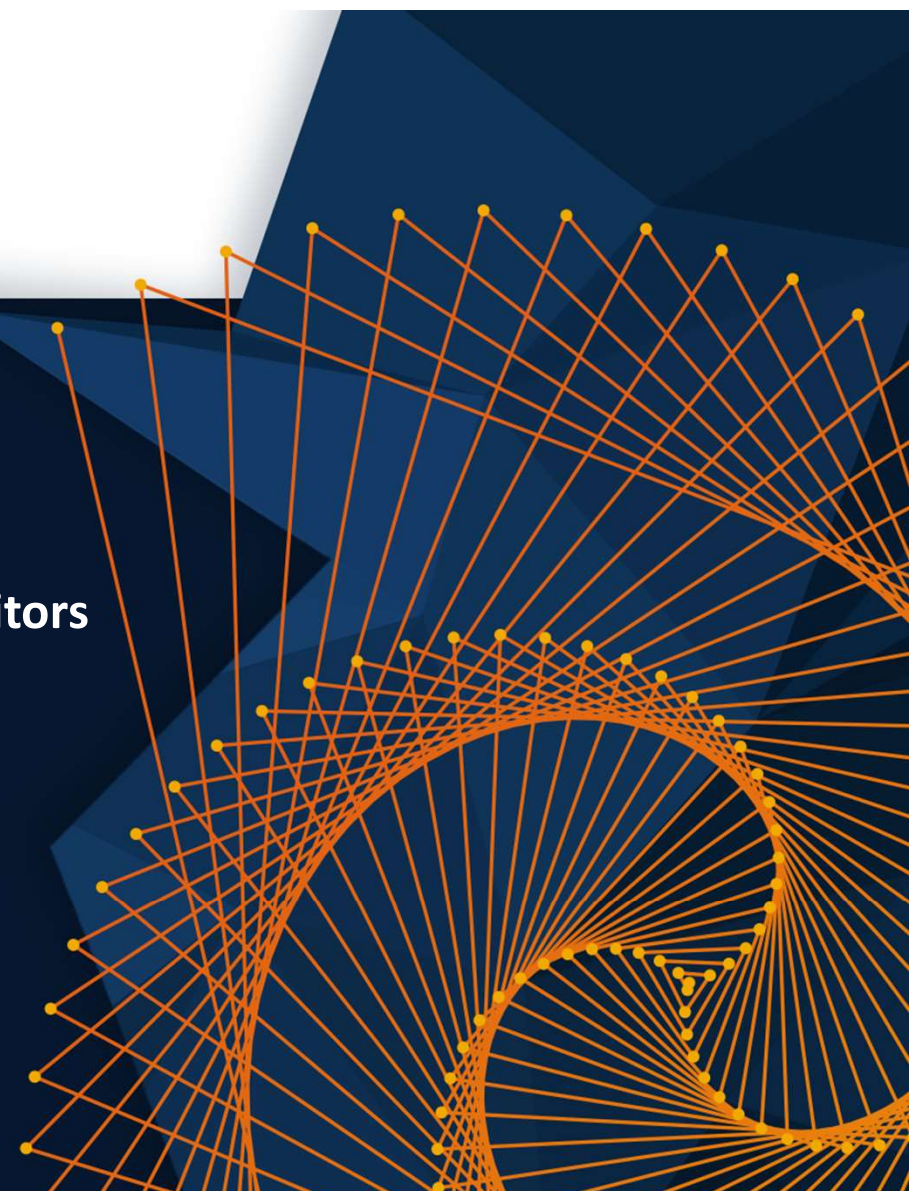


November 13–14, 2024 | Online

Atrial Fibrillation Detection with Ensemble of Features Based CNN for Insertable Cardiac Monitors

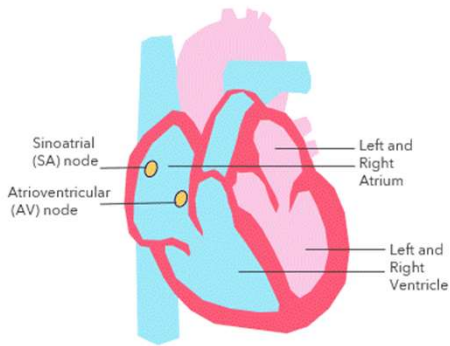
Shantanu Sarkar PhD
Medtronic Inc.

MATLAB **EXPO**

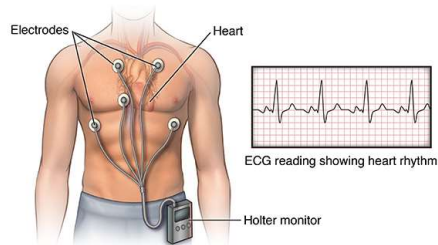


Electrocardiography (ECG)

Monitoring and Diagnosis options



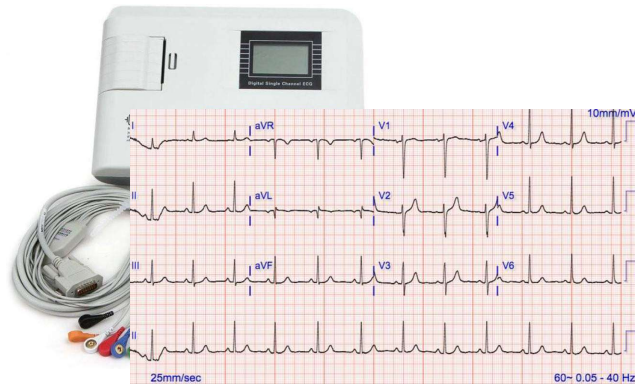
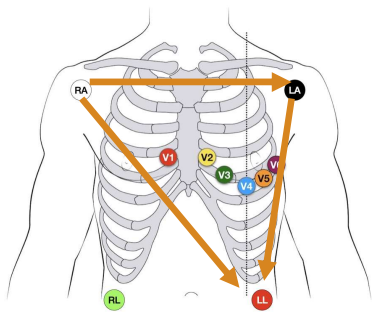
Holter Monitoring



Wearables / External Monitoring systems



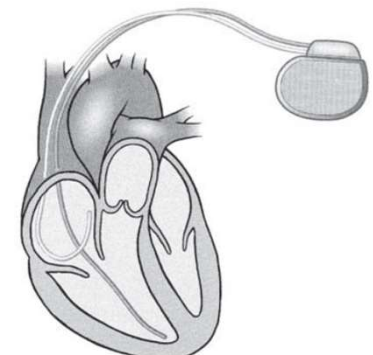
In Office ECG



Implantable Monitors



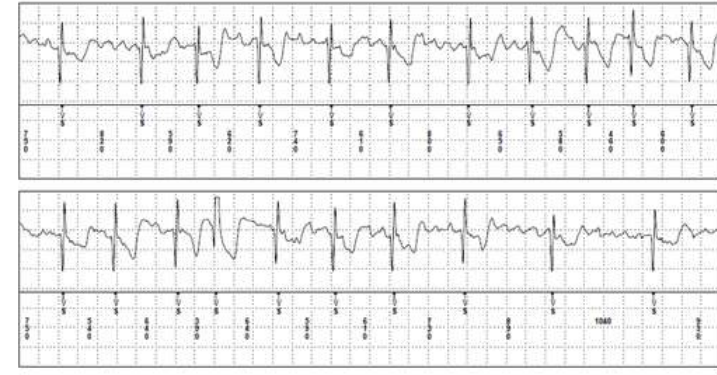
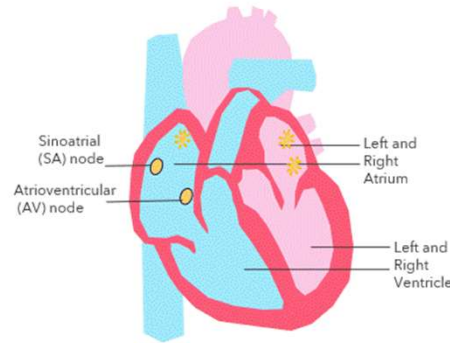
Implantable Therapy devices



Why Atrial Fibrillation matters

Stroke, Heart Failure, Symptoms

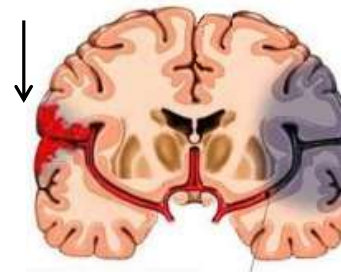
- Atrial fibrillation (AF) can lead to
 - Stroke
 - Progression to Heart Failure (HF)
 - Debilitating symptoms
- **AF is often intermittent and asymptomatic**
- Cryptogenic Stroke
 - 25% of ischemic strokes are cryptogenic
 - May have underlying undiagnosed AF
 - Detection of AF changes treatment
 - antiplatelets to oral anticoagulation



Stroke etiologies

Vessel Rupture (15%)

Artery Occlusion (85%)



• **Cryptogenic (25-40%)**
Unknown cause

Adams HP Jr, *Stroke*. Jan 1993; 24: 35-41;
Camm et al, *European Heart Journal*. 2012; 33, 2719-2747

AF – The Clinical Questions

Clinical Diagnostic Questions

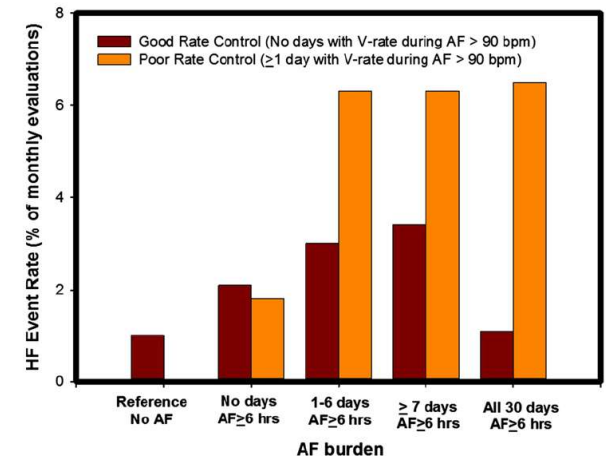
1. Does patient have AF ?
2. How much AF does patient have ?
3. What is the temporal characteristics of AF?
4. What is the ventricular rate during AF?
5. Does patient have clinical risk factors ?

Treatments

1. Anticoagulation management
2. Rhythm Control
 - a) AF ablation
 - b) Antiarrhythmic drugs
3. Rate Control
 - a) AV node ablation and pacing
 - b) Beta Blockers, Digoxin, etc.

