

AI-ENHANCED ECG INTERPRETATION



Streamlining *human* capability

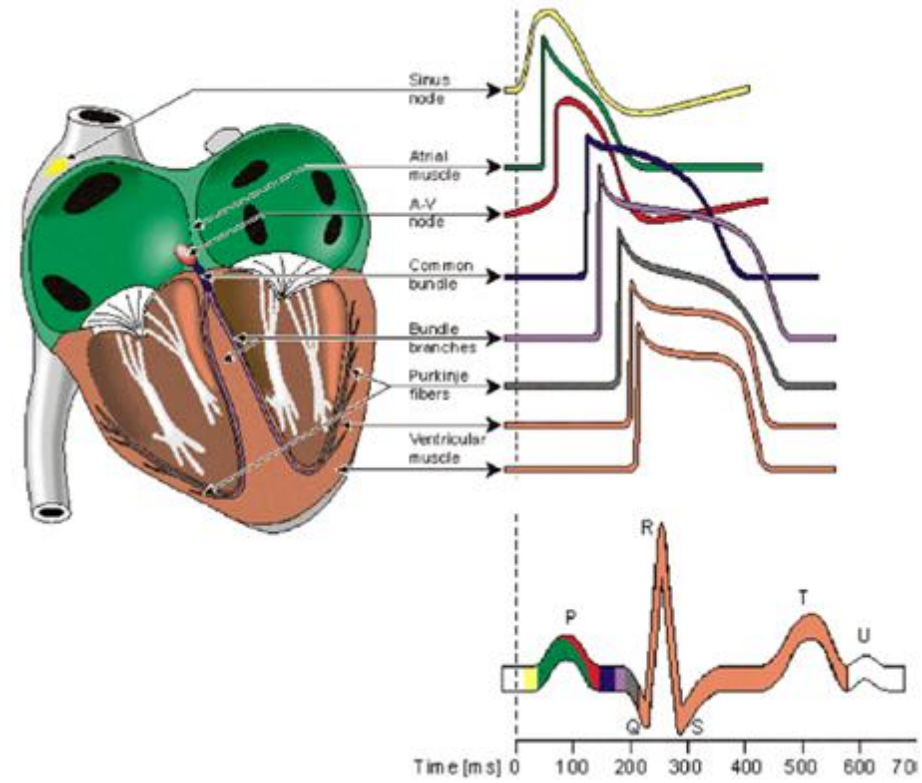
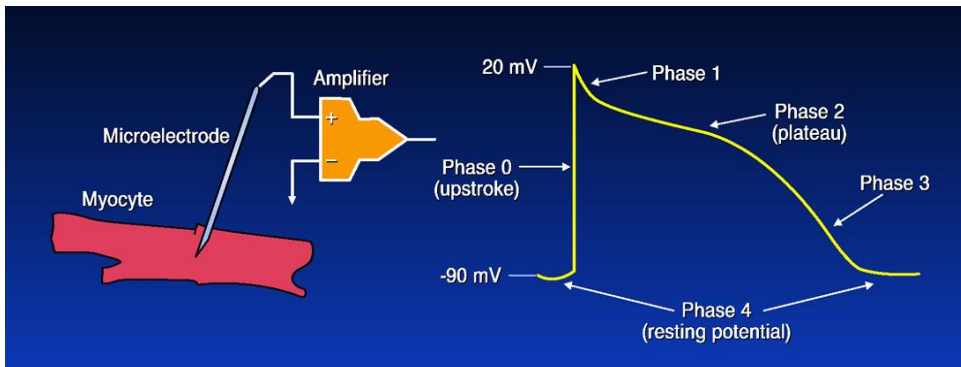
- First pass interpretation
- Triage work flow
- Scalability

Beyond *human* capability

- Seeing what a clinician cannot
- 'Value-added' ECG read
- Moving beyond normal/abnormal

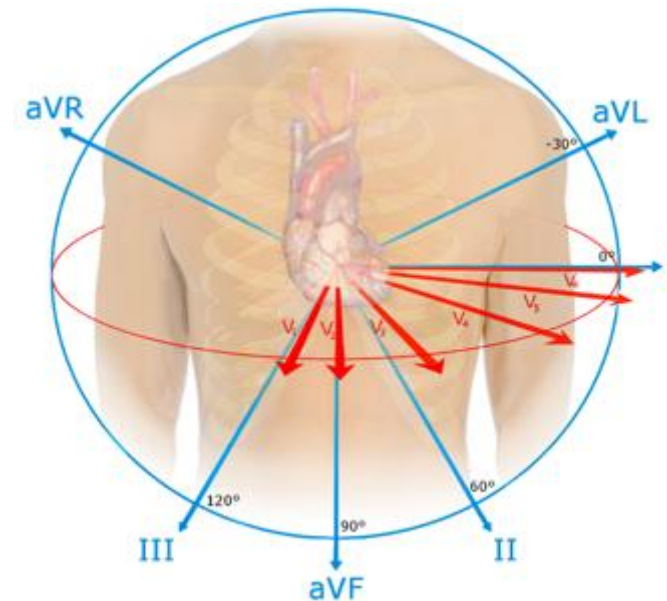
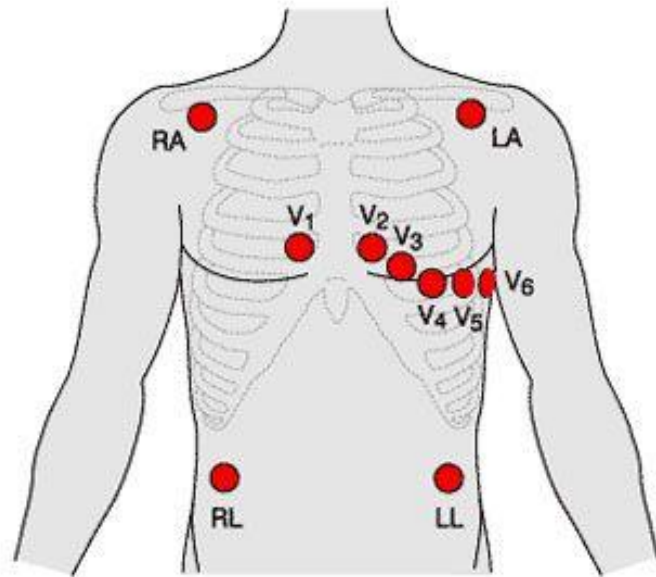
ECG Introduction

- Electrocardiography (ECG) is the recording of the heart electrical activity.



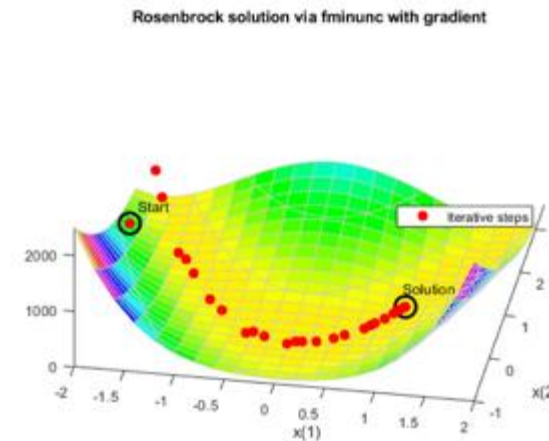
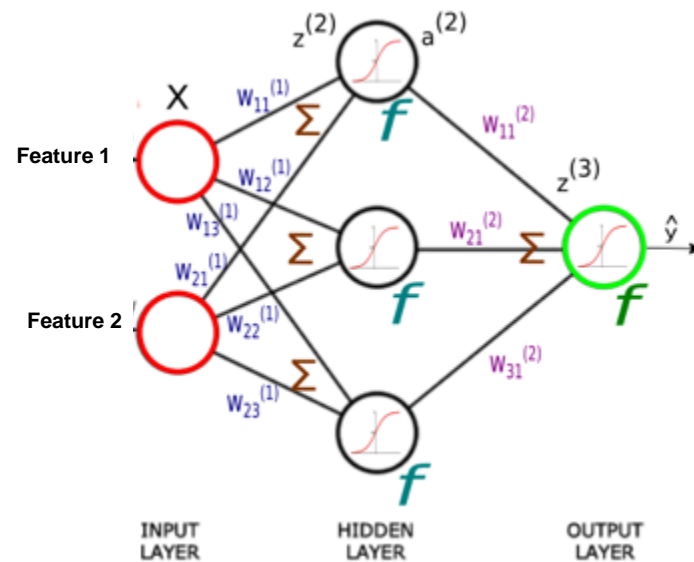
ECG Introduction

- Each ECG lead presents the projection of the electrical field in different direction
- In typical 12 lead ECG we get information in two planes.

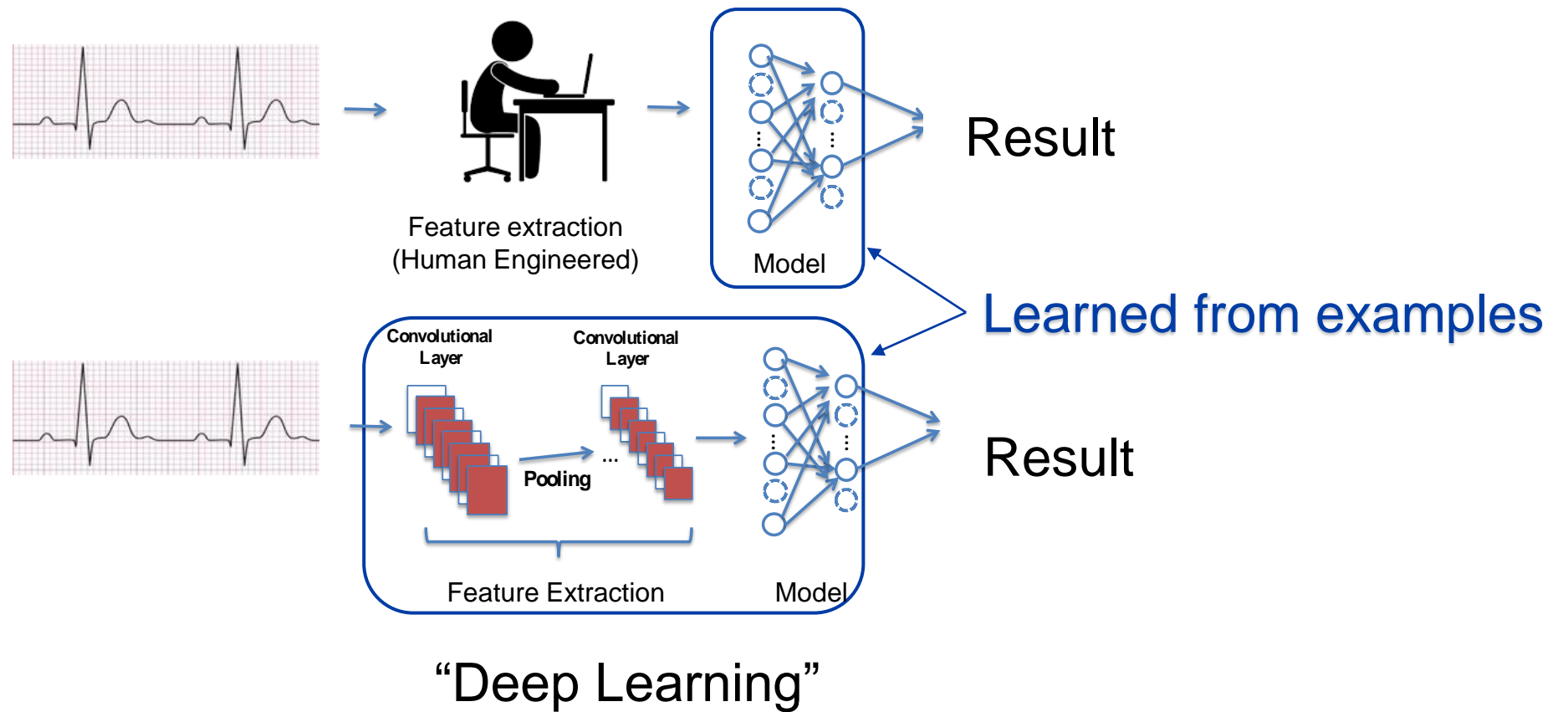


Can We Use ECG for Screening?

- A clinician cannot assess EF from an ECG
- Can an AI model?




