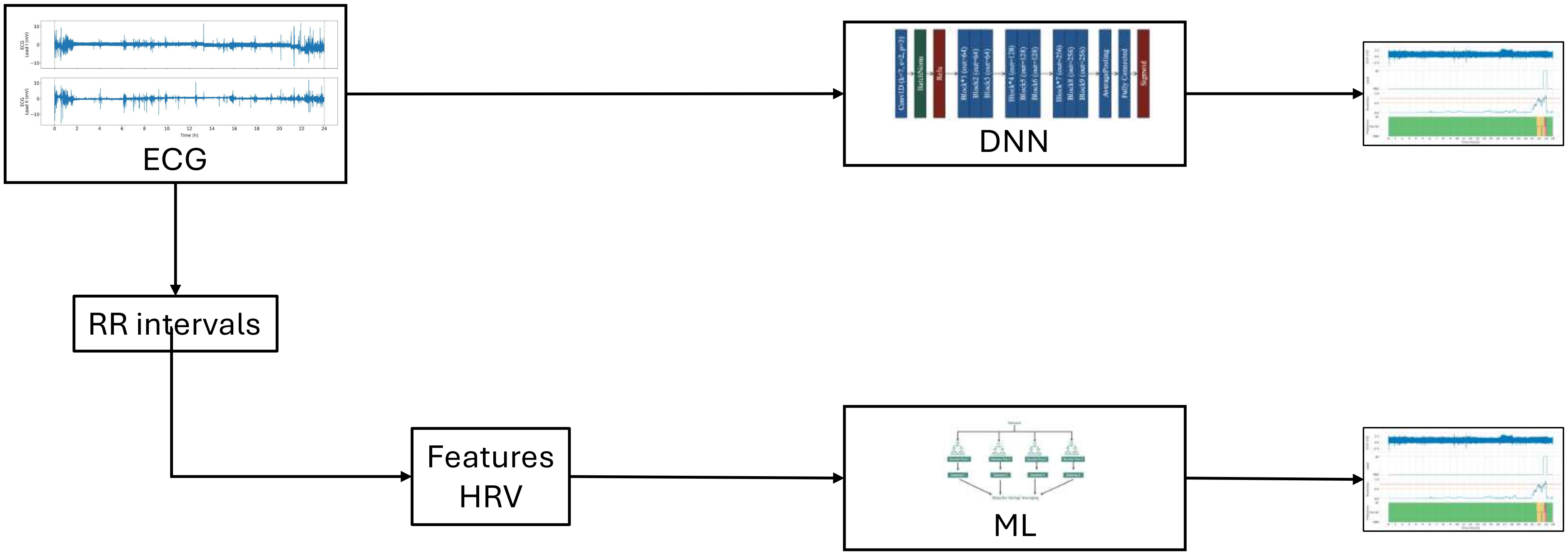
AF risk identification



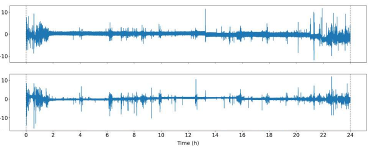
Age and sex comparison



Model comparison