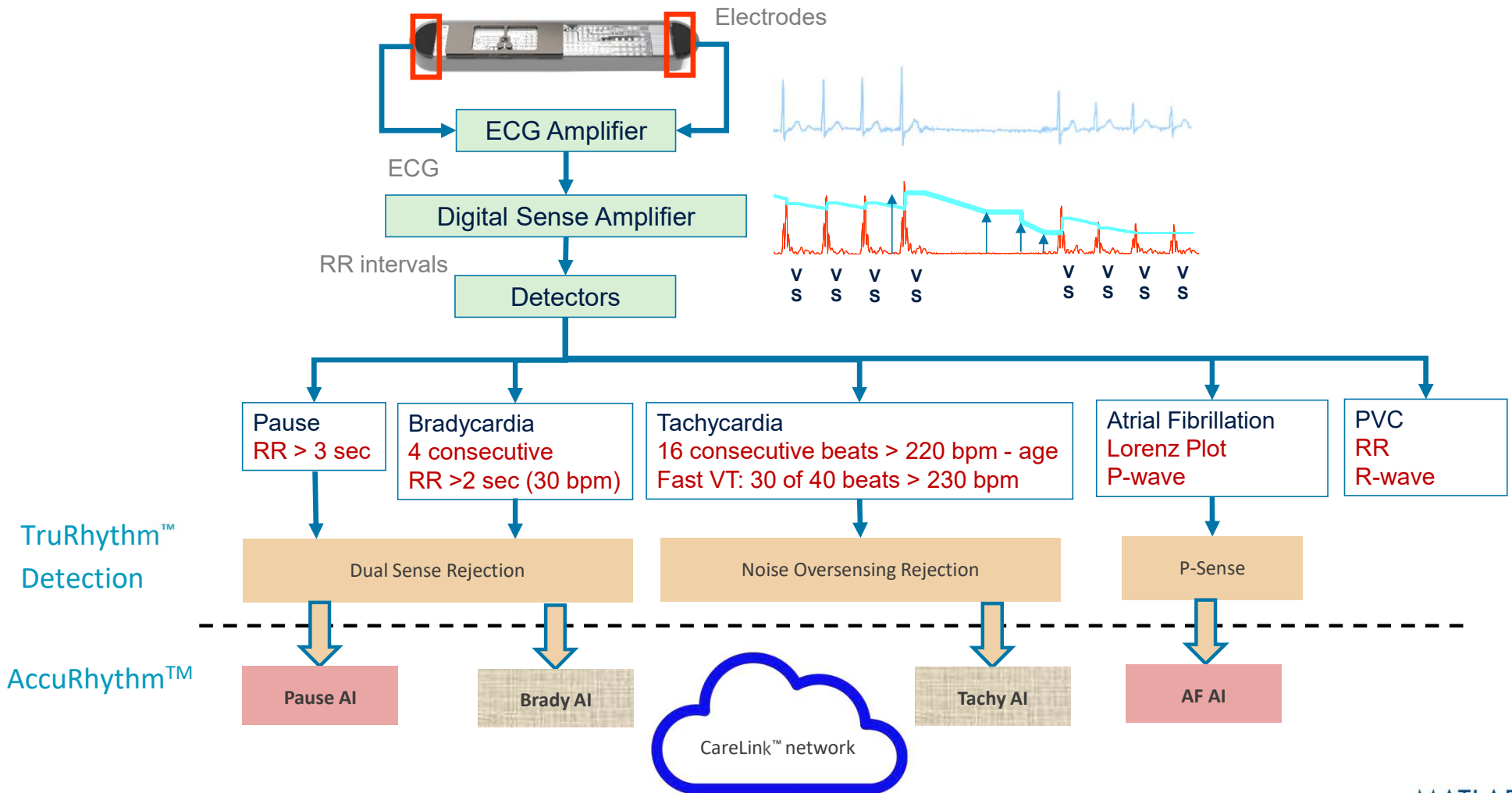
Kaplan RM et al. Circulation. 2019 Nov 12;140(20):1639-1646.
Sarkar S et al. Am Heart J. 2012 Oct;164(4):616-24.

		CHA ₂ DS ₂ -VASc Score				
		0	1	2	3-4	≥5
Maximum Daily AF Duration		n=2922 (13.4%)	n=2151 (9.9%)	n=4554 (20.9%)	n=7164 (32.9%)	n=4977 (22.9%)
	No AF n=16815 (77.2%)	0.33% 40 events	0.62% 46 events	0.70% 95 events	0.83% 139 events	1.79% 157 events
	AF 6 min–23.5 h n=3381 (15.5%)	0.52% 11 events	0.32% 4 events	0.62% 17 events	1.28% 42 events	2.21% 36 events
	AF >23.5h n=1572 (7.2%)	0.86% 4 events	0.50% 3 events	1.52% 19 events	1.77% 28 events	1.68% 13 events



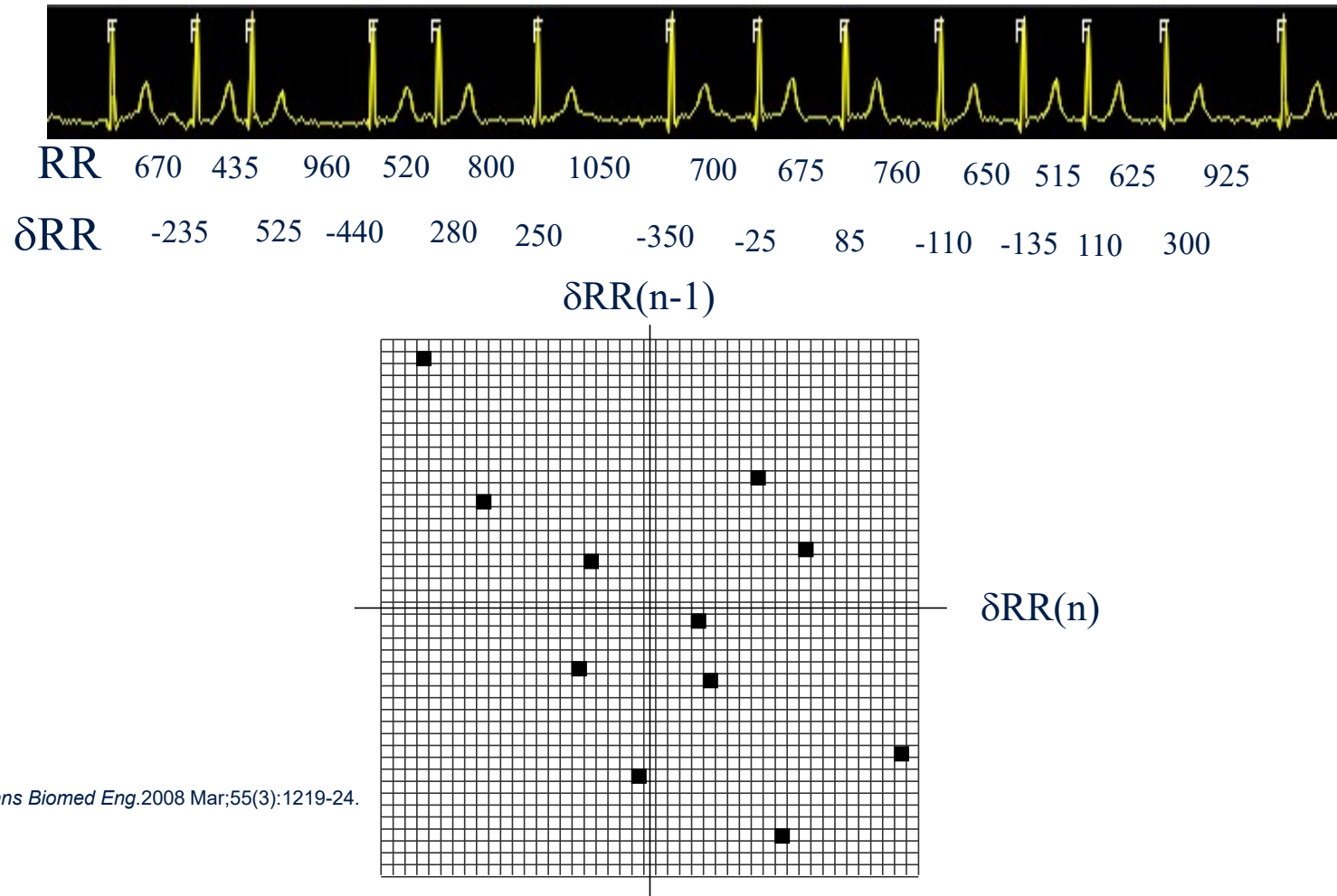
Adjusted Hazard Ratio	Reference	2.1*	2.0	2.8 [#]	5.3*	3.9*	5.8*	1.2	6.7*	*P < .001; *P = .006
Evaluations	10,375	3283	333	300	126	354	96	611	93	
Patients	1042	419	138	135	90	116	60	118	31	

R-wave Sensing and Cardiac Arrhythmia Detection in ICMs



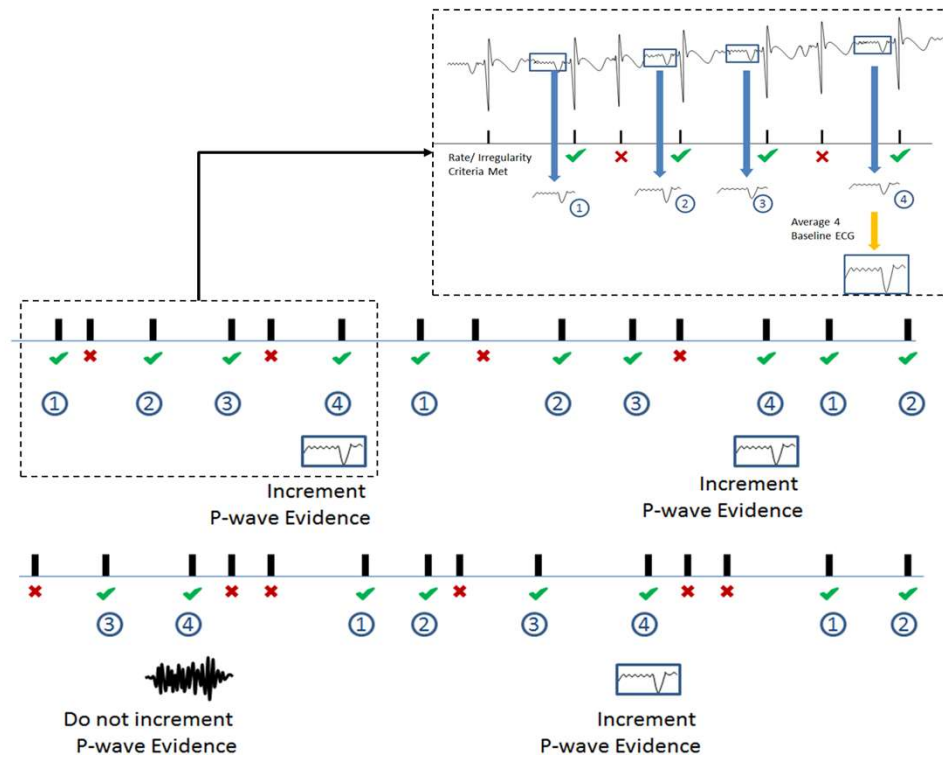
AF Detector Principle: Unpredictability of RR intervals

- Lorenz plot



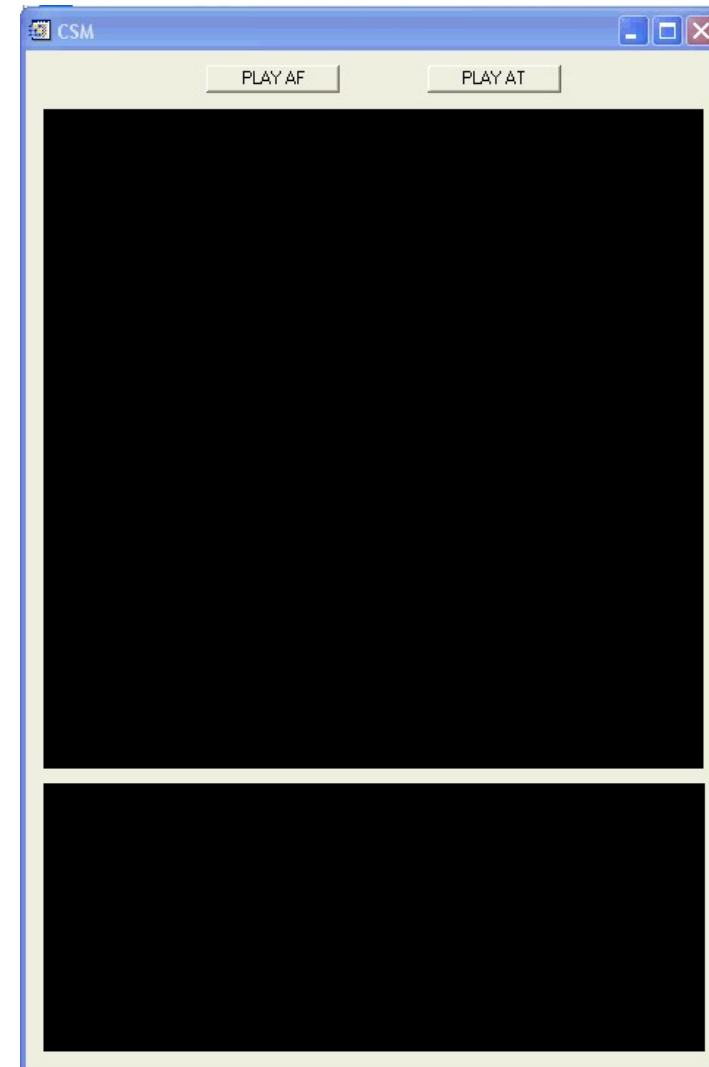
Sarkar S et al. *IEEE Trans Biomed Eng.* 2008 Mar;55(3):1219-24.