Machine Learning vs Deep Learning



Letter | Published: 07 January 2019

Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram

Zachi I. Attia, Suraj Kapa, Francisco Lopez-Jimenez, Paul M. McKie, Dorothy J. Ladewig, Gaurav Satam, Patricia A. Pellikka, Maurice Enriquez-Sarano, Peter A. Noseworthy, Thomas M. Munger, Samuel J. Asirvatham, Christopher G. Scott, Rickey E. Carter & Paul A. Friedman 

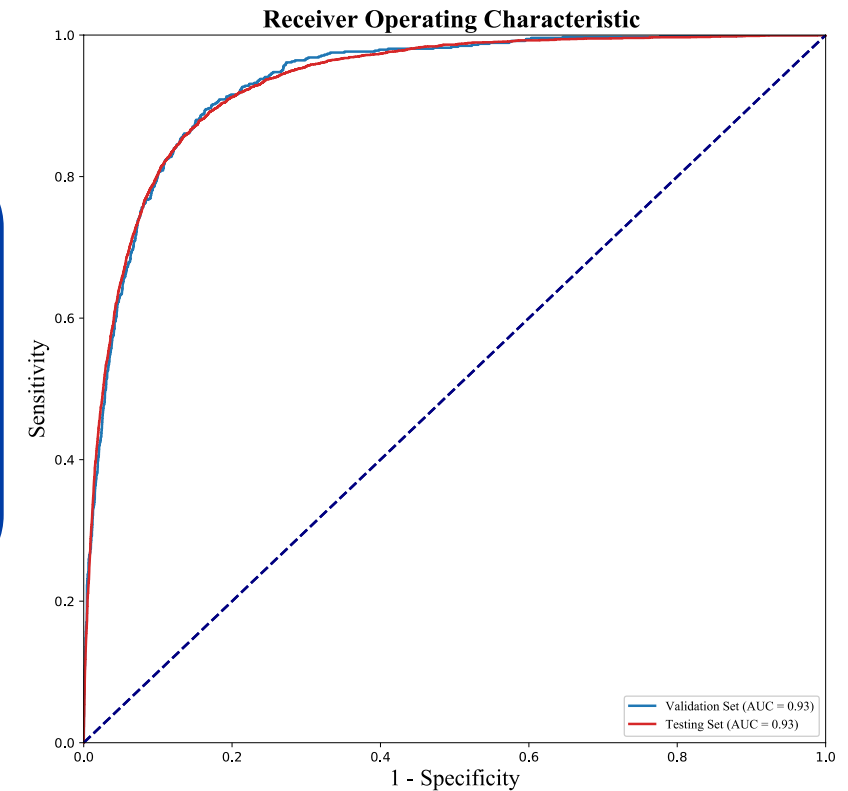
Nature Medicine **25**, 70–74(2019) | [Cite this article](#)

Results

Area Under ROC Curve (AUC) was selected to evaluate the model

Similar ROC for validation and hold out data

- **AUC of EF network = 0.93** (perfect test = 1.0)
 - **Sensitivity = Specificity = 86%**
- Compares favorably with other medical tests:
 - Mamography for breast cancer = 0.85
 - Cervical cytology (Pap smear) = 0.70
 - PSA (prostate cancer) = 0.92



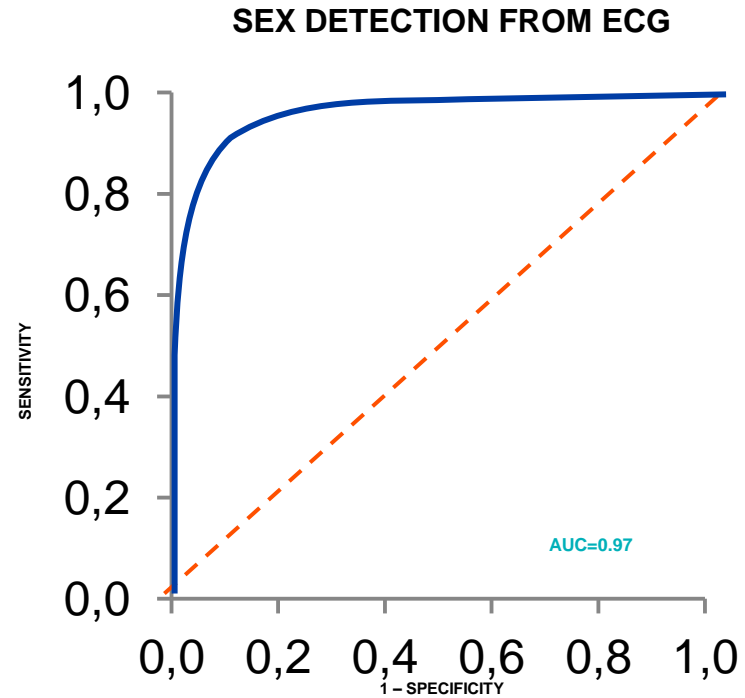
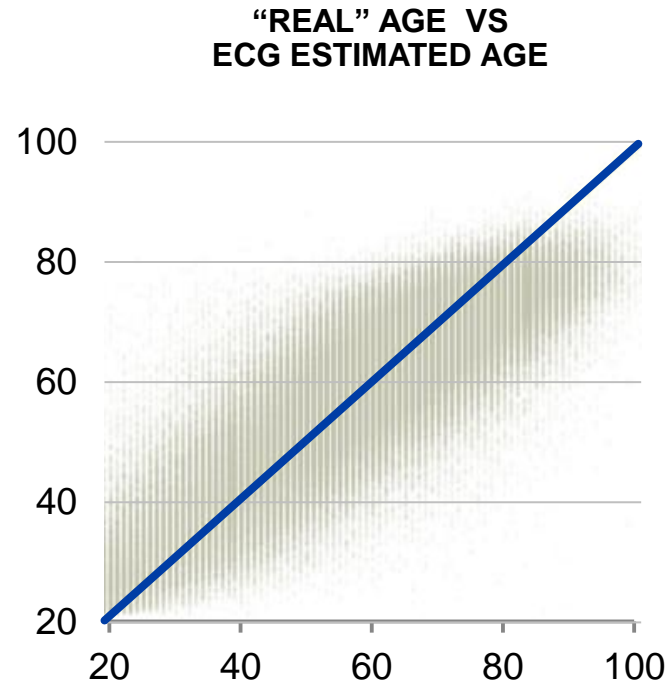
Improving the EF model

Both age and sex affect systolic function, will adding them as inputs help the model ?

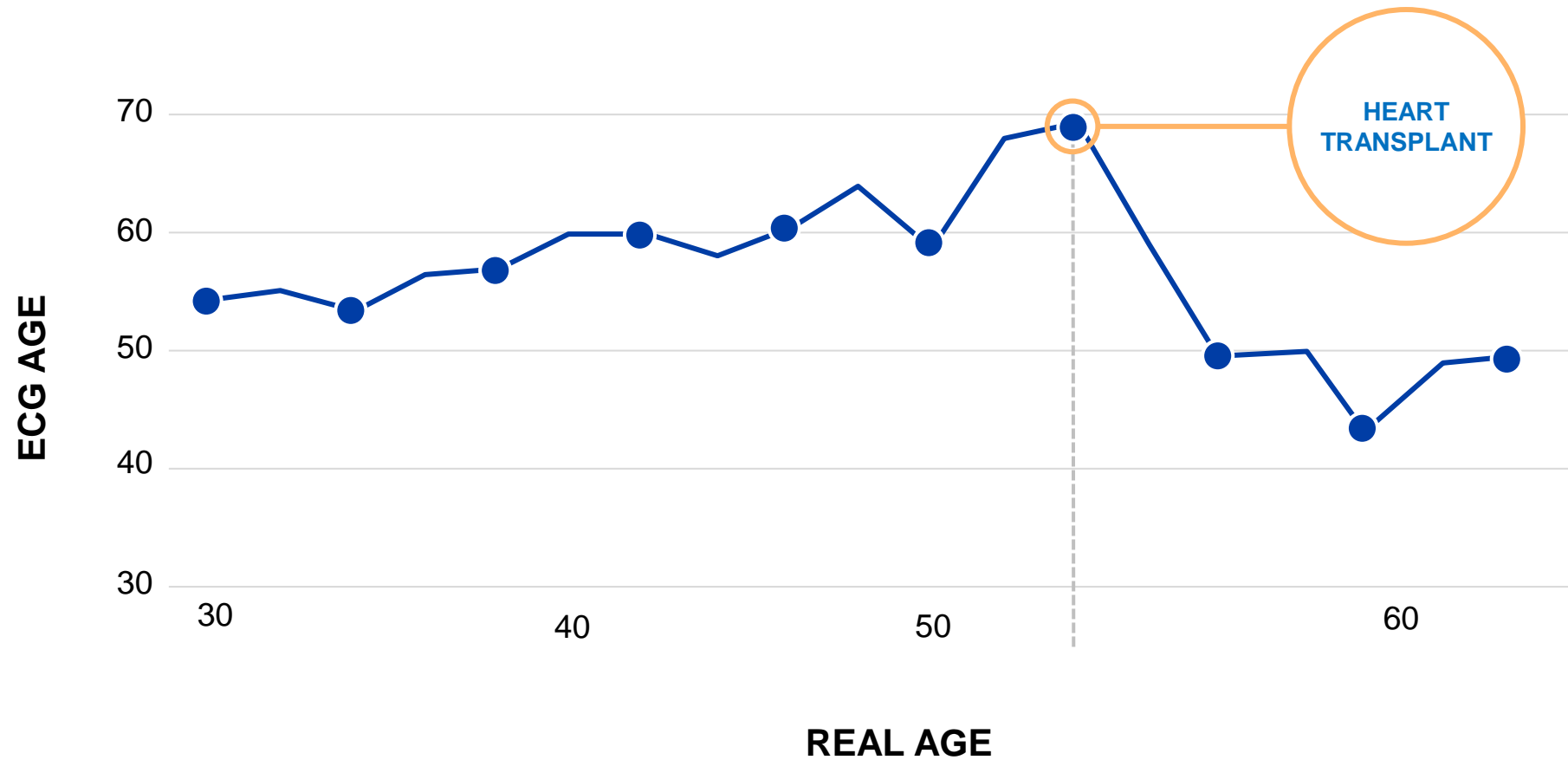
NO

Maybe it can guess it?

Age and Sex from ECG



Patient #1 : Progression of ECG Age in a Patient with Multiple ECGs





Accelerated Aging in *LMNA* Mutations Detected by Artificial Intelligence ECG—Derived Age

Shahar Shelly, MD; Francisco Lopez-Jimenez, MD; Audry Chacin-Suarez, MD;
Michal Cohen-Shelly, BSc; Jose R. Medina-Inojosa, MD; Suraj Kapa, MD;
Zachi Attia, MD; Anwar A. Chahal, MD; Virend K. Somers, MD;
Paul A. Friedman, MD; and Margherita Milone, MD, PhD

Abstract

Objective: To demonstrate early aging in patients with lamin A/C (*LMNA*) gene mutations after hypothesizing that they have a biological age older than chronological age, as such a finding impacts care.