Model comparison

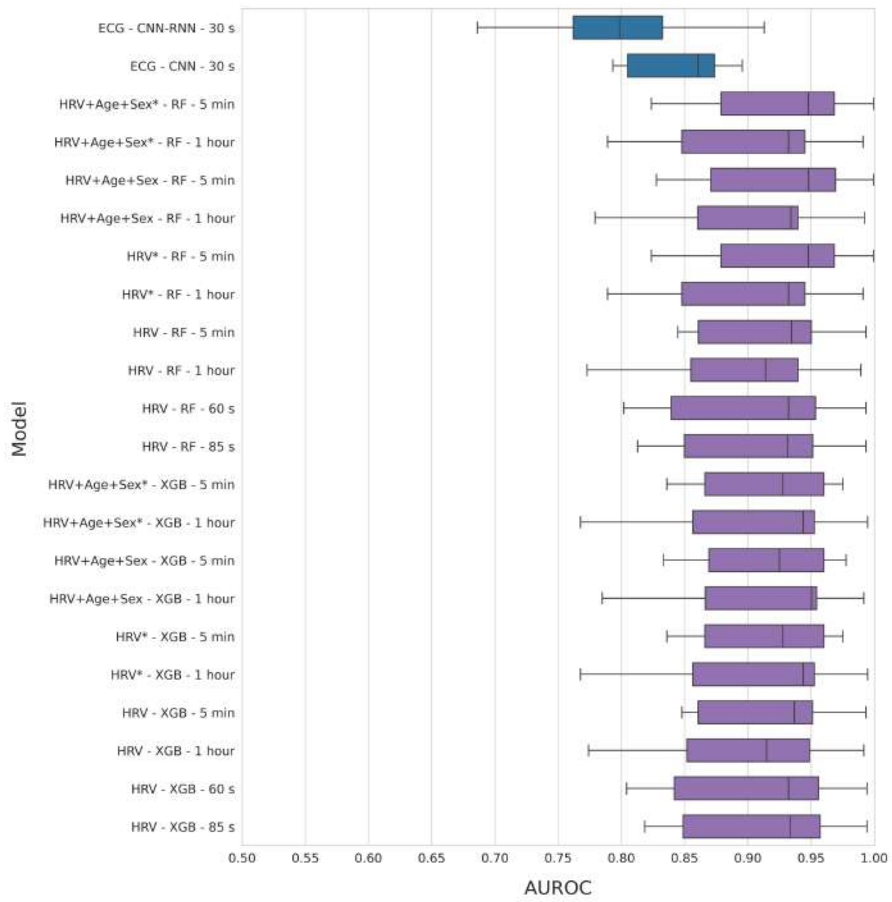


ECG

RR intervals

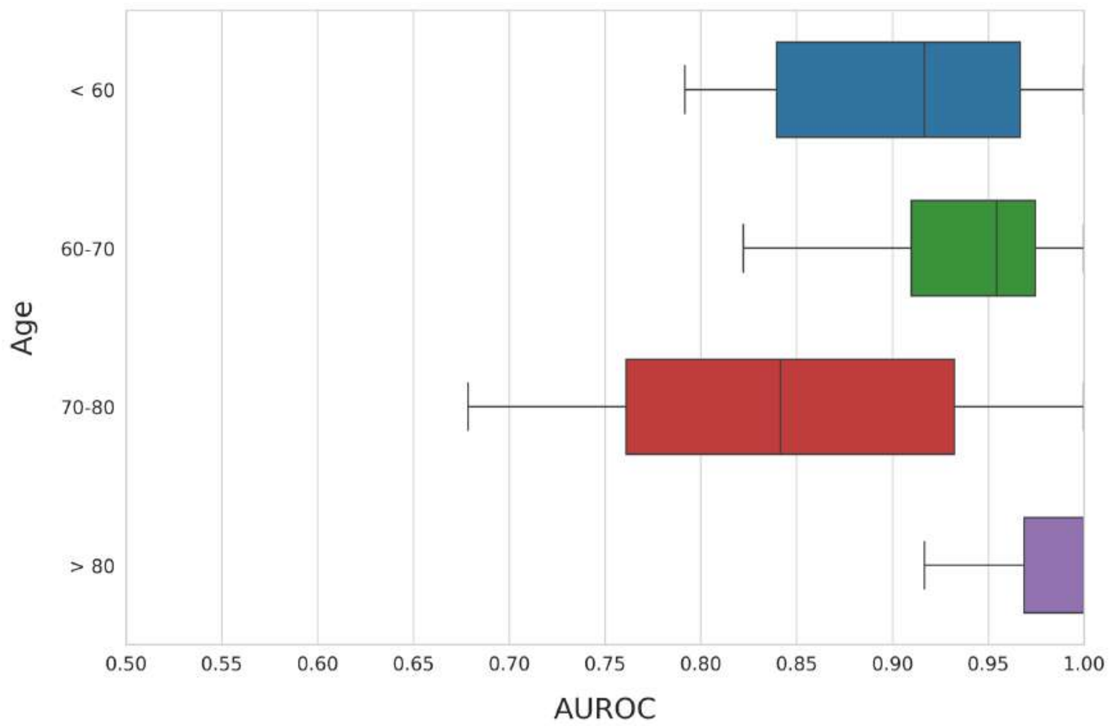
HRV

Higher = better