AF detection in Insertable Cardiac Monitor



Lorenz Plot

AF Evidence



Sarkar S et al. IEEE Trans Biomed Eng. 2008 Mar;55(3):1219-24.
 Pürerfellner H et al. Heart Rhythm. 2014; 11(9):1575-83.
 Sanders P et al. Heart Rhythm. 2016; 13(7):1425-30.
 H Pürerfellner, et al. EP Europace 20 (Fl_3), f321-f328

Ambulatory AF monitoring

Duration Sensitivity
98.9%

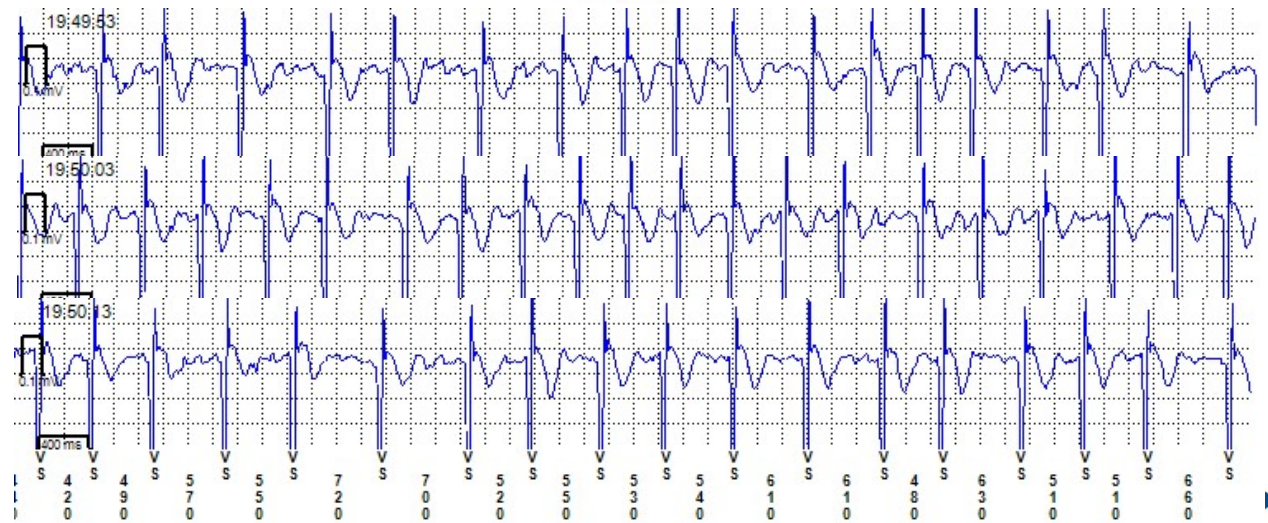
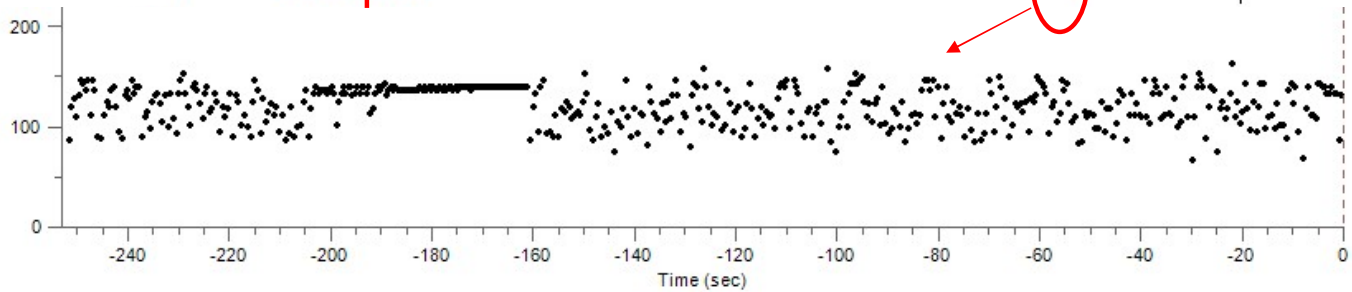
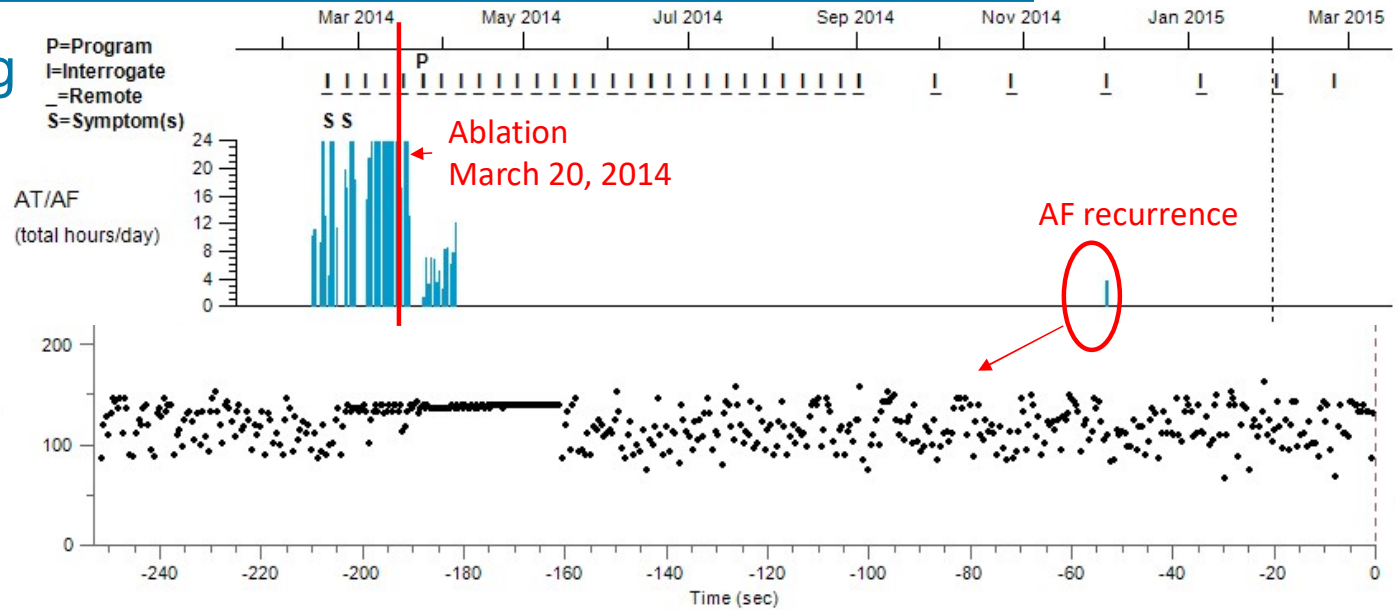
Duration Specificity
99.8%

Episode* Sensitivity
97%

Episode PPV*
85%

* >2min

*Pts w/ Hx of AF

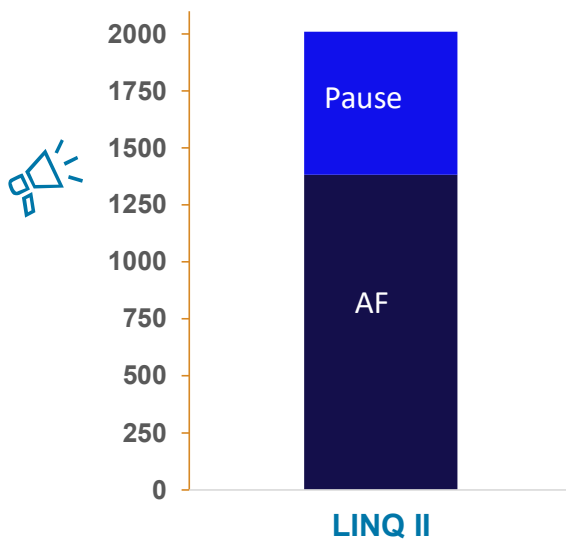


H Pürerfellner, et al. EP Europace 20 (FI_3), f321-f328

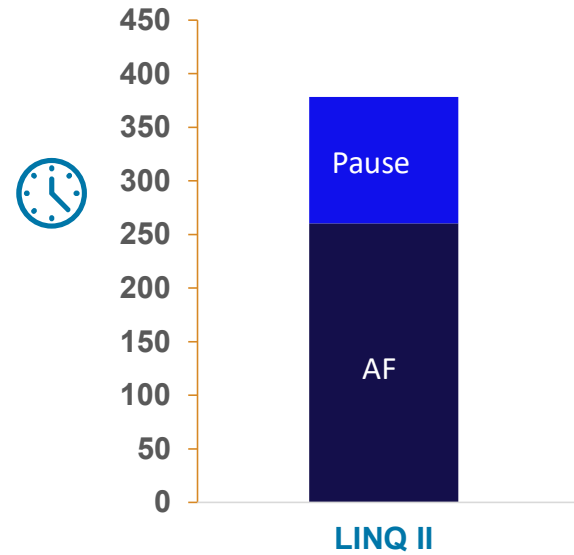
False Alerts and Episode Review Burden

Still an unmet clinical need

Annual False Alerts for Clinic w/ 200 ICMs



Annual False Alert Clinic Review Time (Hours)