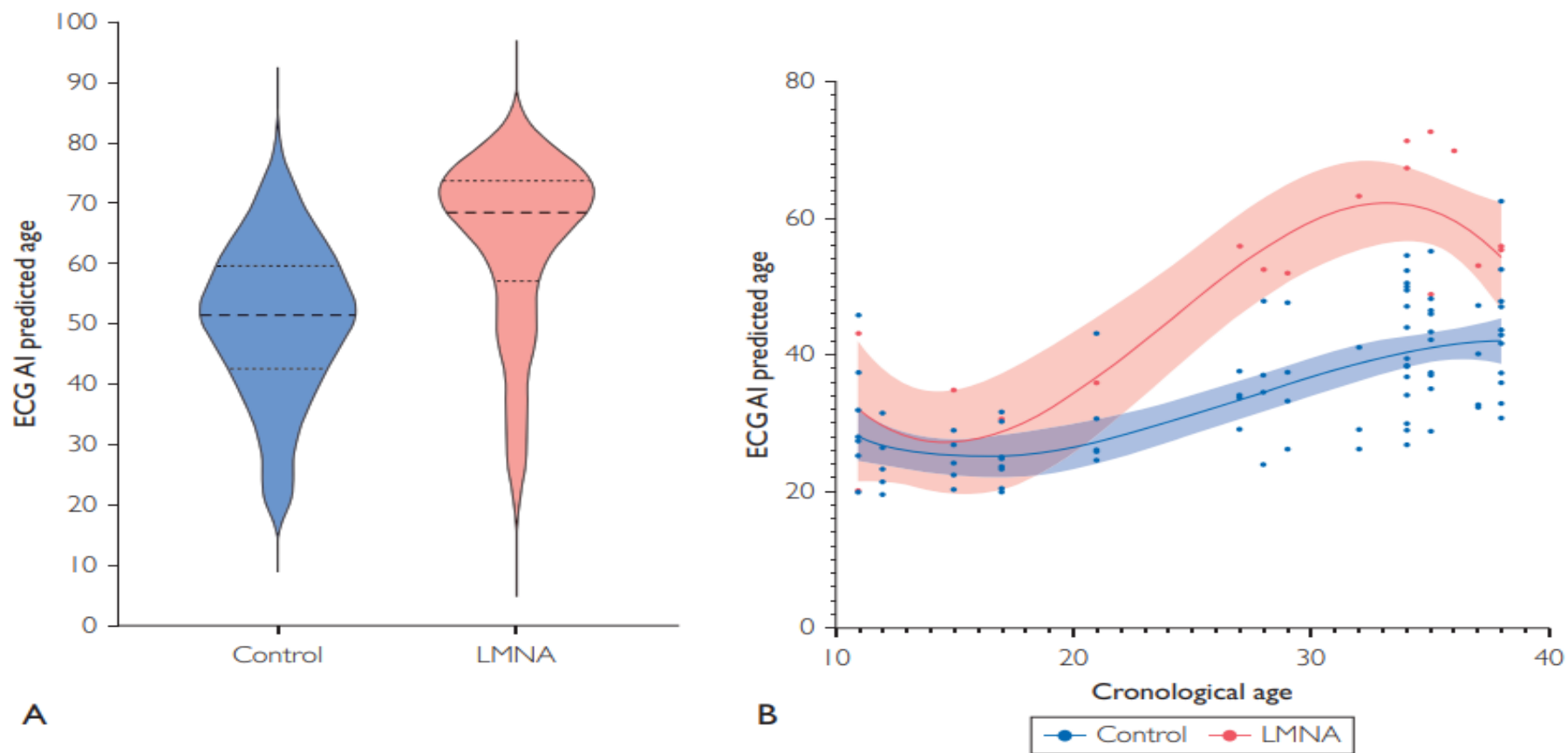
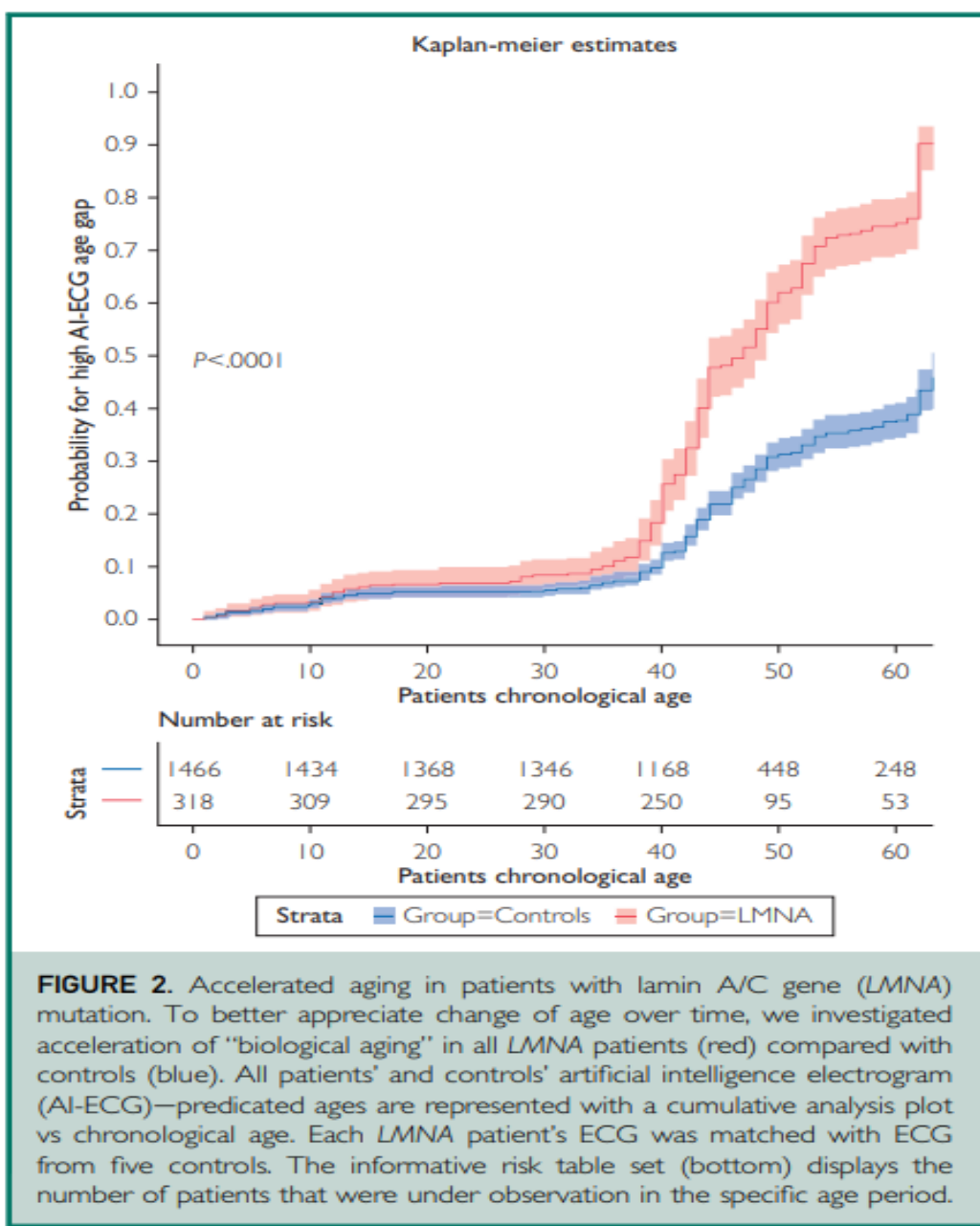


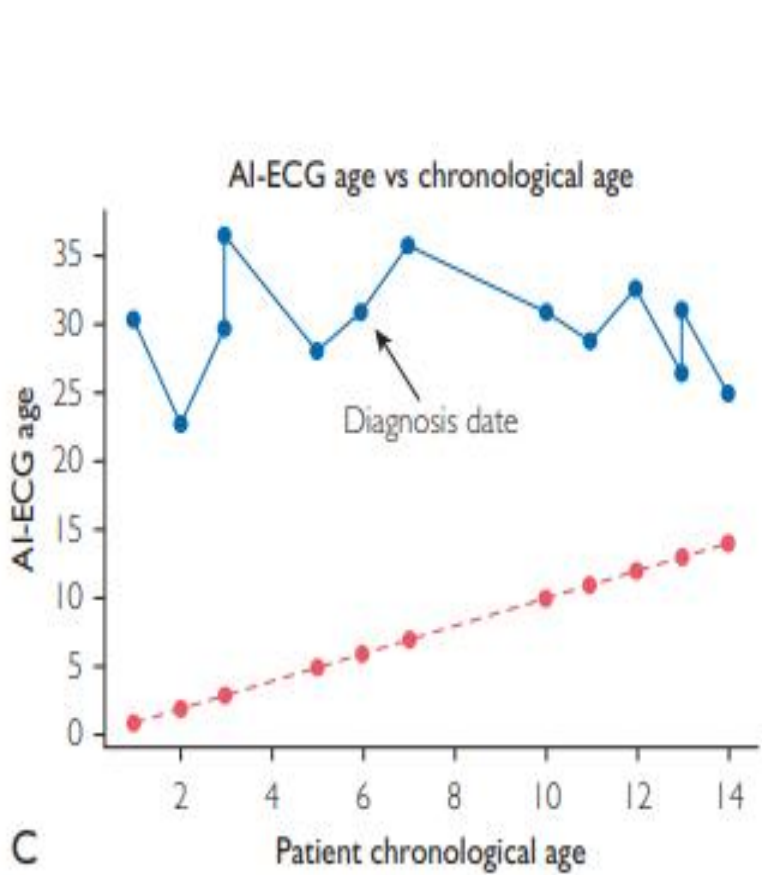
FIGURE 1. Patients with *LMNA* mutation have higher predicted age compared with controls. Comparing our cohort predicted age using whisker plots (A) comparing *LMNA* patients (red) predicted biological vs controls (blue). We show significant difference ($P < .001$) in age predicted by our neural network between the two groups. B, Linear regression analysis comparing *LMNA* patients (upper line, red dots) vs controls (lower line, blue dots), plotting predicted age vs chronological age. We show higher predicted age compared with chronological age in *LMNA* patients compared with controls. AI, artificial intelligence; ECG, electrocardiogram; *LMNA*, lamin A/C gene.