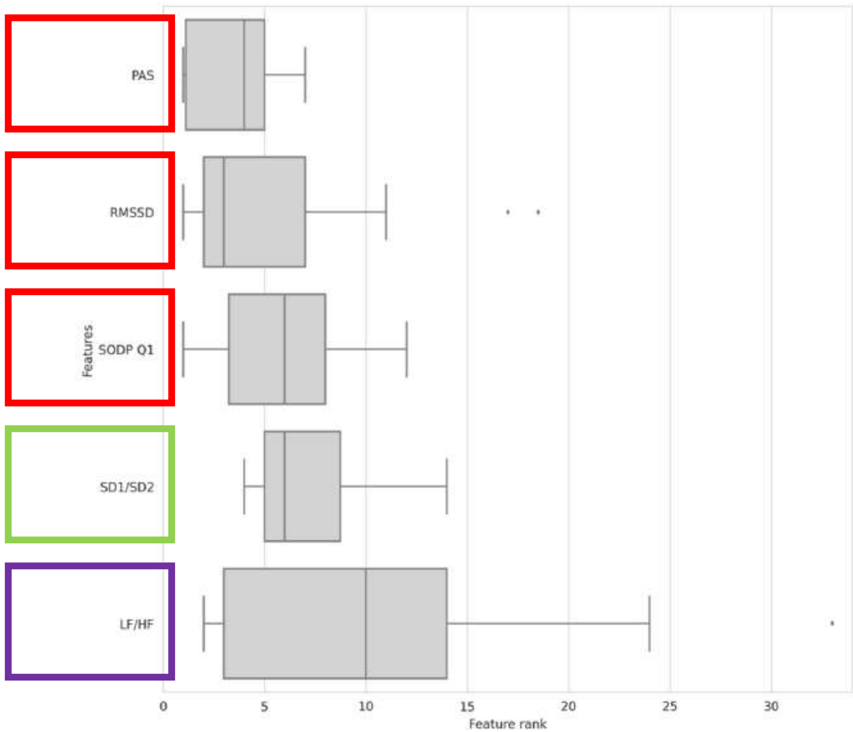
Age-group comparison

- 4 groups
  - < 60
  - 60-70
  - 70-80
  - > 80
- Best results
  - > 80
  - Prevalence 20%