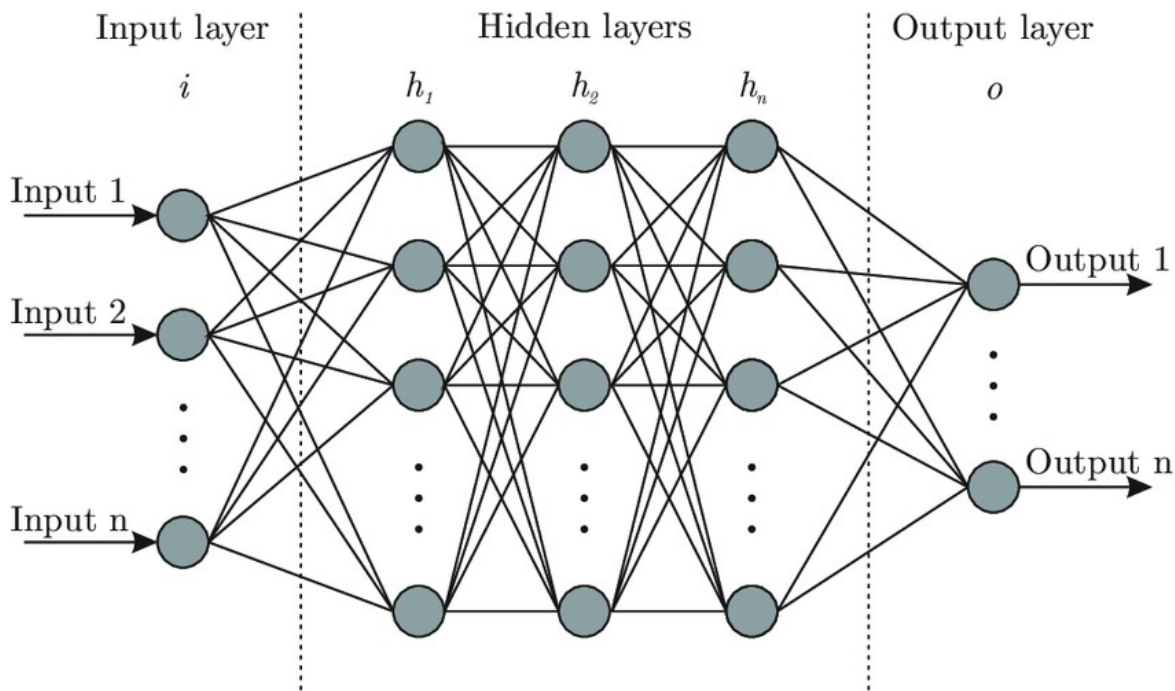


SOURCE: OUSDIGIAN, K. CHENG, YJ. KOEHLER, J. RADTKE, A. ROSEMAS, S. ROGERS, J. ARTIFICIAL INTELLIGENCE DRAMATICALLY REDUCES ANNUAL FALSE ALERTS FROM INSERTABLE CARDIAC MONITORS. AMERICAN HEART ASSOCIATION (AHA). PRESENTED AT AHA CONFERENCE. NOVEMBER 2021

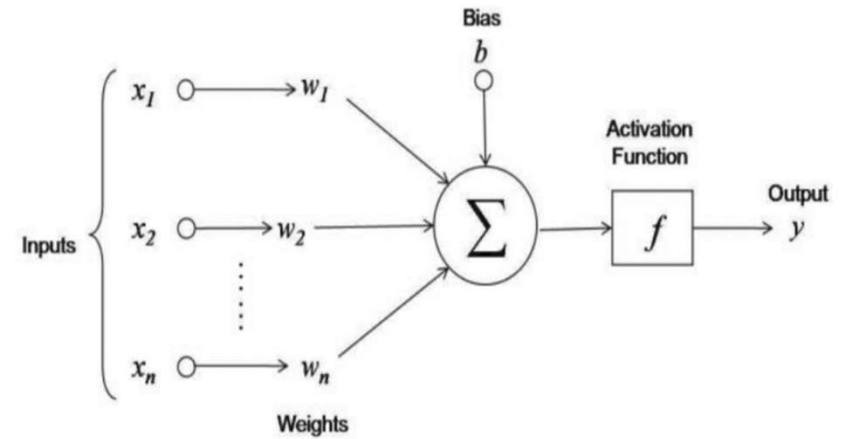
Artificial neural network

CLASSIFICATION: FEATURES TO CLASSES

Network



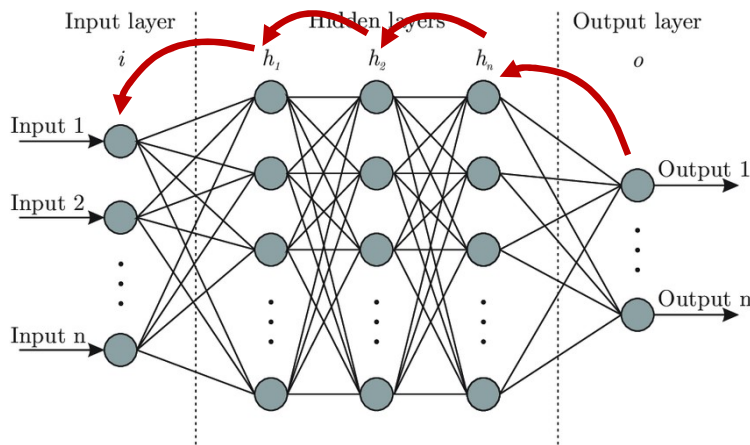
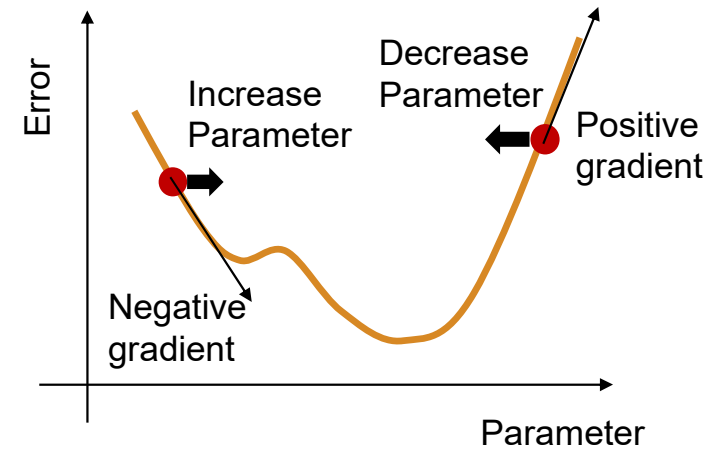
Each node of network



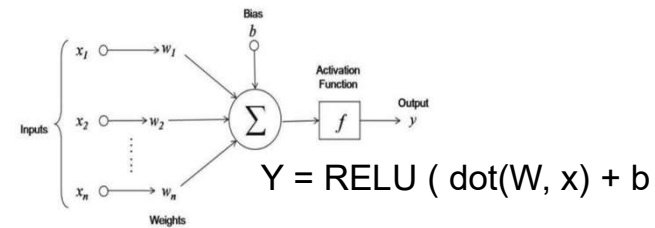
Training the network

GRADIENT DESCENT, THE CHAIN RULE, AND BACKPROPAGATION

$$\text{Updated Parameter} = \text{Current Parameter} - \text{Learning Rate} \times \text{Gradient of Error wrt Parameter}$$



$$\begin{aligned} h_1 &= \text{RELU}(\text{dot}(W_1, i) + b_1) \\ h_2 &= \text{RELU}(\text{dot}(W_2, h_1) + b_2) \\ h_3 &= \text{RELU}(\text{dot}(W_3, h_2) + b_3) \\ o &= \text{RELU}(\text{dot}(W_4, h_3) + b_4) \end{aligned}$$



$$f(W_1, W_2, W_3, W_4) = a(W_4, b(W_3, c(W_2, d(W_1))))$$

$$\text{Chain rule: } \frac{d}{dx}[f(g(x))] = f'(g(x)) \cdot g'(x)$$

DEEP LEARNING

CONVOLUTION NEURAL NETWORKS (CNN)

[CNN Explainer](#)

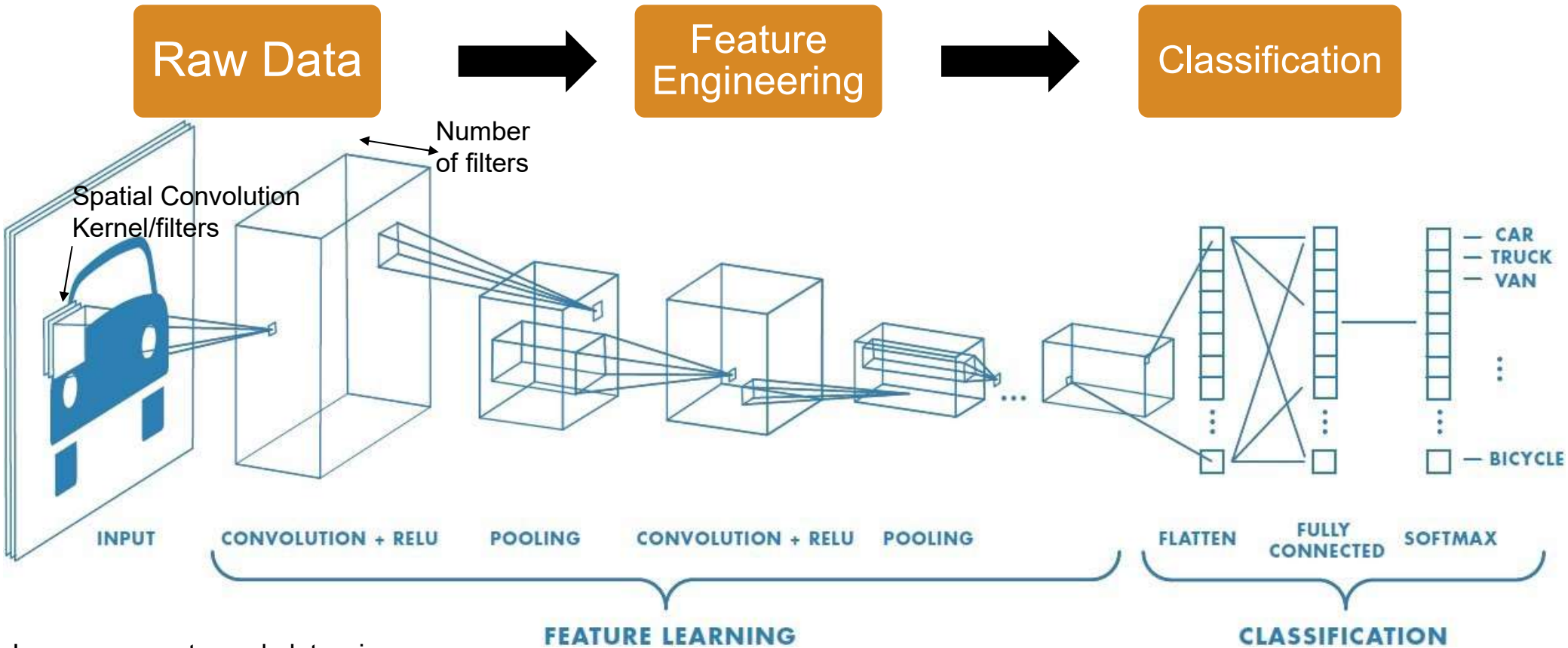
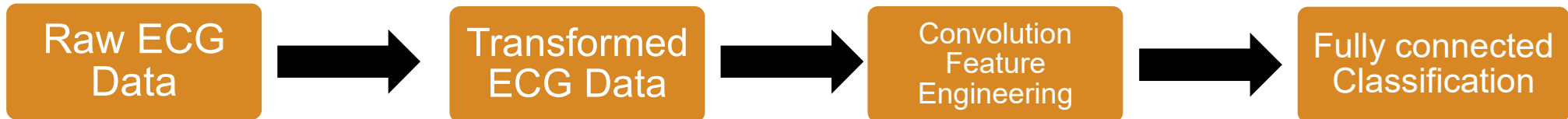
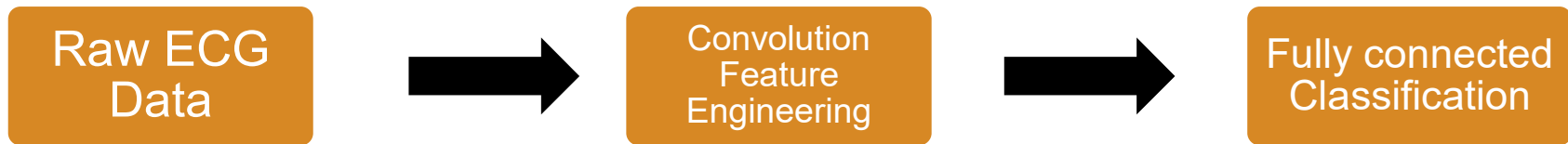