Accelerated Biological Aging in Patients with Lamin A/C Gene Mutations

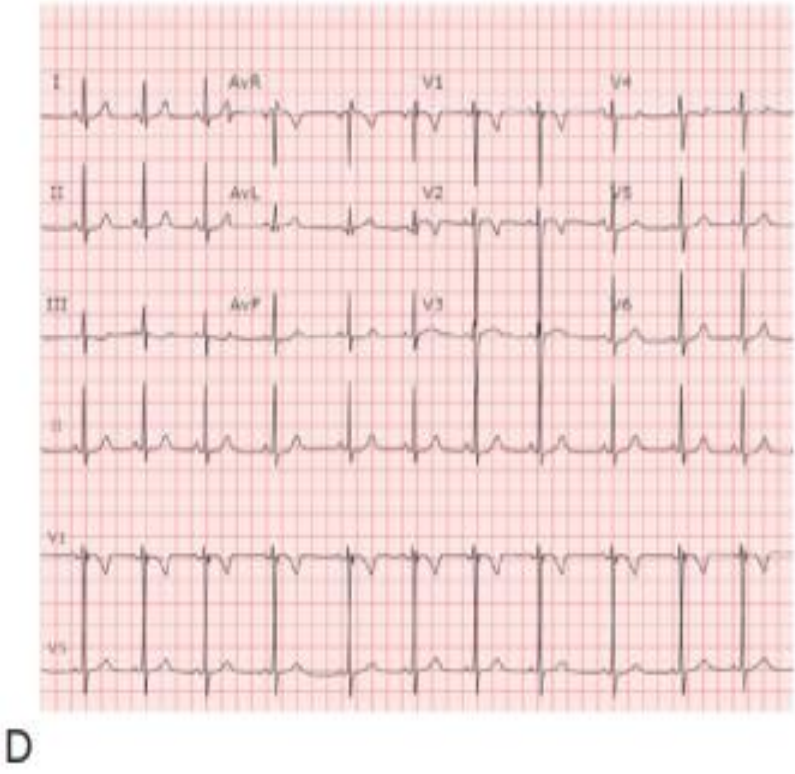
Shelly et al, *Mayo Clin Proc* 2023



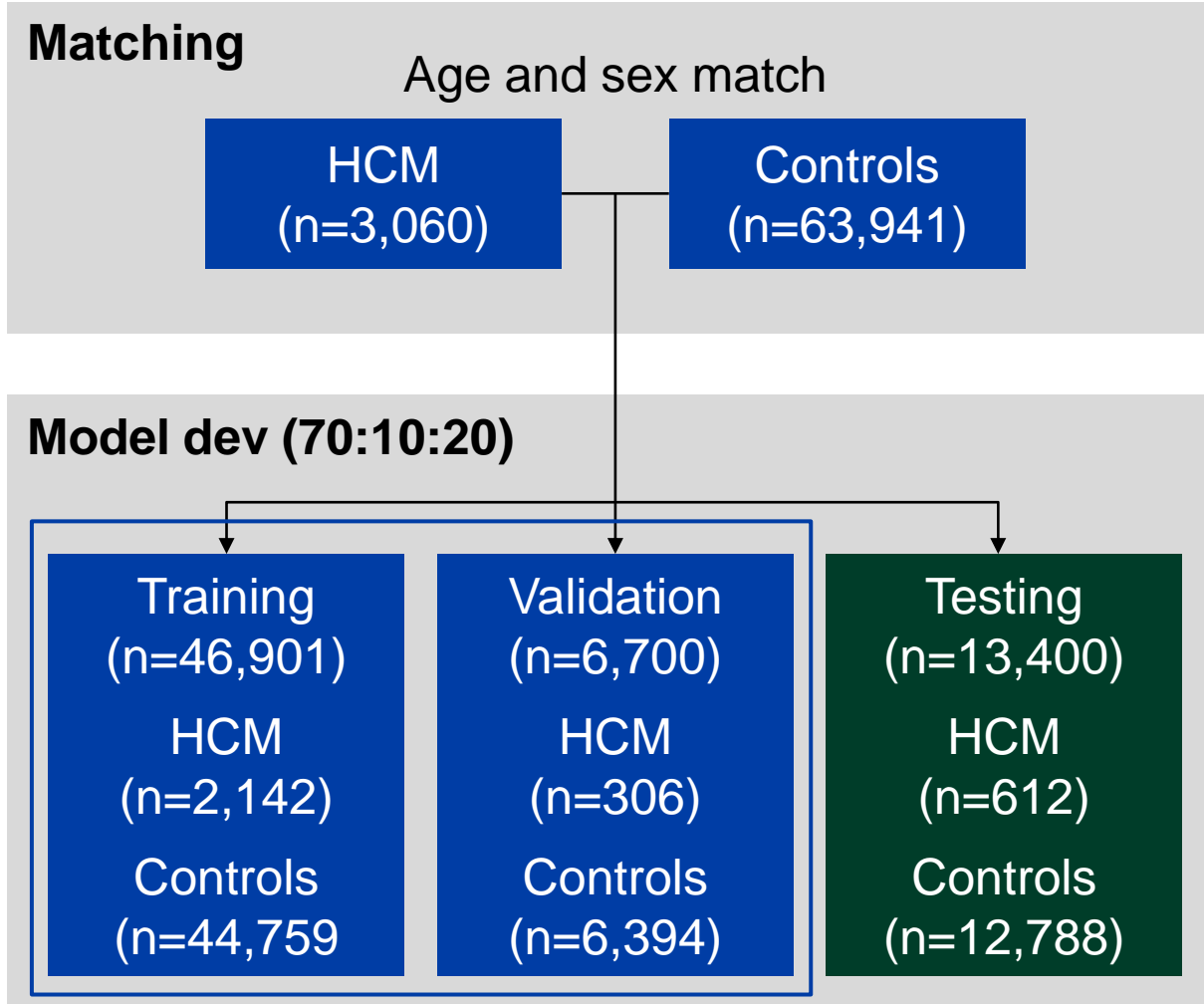
Patient #2 - Serial ECGs in a patient with lamin A/C mutation



Normal sinus rhythm
Normal ECG

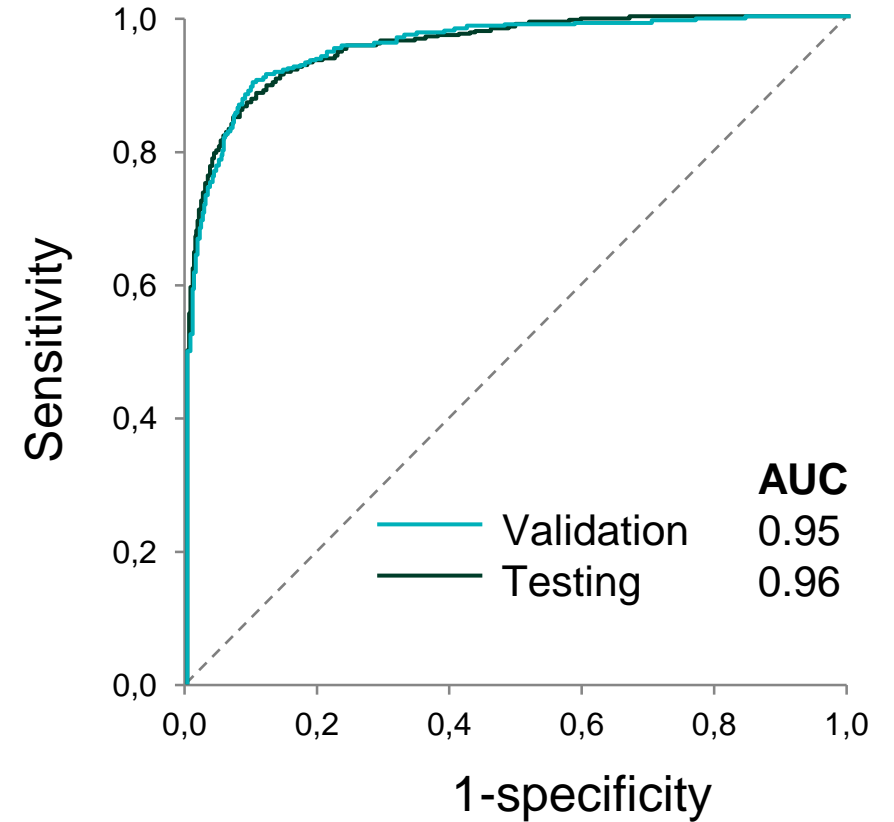
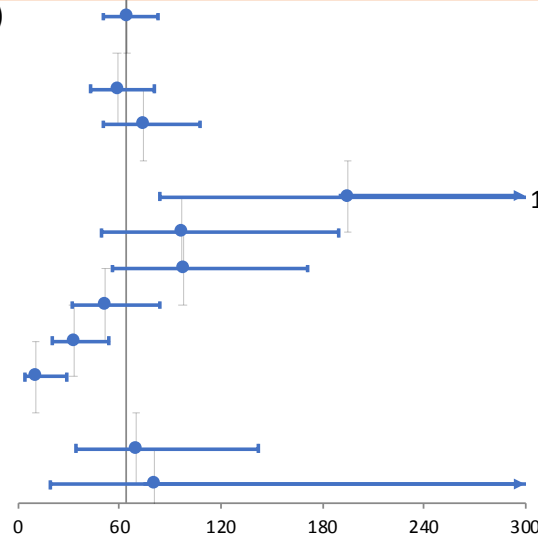


Hypertrophic Cardiomyopathy

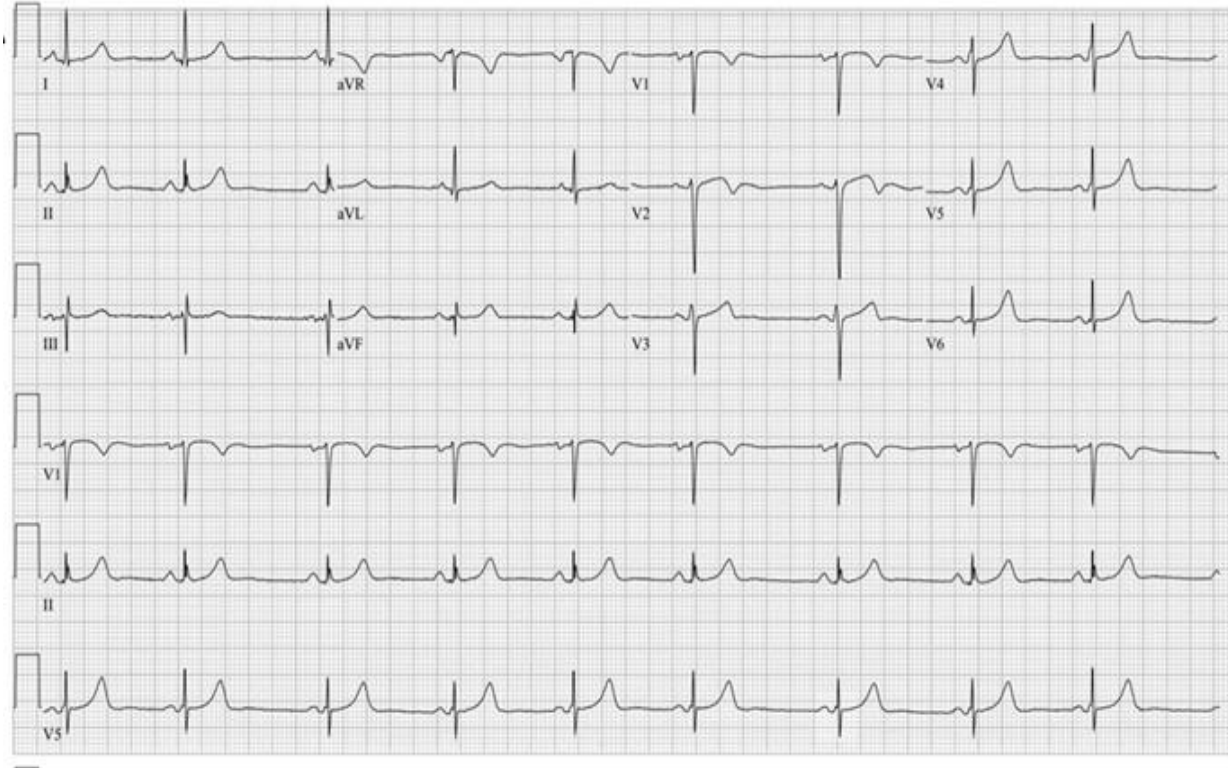


HCM - Results

Group	Sensitivity	Specificity	Odds Ratio	OR (95% CI)
Overall	87 (534/612)	90 (11562/12788)		64.6 (50.5-82.5)
Sex				
Male	87 (301/346)	90 (6518/72662)		58.6 (42.5-80.9)
Female	88 (233/266)	91 (5044/5526)		73.9 (50.7-107.7)
Age (yrs)				
<40	95 (108/114)	92 (1636/1787)		195.0 (84.3-451.2)
40-49	90 (92/102)	91 (1546/1693)		96.8 (49.3-189.9)
50-59	90 (125/139)	92 (2627/2868)		97.3 (55.2-171.7)
60-69	84 (112/133)	91 (3130/3452)		51.8 (32.1-83.8)
70-79	80 (83/104)	89 (2151/2412)		32.6 (19.8-53.5)
≥80	70 (14/20)	82 (472/576)		10.6 (4-28.2)
ECG characteristics				
LVH	97 (263/271)	68 (805/1184)		69.8 (34.2-142.6)
Normal ECG	93 (25/27)	87 (361/417)		80.6 (18.6-349.6)



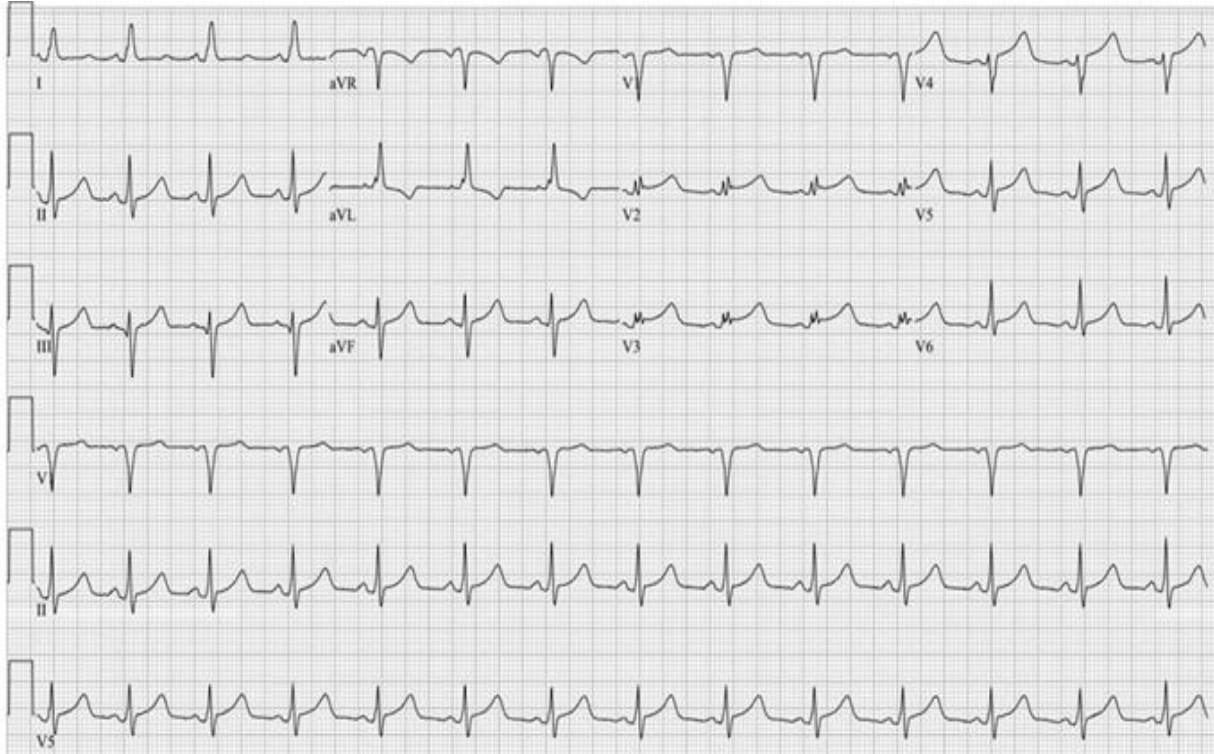
Patient #3: 25-year-old woman with HCM



72.6% probability of HCM!