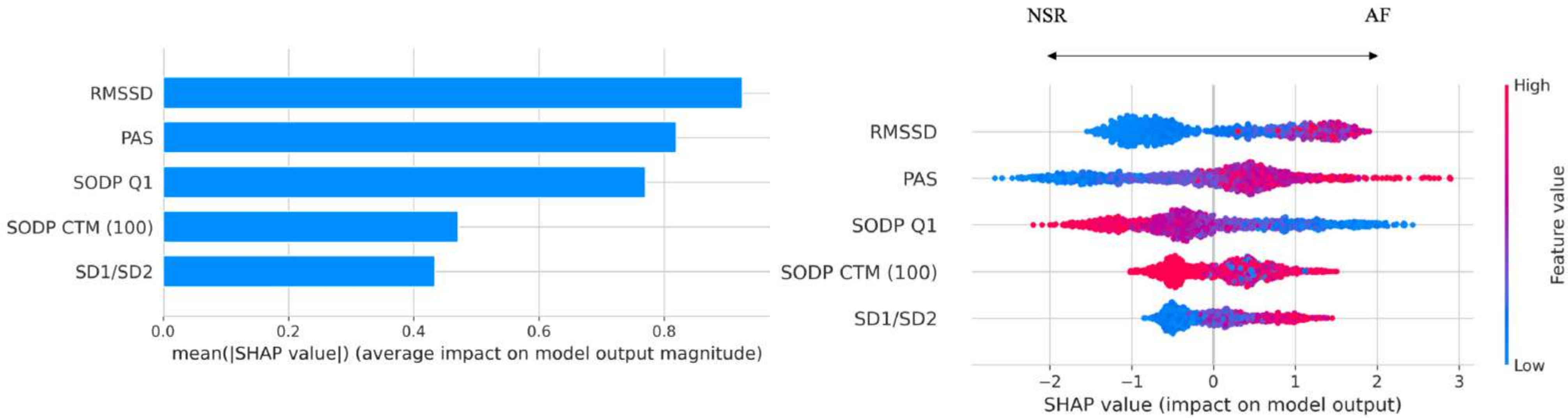


Features importance

- Short-term variability
  - PAS
  - RMSSD
  - SODP Q1
- Long-term variability
  - SD1/SD2
- ANS
  - LF/HF



Features importance



- High RMSSD → more variability → AF
- High PAS → more variability → AF
- More SODP Q1 → more DC-DC (linked to PAS) → NSR

Summary

- High performance
  - 0.919 AUROC
- Features importances
  - Short-term variability
- Opportunities
  - AF screening optimisation
  - Lifestyle changes

Recommendations for screening to detect AF

Recommendation	Class[a]	Level[b]
Opportunistic screening for AF by pulse taking or ECG rhythm strip is recommended in patients ≥65 years of age.[188,211,223,225]	I	B
It is recommended to interrogate pacemakers and implantable cardioverter defibrillators on a regular basis for AHRE.[c224,226]	I	B
When screening for AF it is recommended that:[217,218] • The individuals undergoing screening are informed about the significance and treatment implications of detecting AF. • A structured referral platform is organized for screen-positive cases for further physician-led clinical evaluation to confirm the diagnosis of AF and provide optimal management of patients with confirmed AF. • Definite diagnosis of AF in screen-positive cases is established only after physician reviews the single-lead ECG recording of ≥30 s or 12-lead ECG and confirms that it shows AF.	I	B
Systematic ECG screening should be considered to detect AF in individuals aged ≥75 years, or those at high risk of stroke.[212,224,227]	IIa	B

AF = atrial fibrillation; AHRE = atrial high-rate episode; ECG = electrocardiogram.
[a]Class of recommendation.
[b]Level of evidence.
[c]See sections 3.2 and 3.3 for diagnostic criteria for AF and AHRE, and section 16 for the management of patients with AHRE.

1

AF long-term Holter ECG Database

2

AF onset forecast

3

AF risk identification during sinus rhythm

4

Conclusions and perspectives

1	2	3	4
AF long-term Holter ECG Database	AF onset forecast	AF risk identification during sinus rhythm	Conclusions and perspectives

Research summary

- New database for AF onset forecast and AF risk identification
  - IRIDIA-AF v1 (published)
  - IRIDIA-AF v2
- AF onset forecast
  - 0.70 AUROC
  - 5 minutes before AF
  - HRV + ML
  - Short-term variability features
- AF risk identification during sinus rhythm
  - 0.90 AUROC
  - HRV + ML
  - Short-term variability features

The thesis

Machine learning models can forecast an incoming paroxysmal atrial fibrillation episode moments before its onset. They demonstrate increasing performance as the prediction gets closer to the event.

Moreover, in the comparative analysis of sinus rhythm recordings from patients with and without paroxysmal atrial fibrillation, machine learning models can identify a specific signature of paroxysmal atrial fibrillation within the sinus rhythm.

Challenges and perspectives

- Data accessibility
- Data annotations on a larger scale
- Scalability and generalisation to new patients or new centres
  - Prospective study
- Class balancing vs imbalance
  - 50% vs 10% (65+)
  - Towards clinical usability

Conclusions

Task	Prediction score		Therapeutic strategies
	Human	Machine Learning	
AF detection	100%	99%	Treatment (anticoagulant)
AF onset forecast	0%	70%	Wearables and PITP Forecasting algorithm in CIED
AF risk identification	75%	90%	Screening optimisation Lifestyle changes