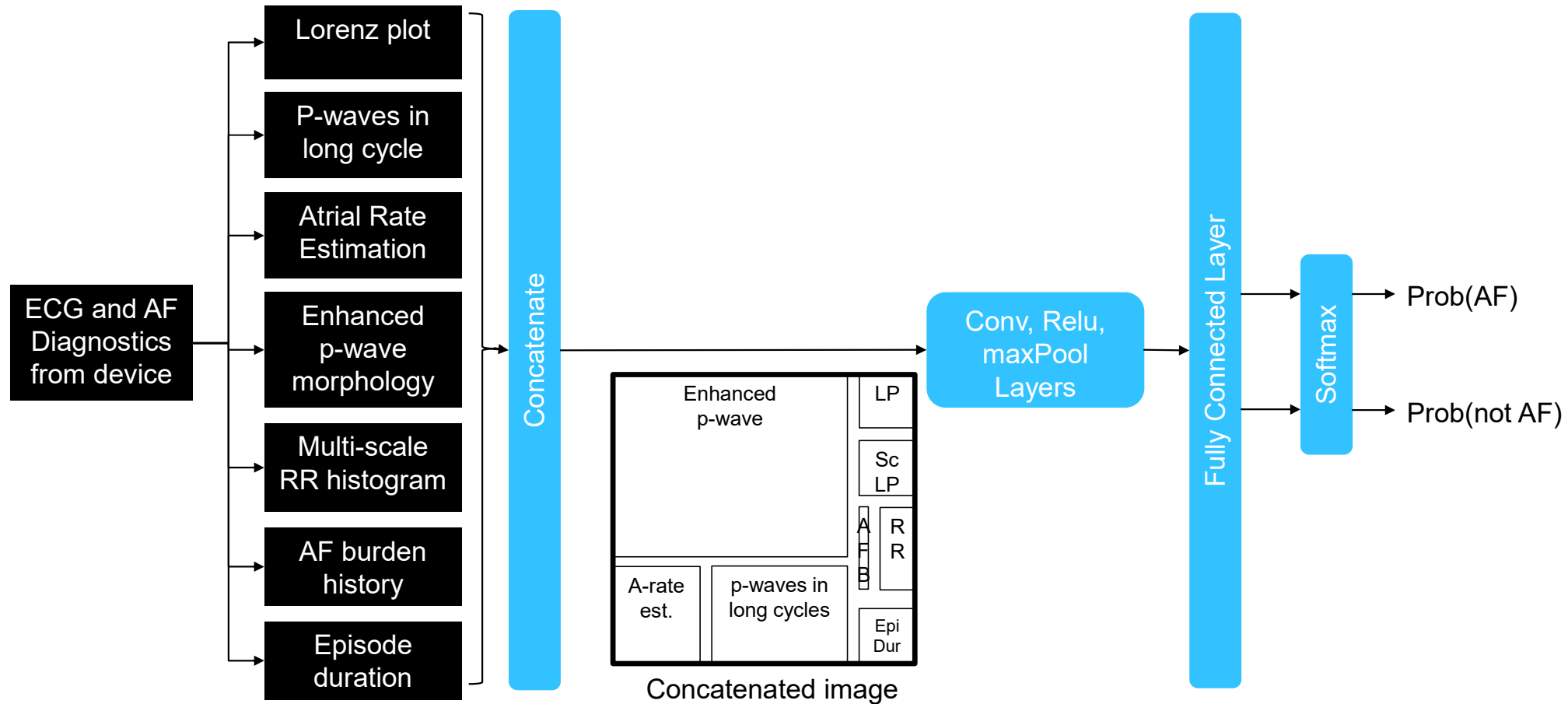
Image source: towardsdatascience.com

Artificial Intelligence for AF detection

VARIOUS POSSIBILITIES



Convolution Neural Networks for AF Detection USING ECG ELEMENTS USED FOR ANNOTATION

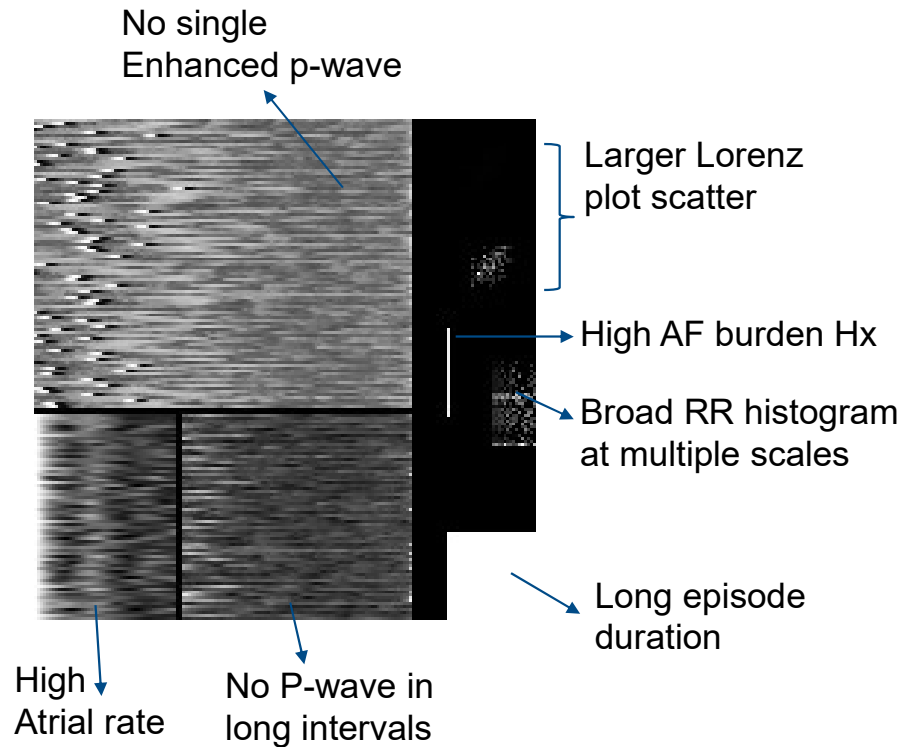


Sarkar S et al. Heart Rhythm O2. 2022 Nov 1;4(1):51-58.