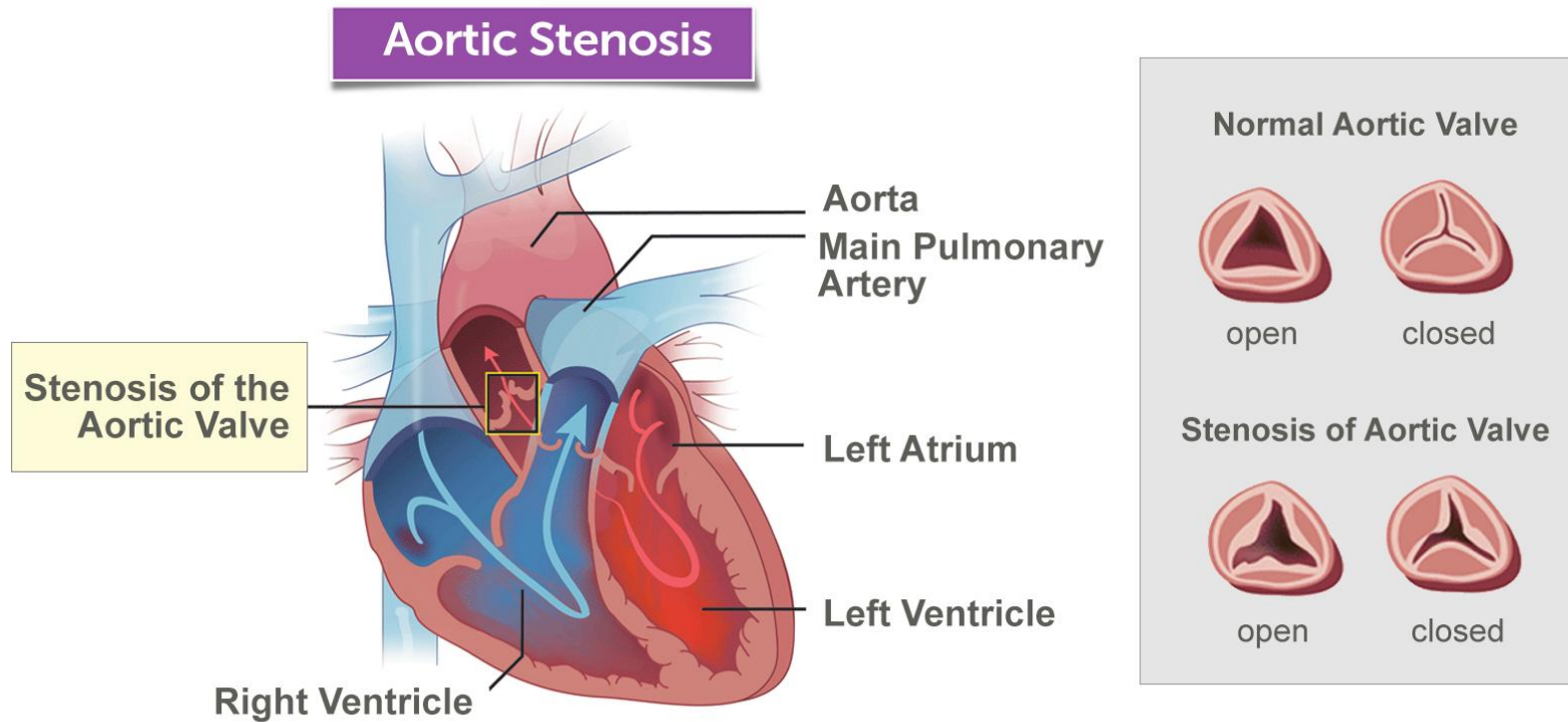
Post-op: Patient undergoes septal myectomy



**ECG becomes more 'abnormal'
but now AI calculates a 2.5%
probability of HCM!**



Detection of Aortic Stenosis



Shelly-Cohen et al. (In review - JACC)

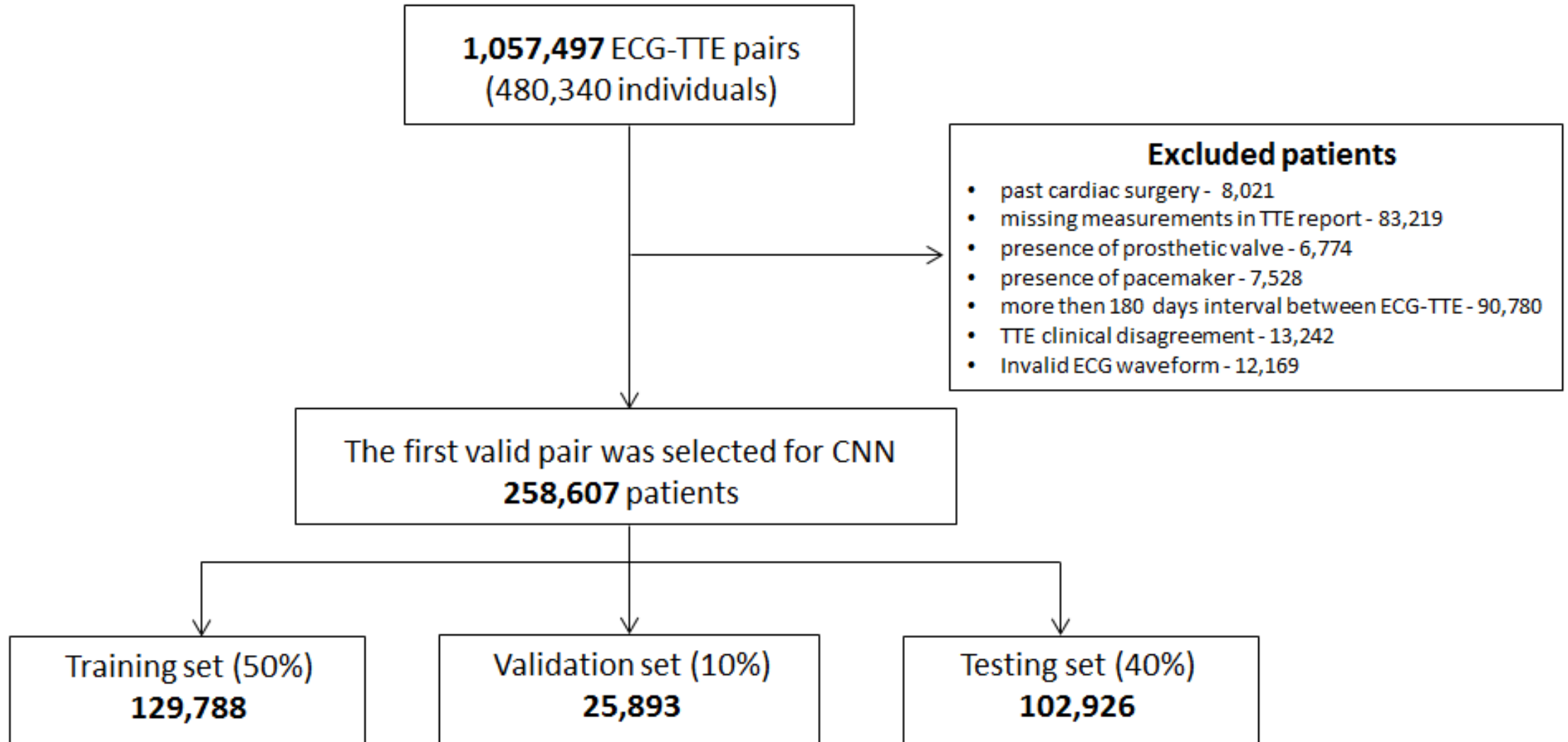
Methods - Labeling Definitions

AS (-)

AS (+)

	AS (-)		AS (+)	
	Normal	Mild	Moderate	Severe
Aortic Valve Area (cm²)	2 or higher	(1.5-2.0)	[1.0 -1.5]	below 1.0
AV Velocity (m/sec)	2.5 or below	(2.5 -3.0)	[3.0 – 4.0)	4 or higher
AV Mean Gradient (mmHg)	10 or below	(10 – 20)	[20 – 40)	40 or higher
Doppler Velocity Index	0.5 or higher	(0.35 – 0.5)	[0.25 -0.35]	Below 0.25

Methods - Cohort Definitions

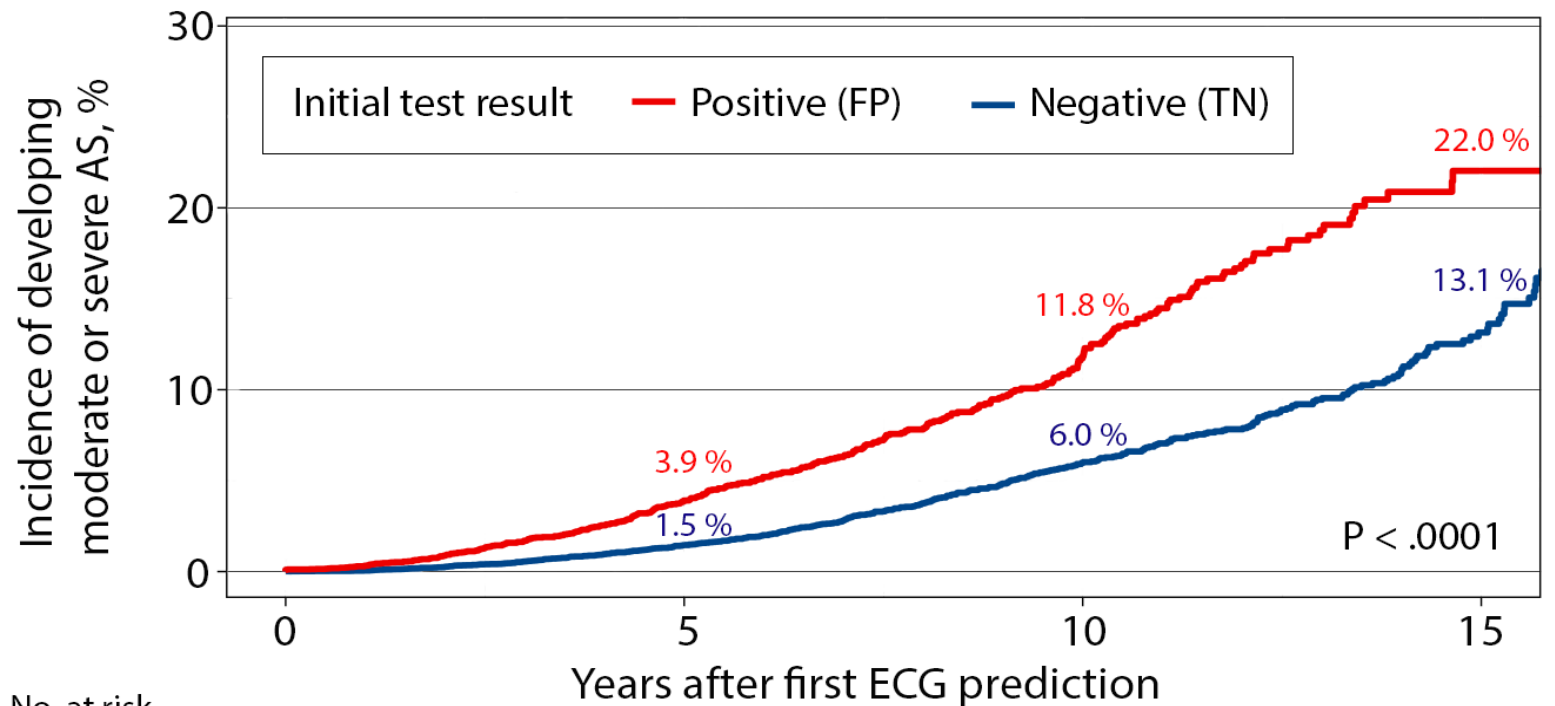
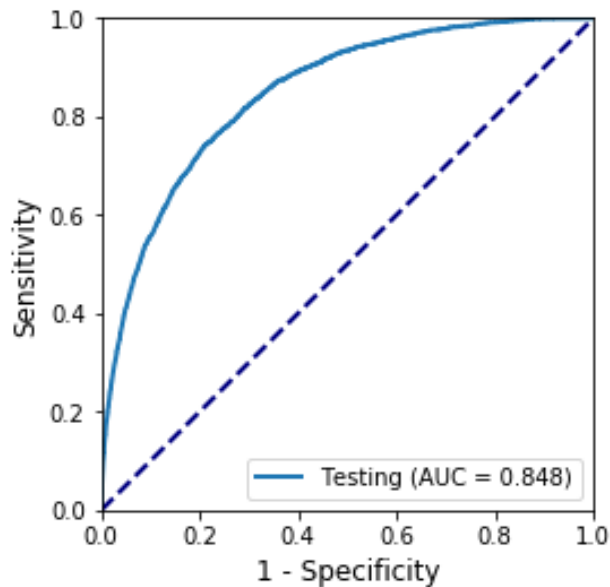


Results

Area Under the Curve : **0.848**

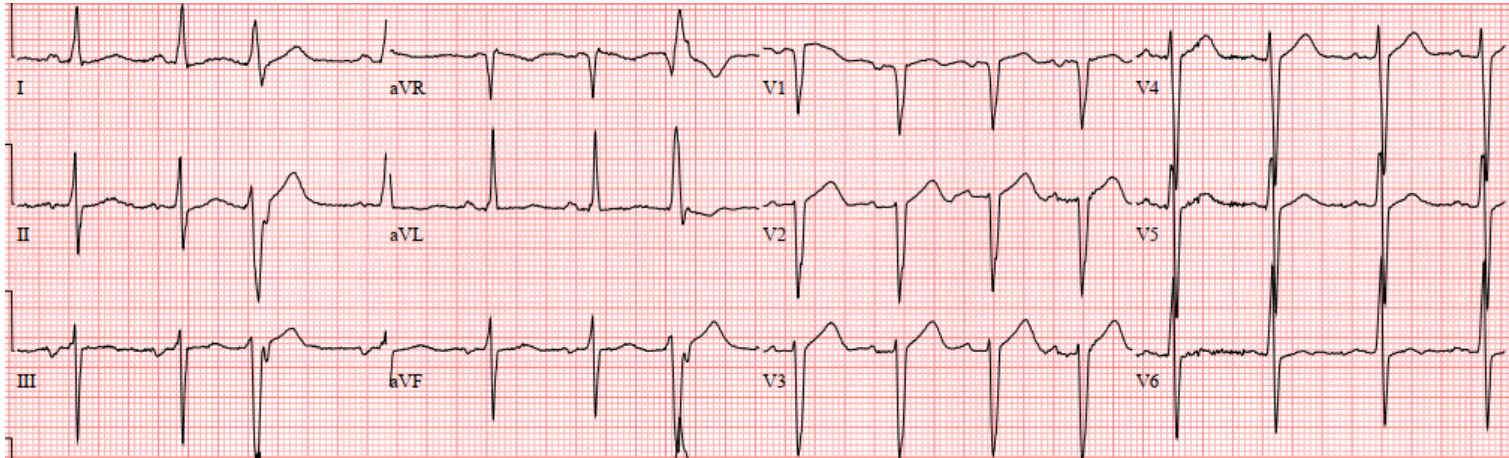
Sensitivity: **78.1%**

Specificity: **74.3%**

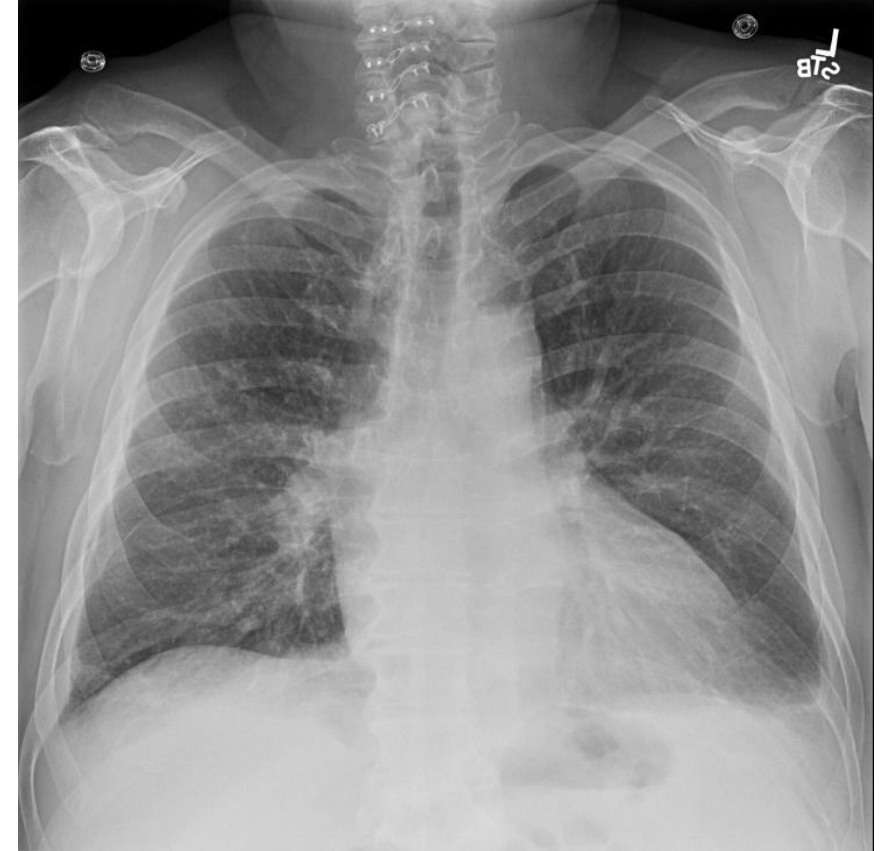


No. at risk	0	5	10	15
Positive (FP)	8474	2880	793	102
Negative (TN)	20718	7969	2654	382

Case #4 :67 year old man presented with increasing dyspnea

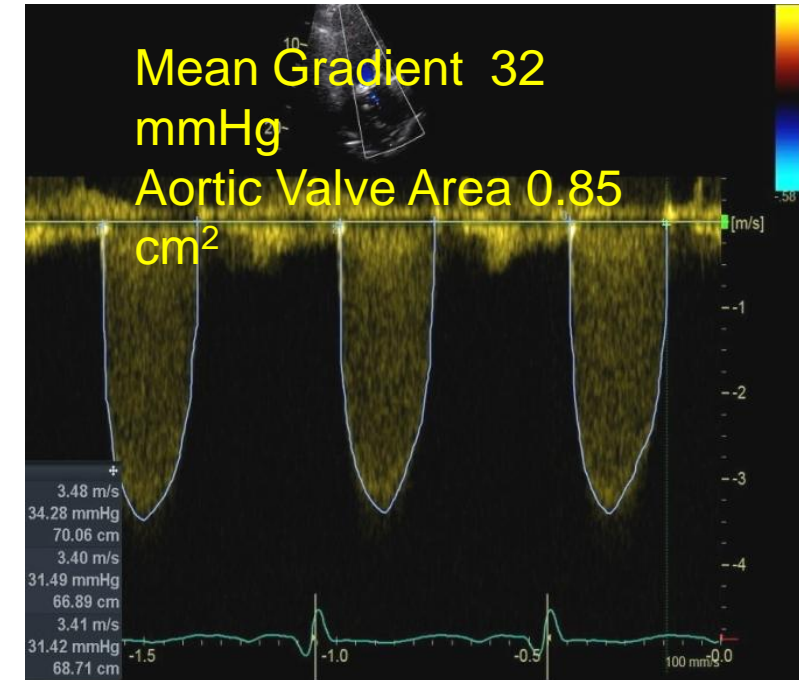
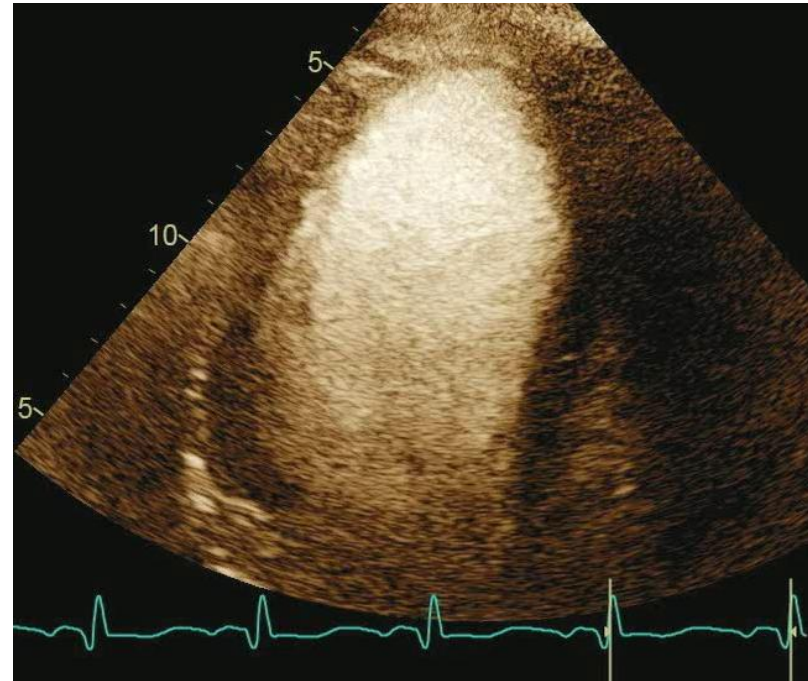
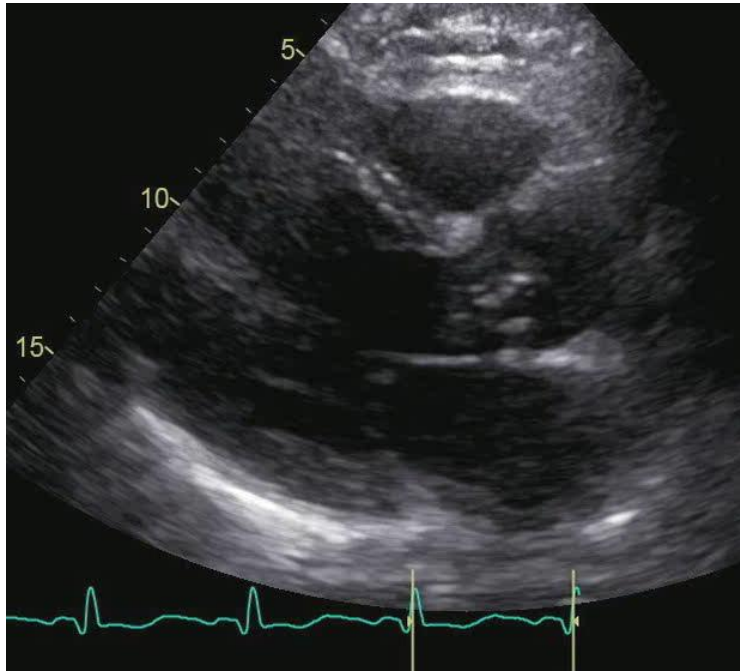


Positive for AS



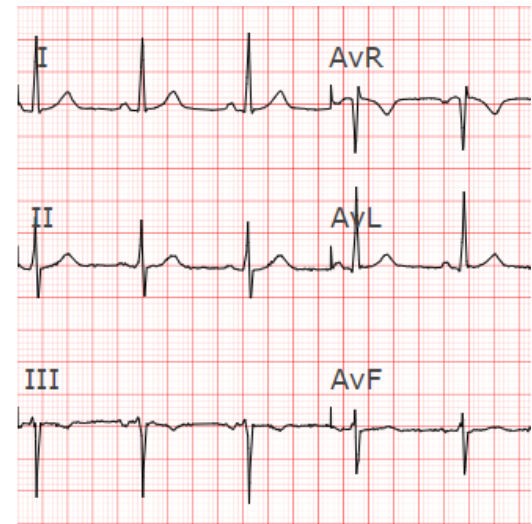
67 year old man presented with heart failure