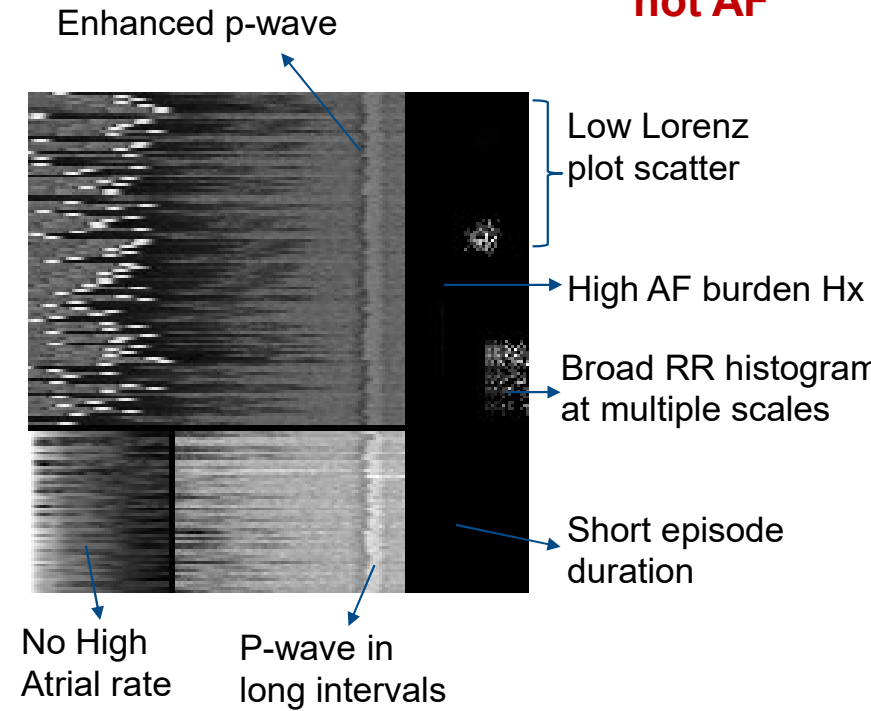
ECG elements

TRANSFORMED ECG ELEMENTS - 2D IMAGE

True AF

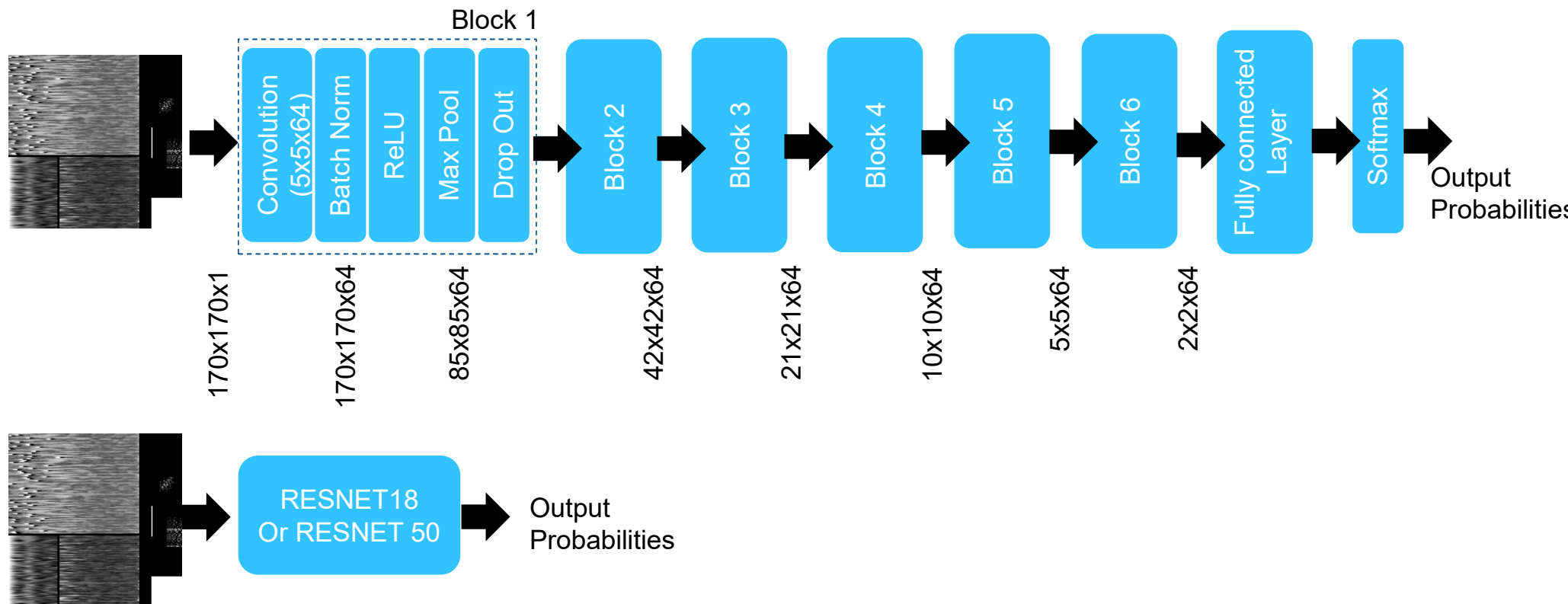


not AF

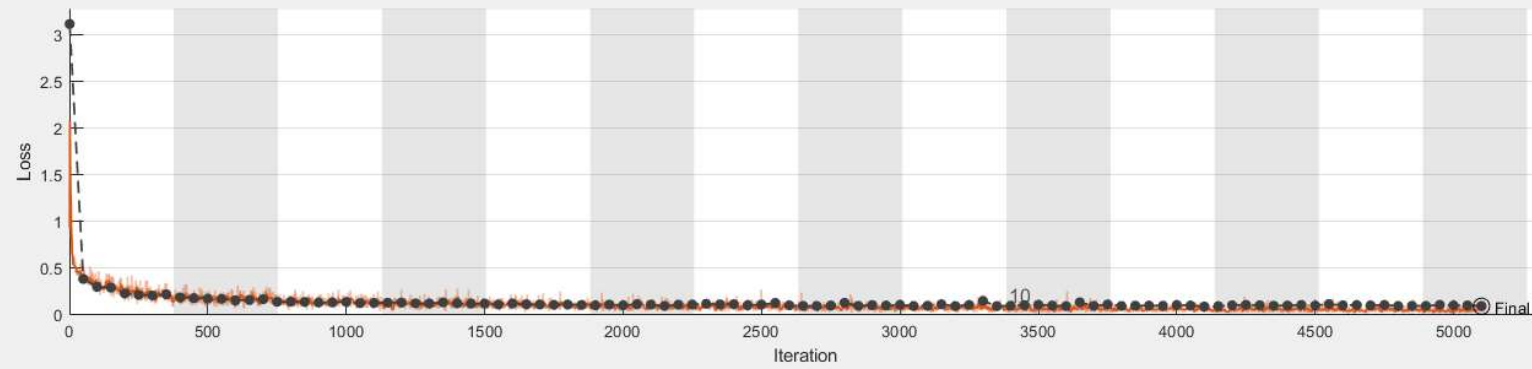
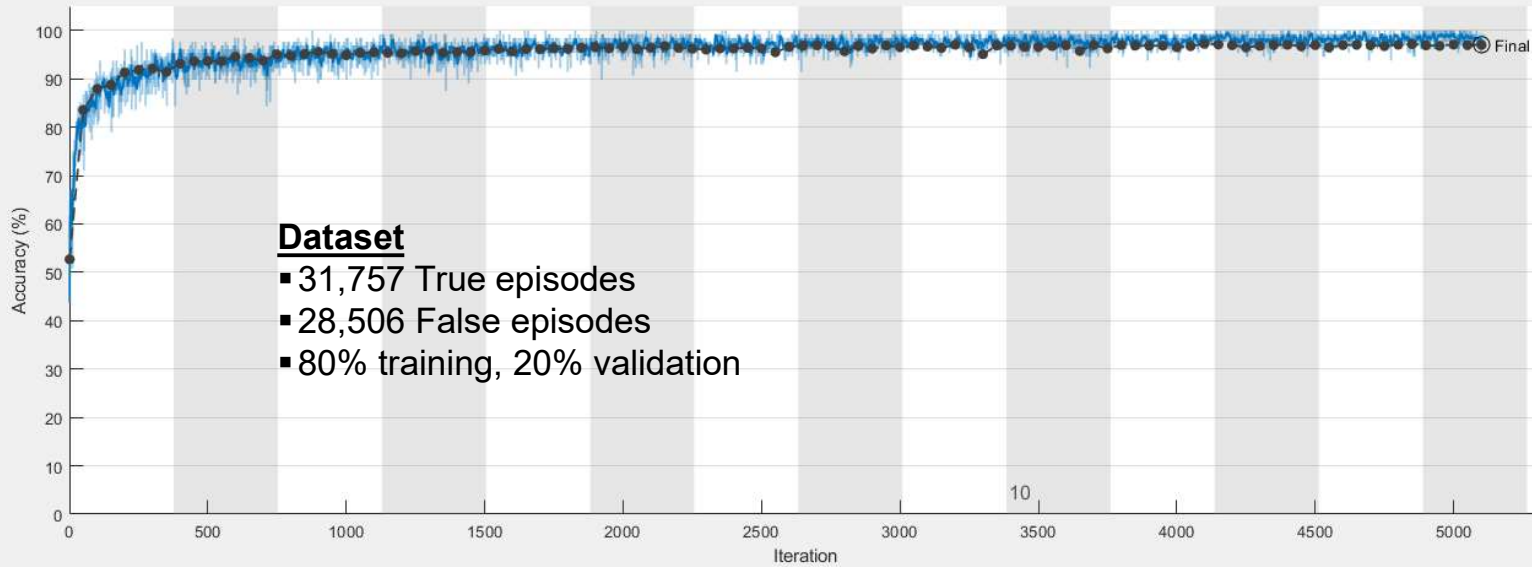


CNN for AF detection

A CUSTOM NETWORK VS RESNET18

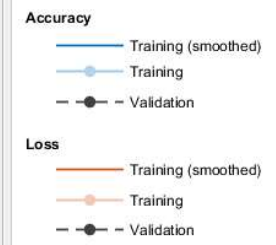


Custom CNN training

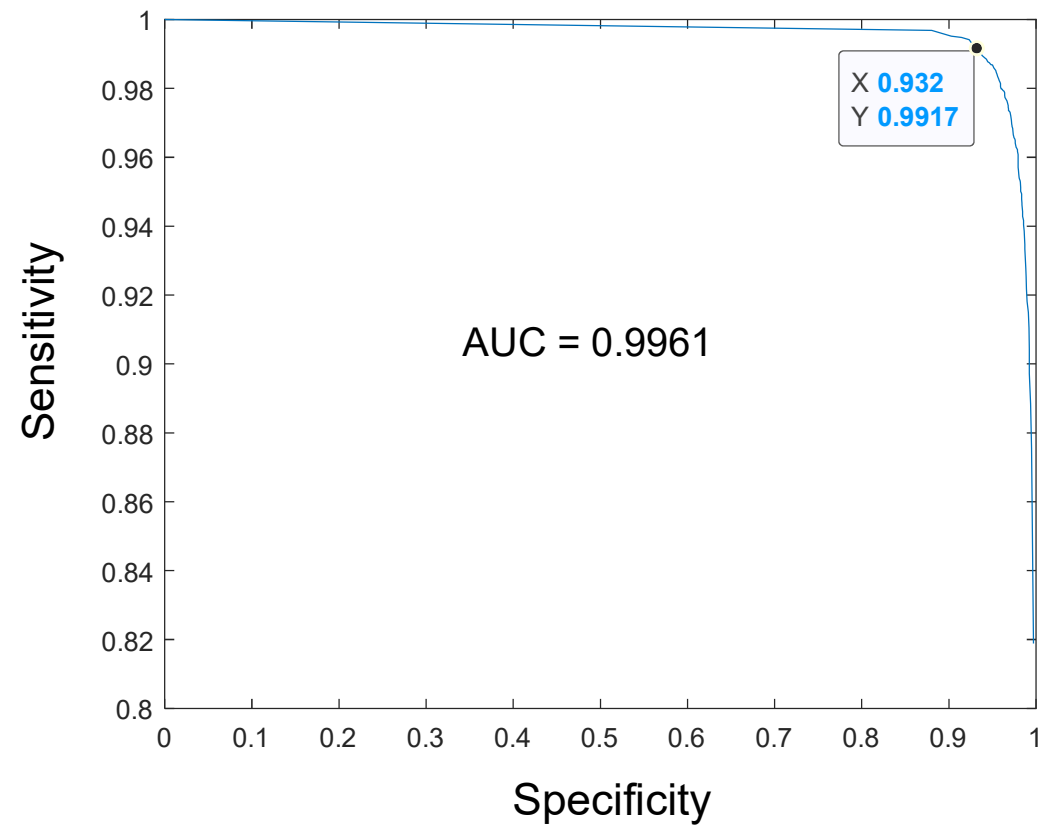
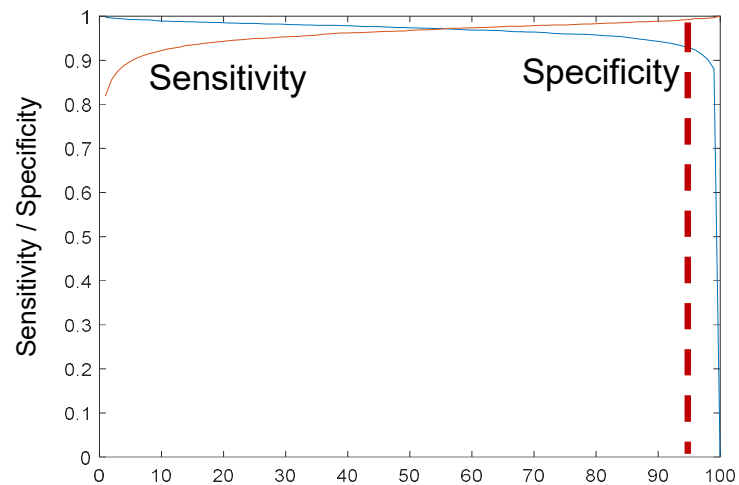
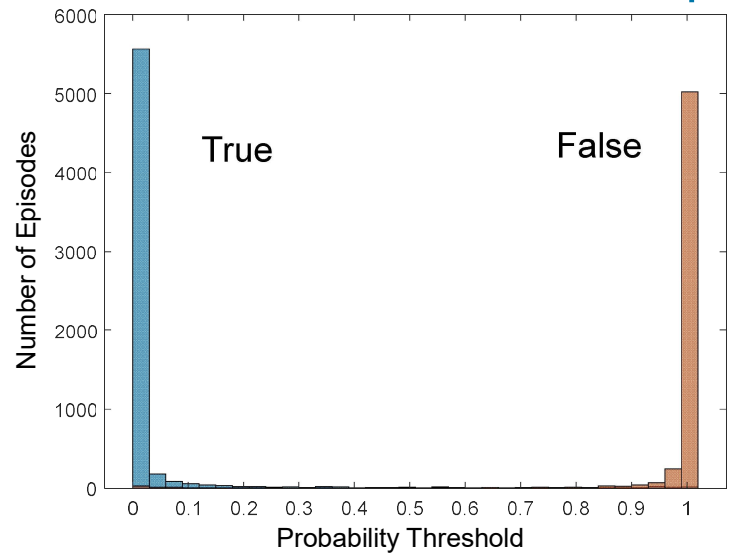


Results	
Validation accuracy:	97.04%
Training finished:	Met validation criterion
Training Time	
Start time:	10 Sep 2024 11:27:11
Elapsed time:	88 min 57 sec
Training Cycle	
Epoch:	14 of 100
Iteration:	5101 of 37600
Iterations per epoch:	376
Maximum iterations:	37600
Validation	
Frequency:	50 iterations
Other Information	
Hardware resource:	Multiple GPUs
Learning rate schedule:	Constant
Learning rate:	0.0005