Severe Aortic Stenosis with reduced LV ejection fraction

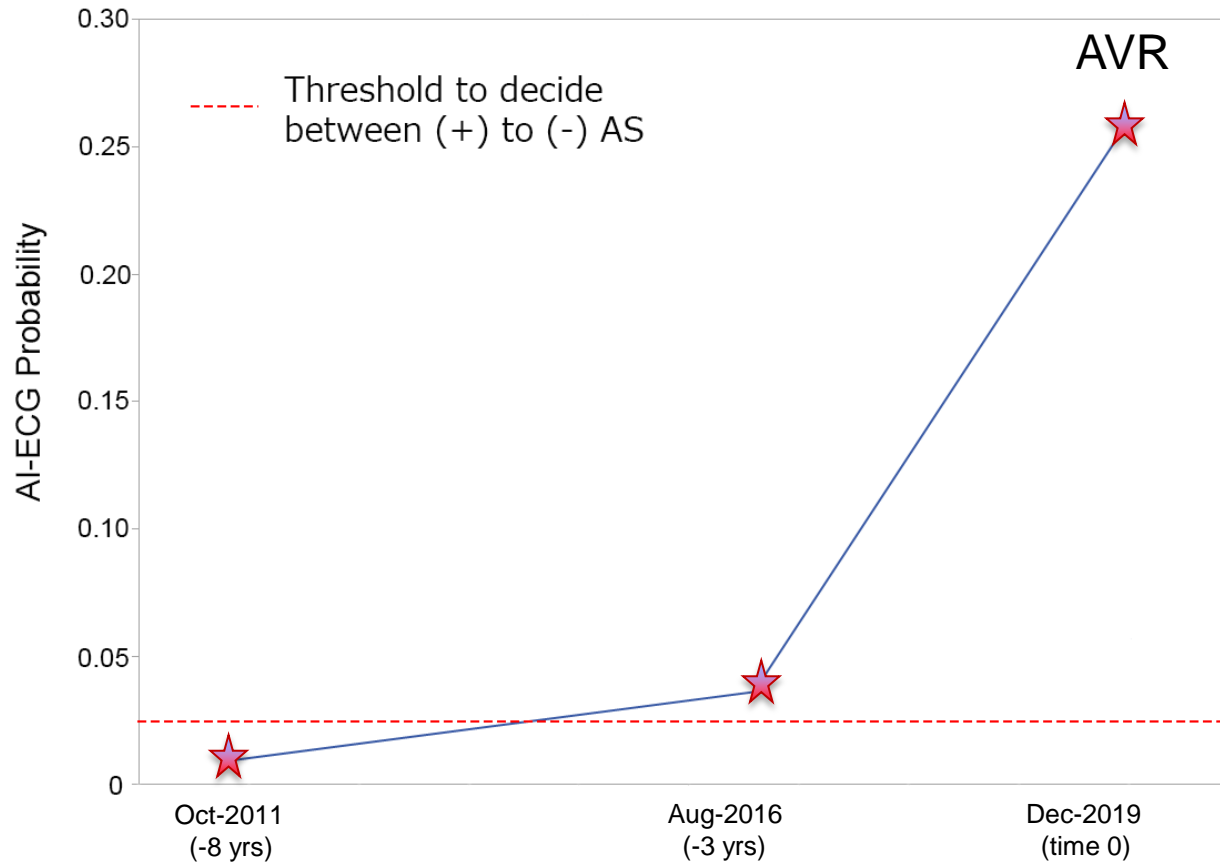


67 year old man with heart failure and severe aortic stenosis ECGs change

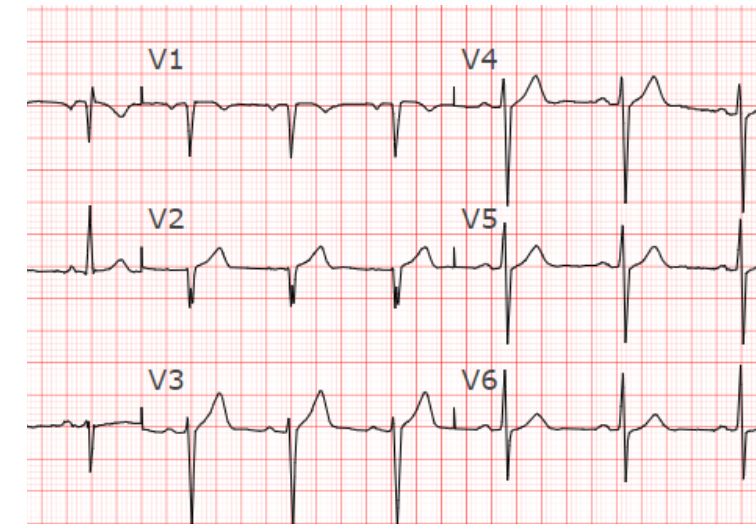
2011 (



AI-EC



3 years earlier)



CG → AS (+)

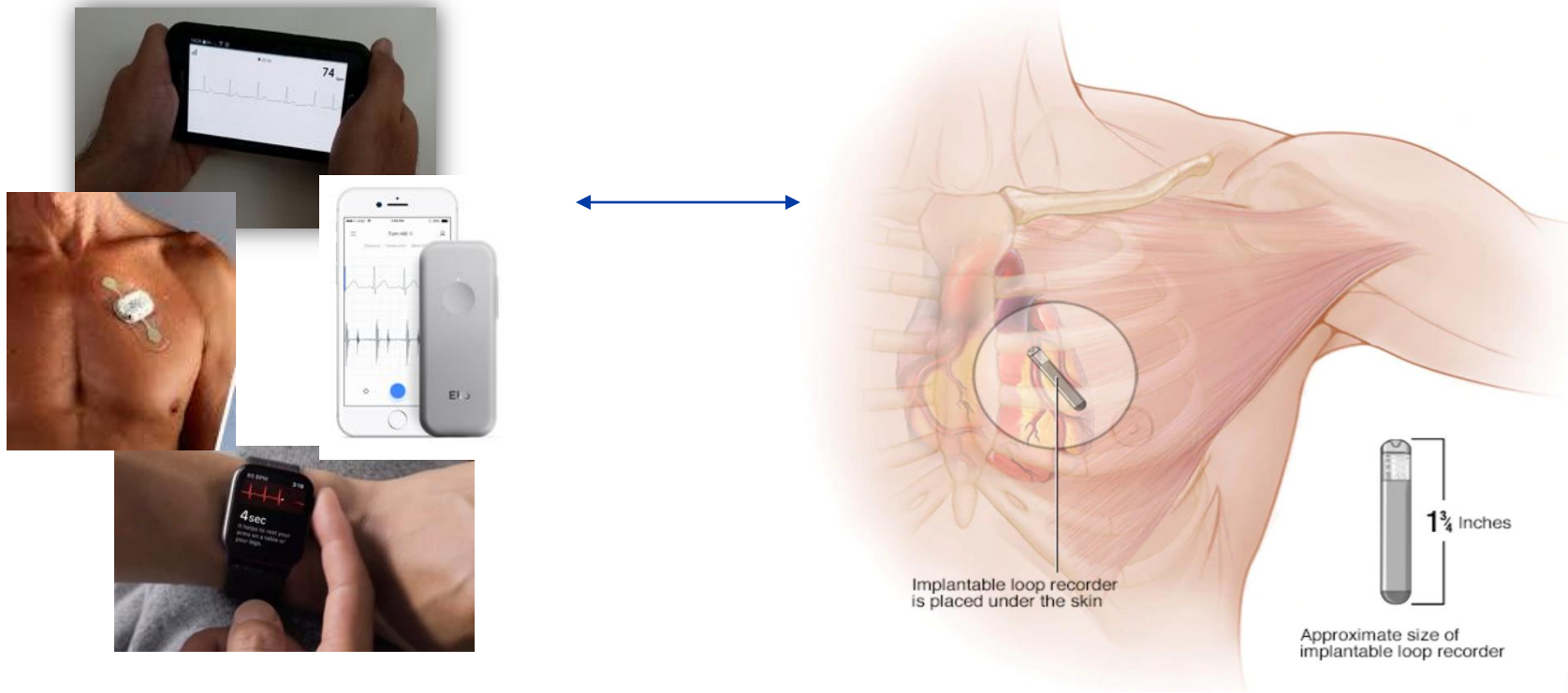
Screening for Paroxysmal Atrial Fibrillation

- Often fleeting
- Sometimes asymptomatic
- Can have major consequences: Stroke

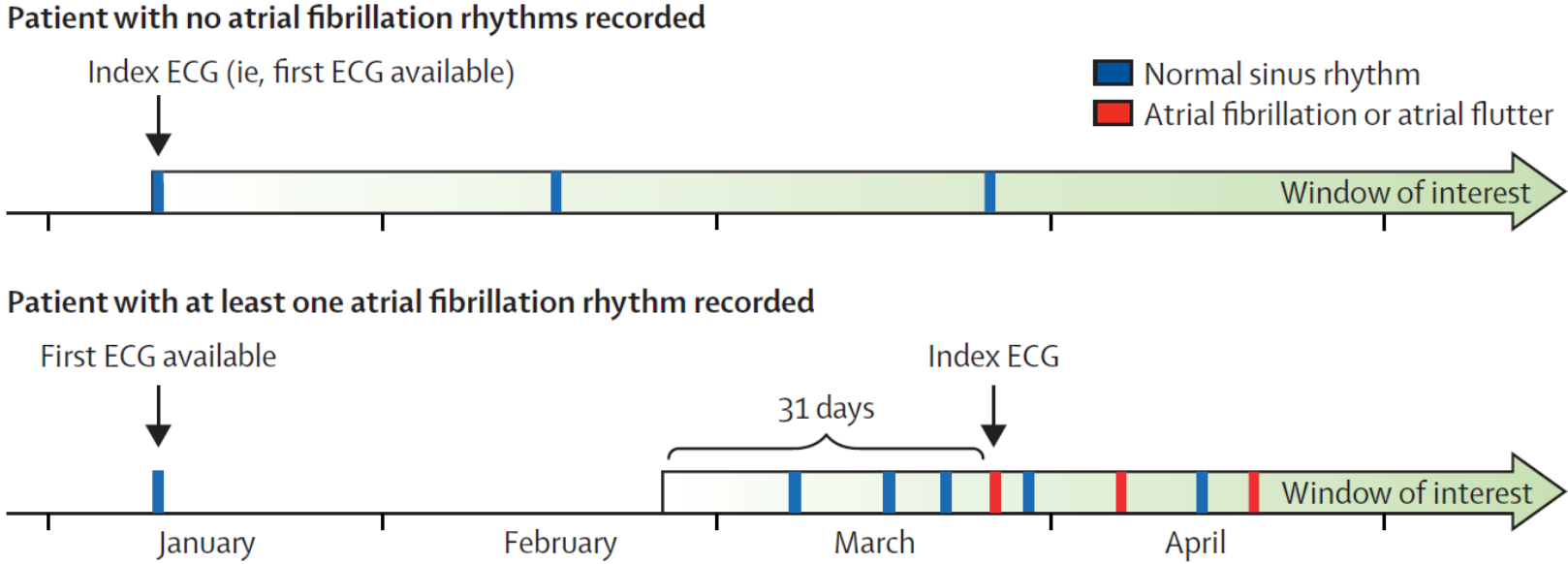


Continuous Monitoring vs Mobile Form Factors

Will short episodes, detected with continuous or near continuous monitoring have the same prognostic significance?



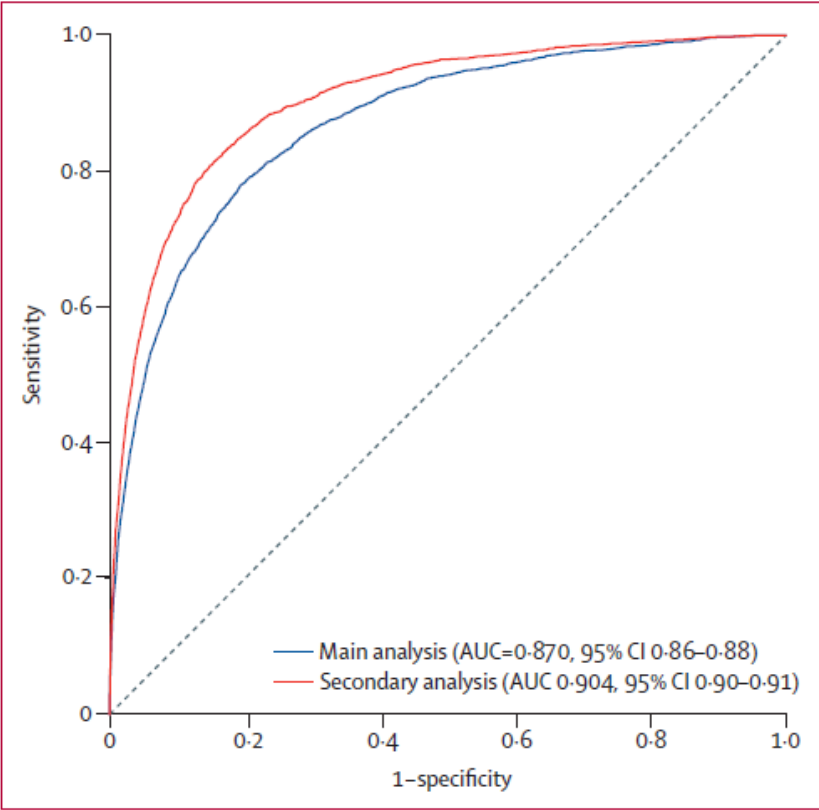
Scanning ECGs in NSR to Determine if AF was Present in the Past!