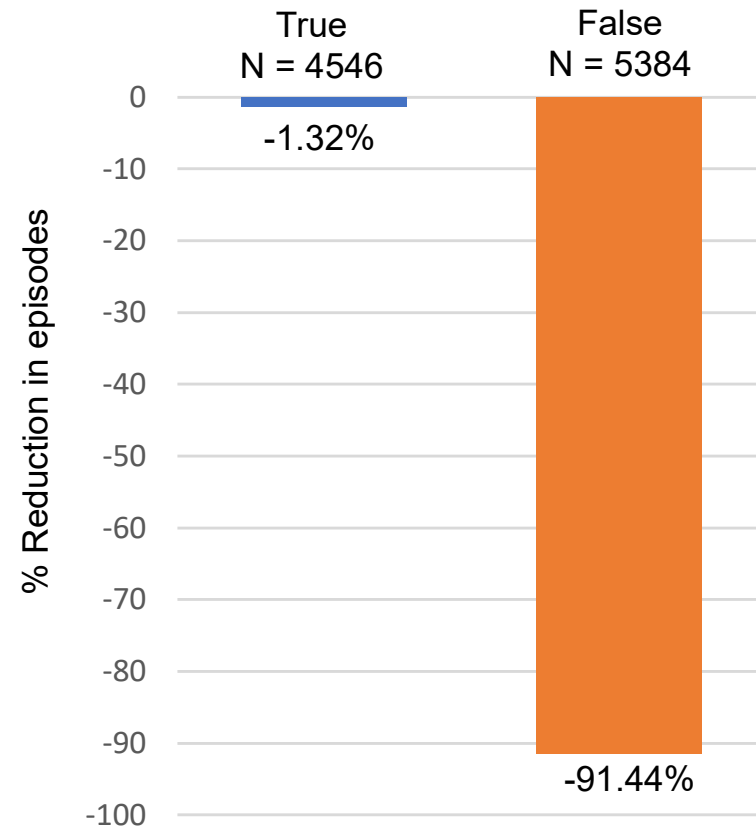
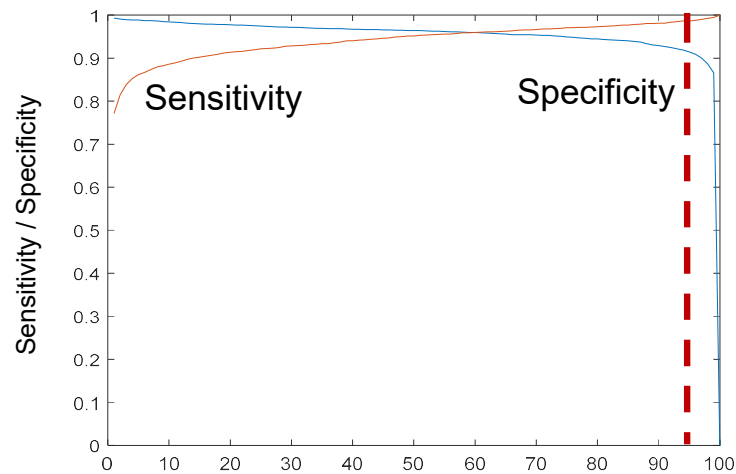
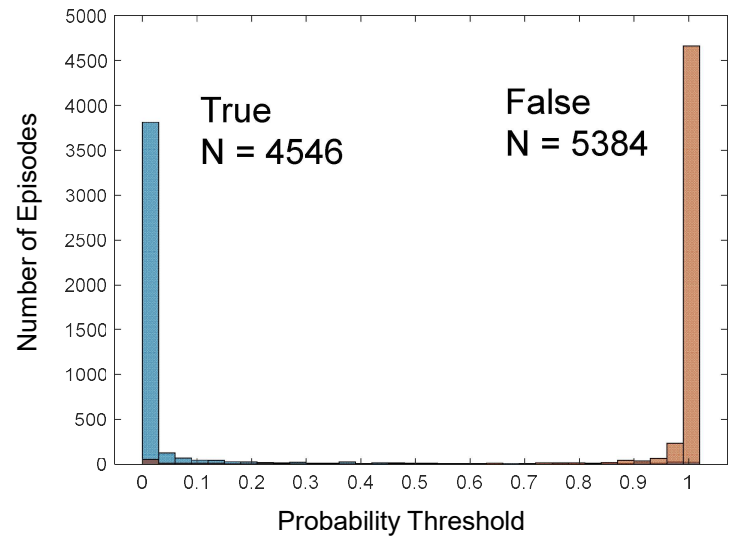
[Learn more](#)



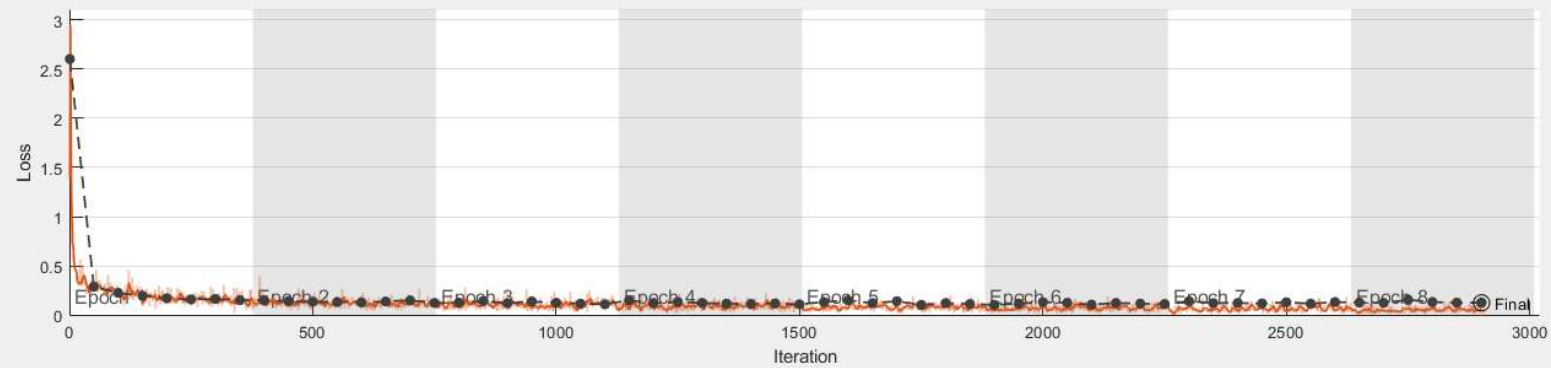
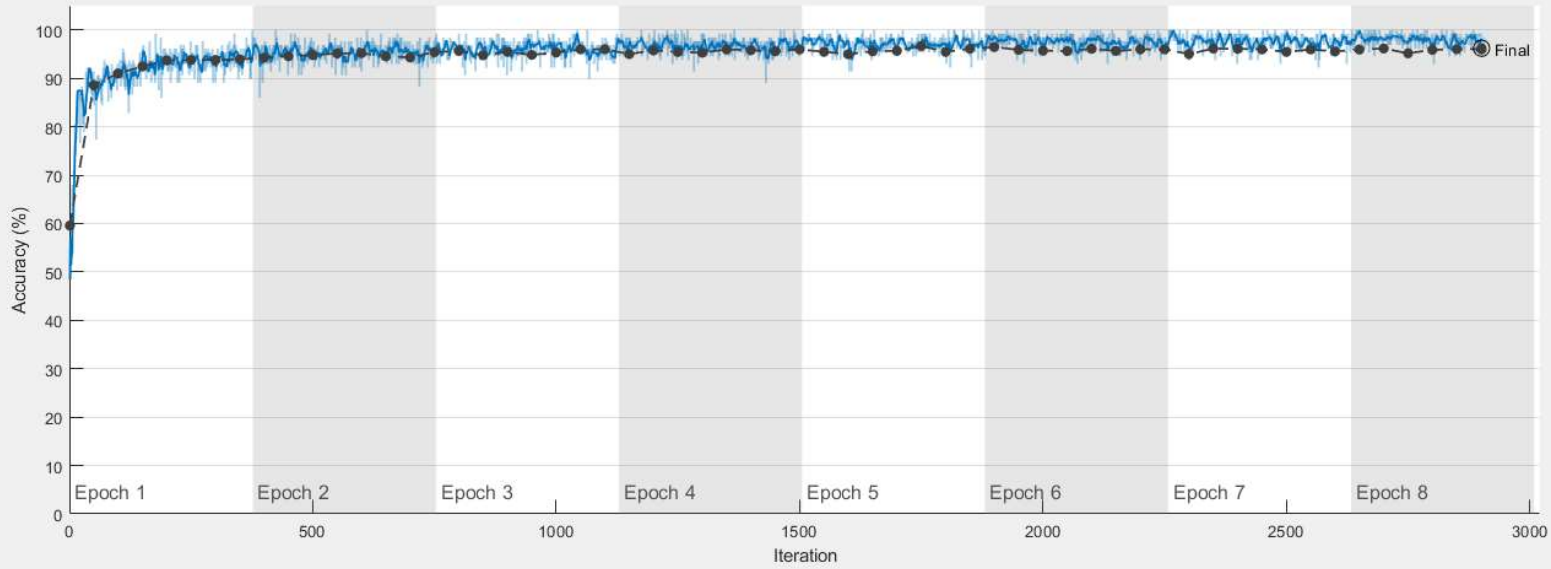
Custom CNN validation – Independent Episodes



Custom CNN Test Set – Independent patients



Resnet18 training



Results

Validation accuracy: 96.20%
Training finished: Met validation criterion

Training Time

Start time: 20-Sep-2021 00:34:20
Elapsed time: 53 min 56 sec

Training Cycle

Epoch: 8 of 100
Iteration: 2901 of 37600
Iterations per epoch: 376
Maximum iterations: 37600

Validation

Frequency: 50 iterations

Other Information

Hardware resource: Multiple GPUs
Learning rate schedule: Constant
Learning rate: 0.0005

[Learn more](#)

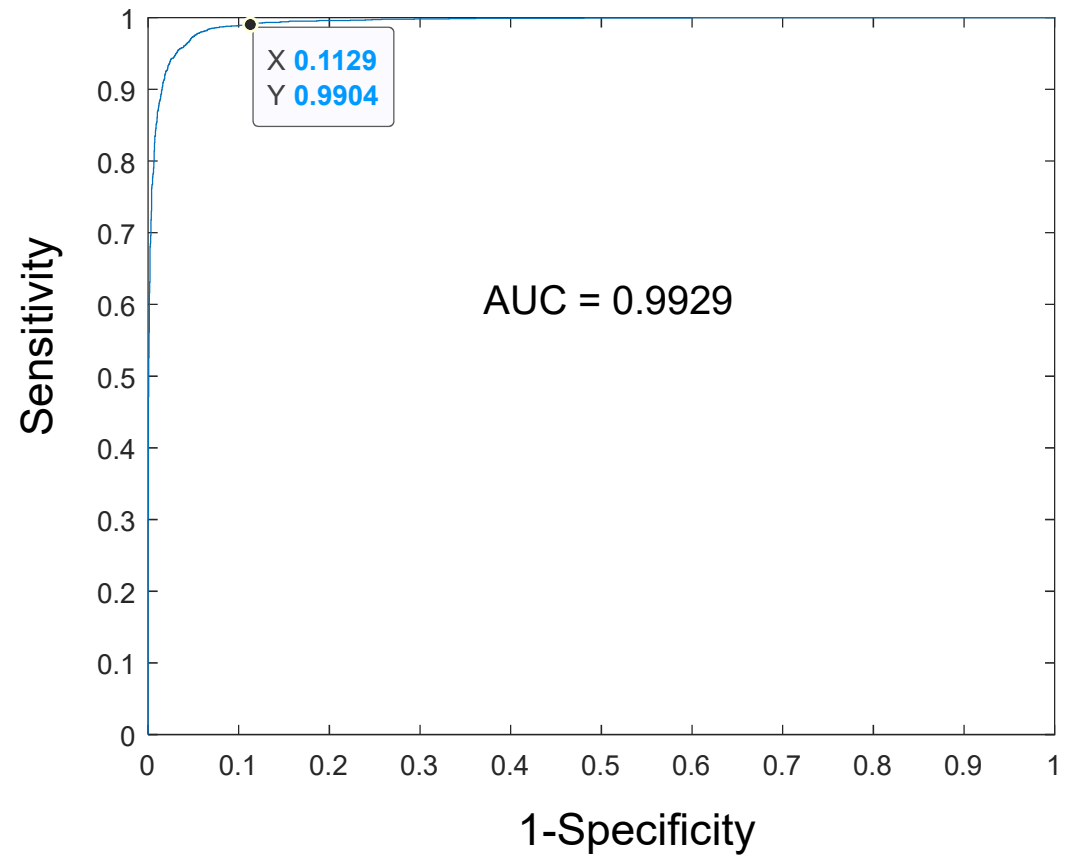
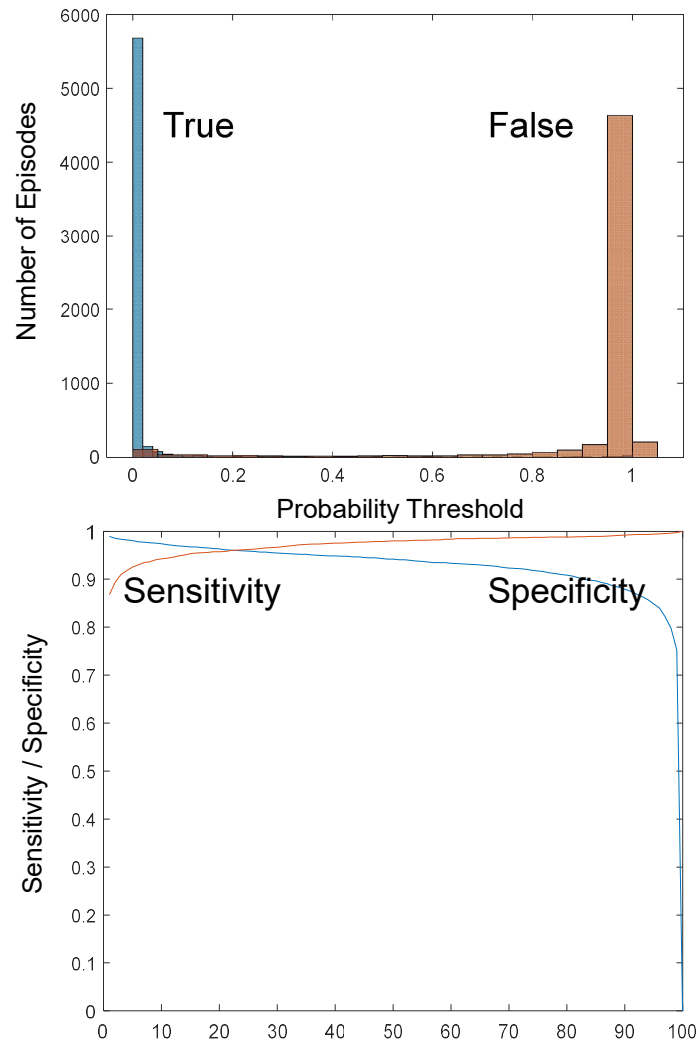
Accuracy

— Training (smoothed)
— Training
- - Validation

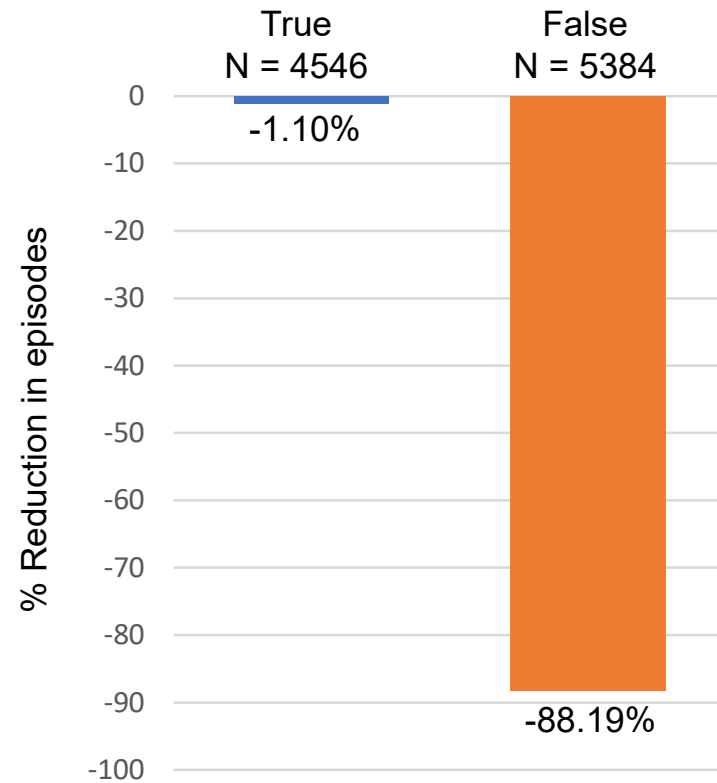
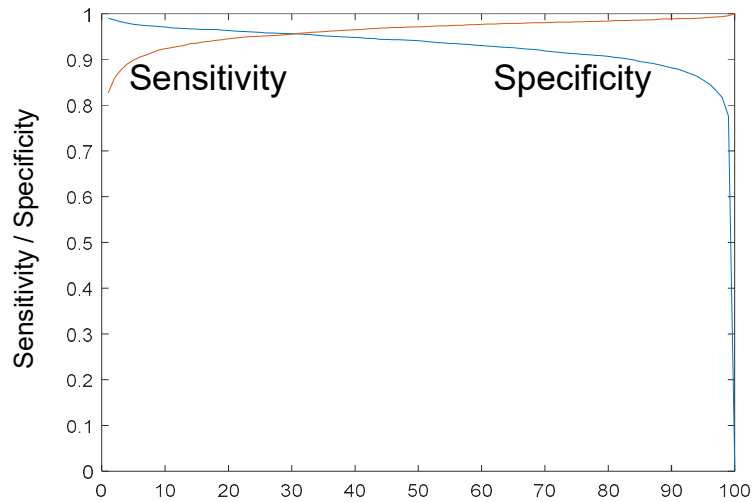
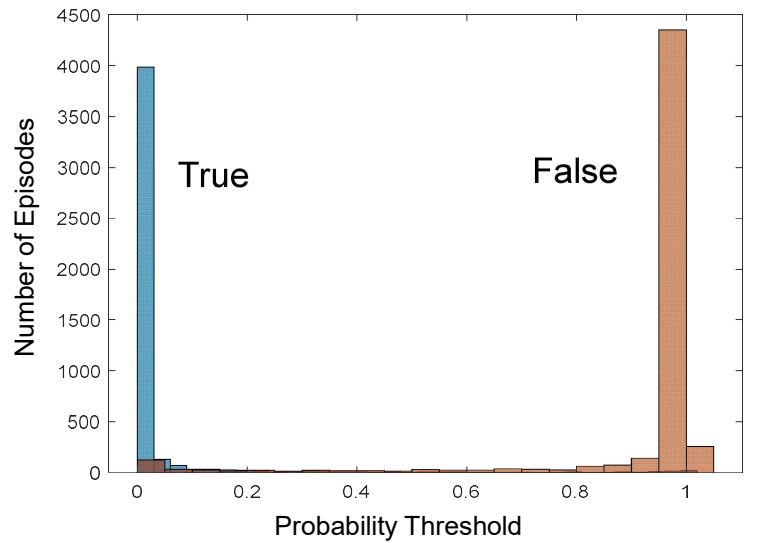
Loss

— Training (smoothed)
— Training
- - Validation

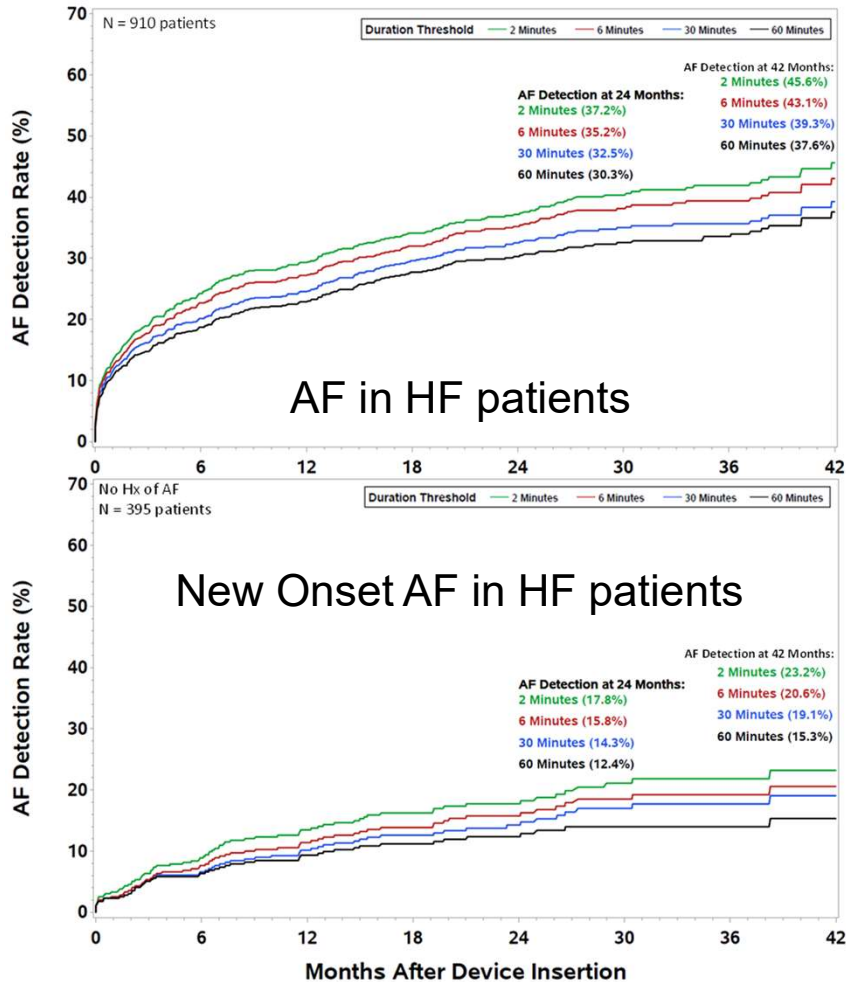
Resnet18 validation – Independent Episodes



Resnet18 Test Set – Independent Patients



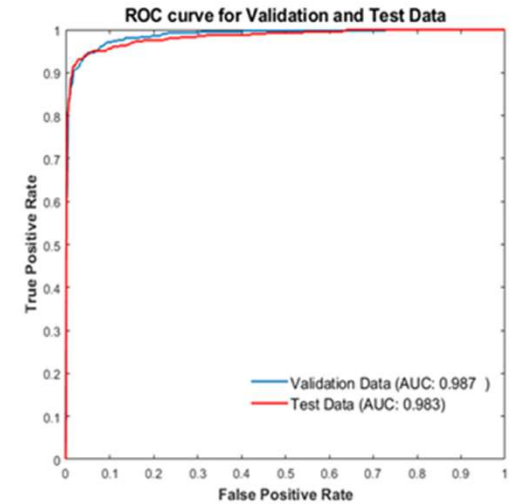
Applications of the AF detector using CNN on Ensemble of features



Subclassifying Atrial Tachyarrhythmia

Validation Dataset Episodes		True AFL/AT		
		YES	NO	
Detected AFL/AT	YES	400	305	56.7%
	NO	13	2949	99.6%
		96.9%	90.6%	

Test Dataset Episodes		True AFL/AT		
		YES	NO	
Detected AFL/AT	YES	390	369	51.4%
	NO	16	2695	99.4%
		96.1%	88.0%	



Majumder S et al. Presented at ESC 2024.

Shahzeb Khan M et al. Presented at ESC 2024.

AF Detection using CNN on Ensemble of features

SUMMARY

- ECG based AI has been shown to reduce false positive AF episodes while maintaining sensitivity
- Specific aspects of ECG, RR intervals and other information are useful in adjudicating AF episodes
- Features derived to encode information useful in adjudicating AF episodes were evaluated as potential input to a convolution neural network (CNN)
 - Lorenz plot; P-wave enhanced ECG Segments; Auto correlation of long intervals, RR interval histogram, AF burden history, episode duration
- Over 90% reduction in false positive AF detection could be obtained with around 1% reduction in false positives
- There is still a residual generalization error of $< 2\%$

MATLAB EXPO



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