Only Normal Sinus ECGs were used !

THE LANCET *Attia et al. 2019*

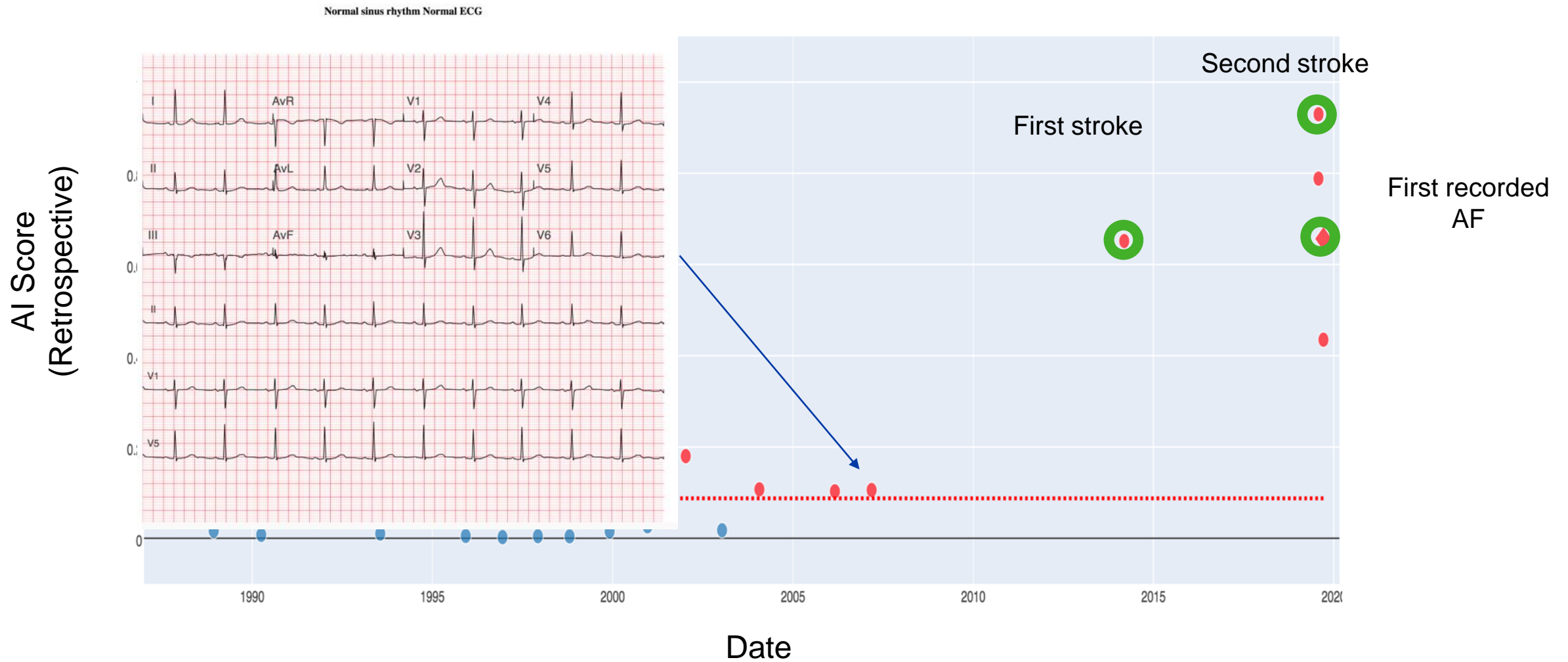
Results- AF Screening



	AUC	Sensitivity	Specificity
Primary	0.87	79.0%	79.5%
Secondary	0.90	82.3%	83.4%

CASE #5 : COULD AI HAVE PREVENTED A STROKE?

Probability of AF/silent AF



Common Risk Factors for CVD and for Sleep Apnea

Older Age

Male Sex

Obesity

Hypertension

Atrial Fibrillation

Awake

CPAP-REM

SNA

RESP

BP

150
100
50
0

150
100
50
0

OSA-REM

SNA

RESP

BP

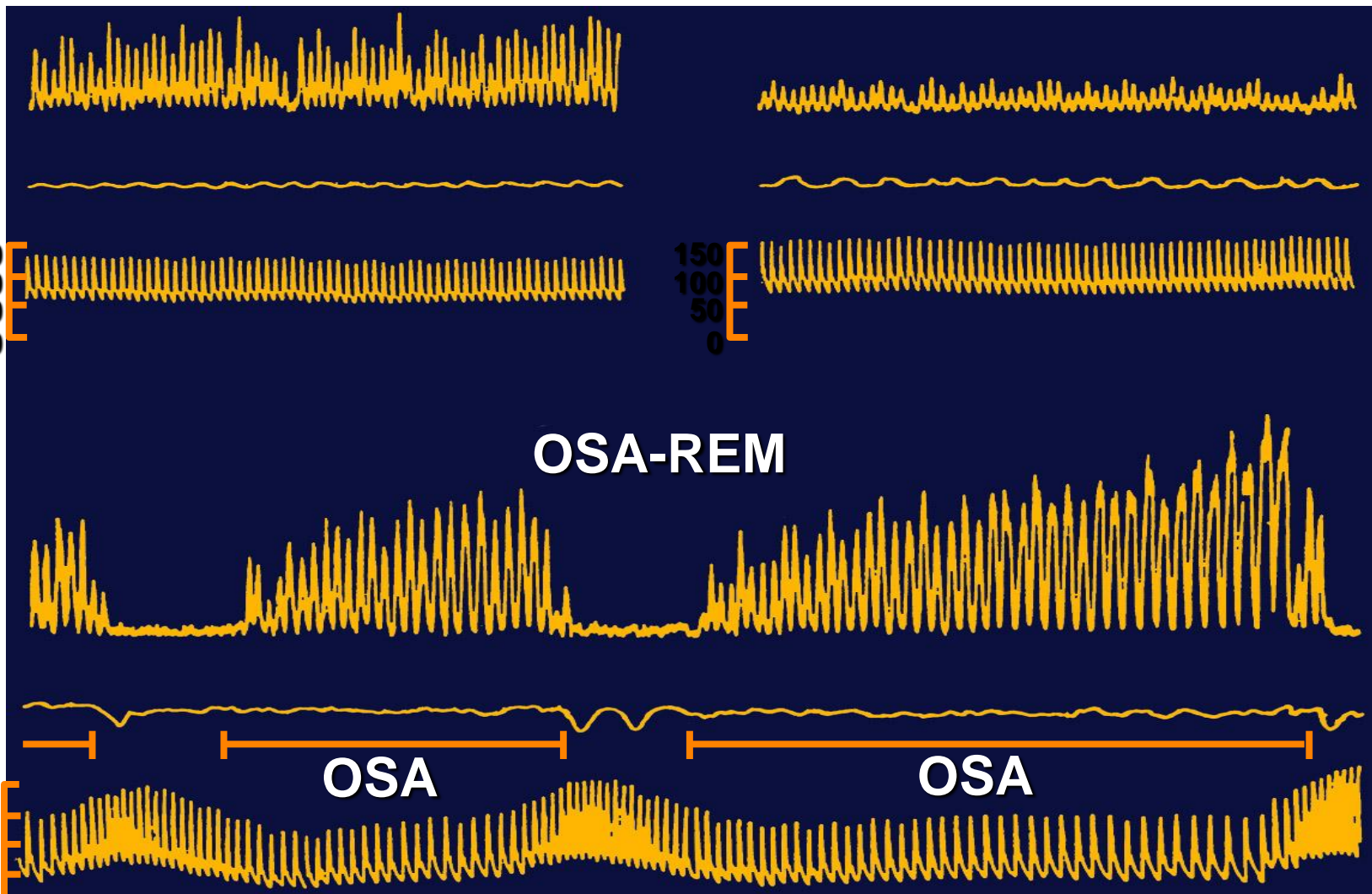
250
200
150
100
50
0

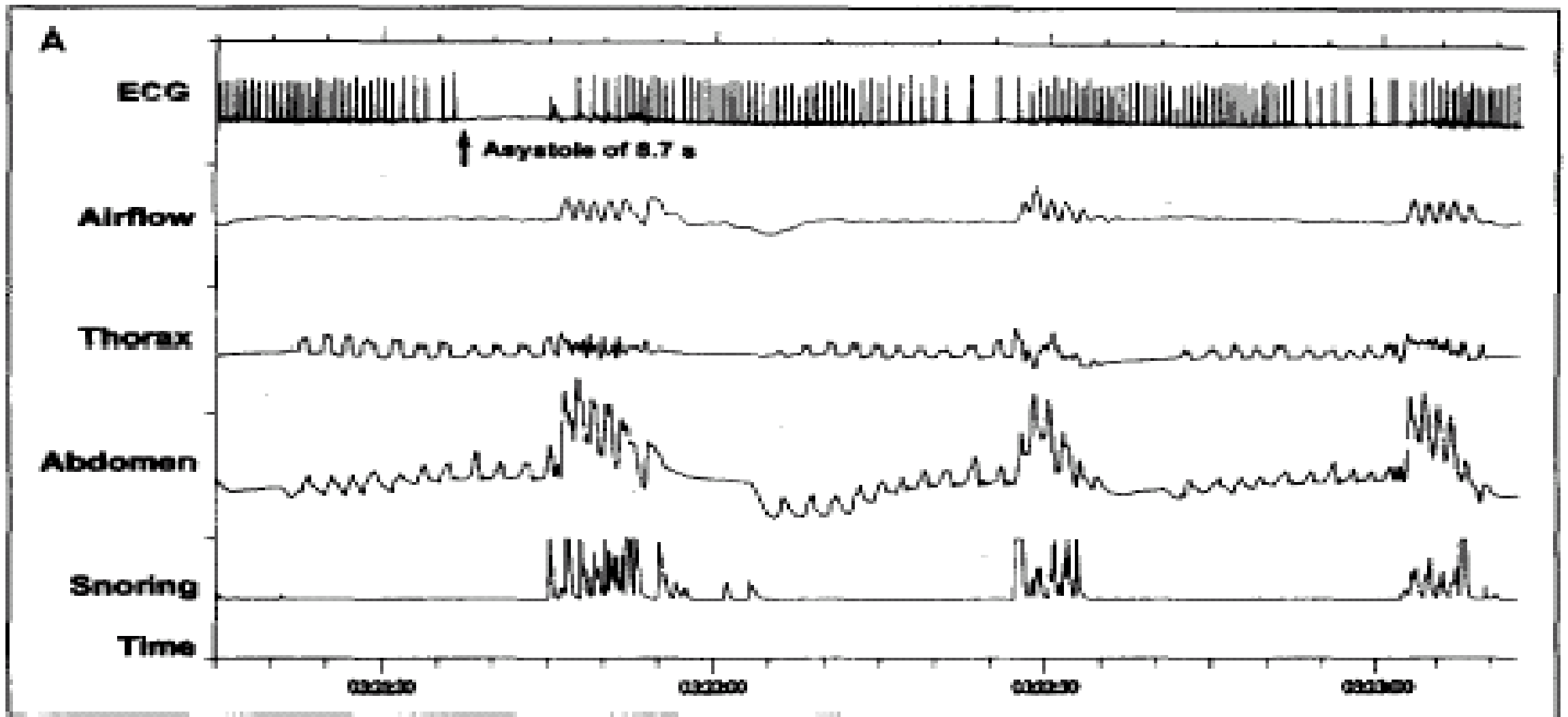
OSA

OSA

10 sec

Somers et al: *JCI*, 1995

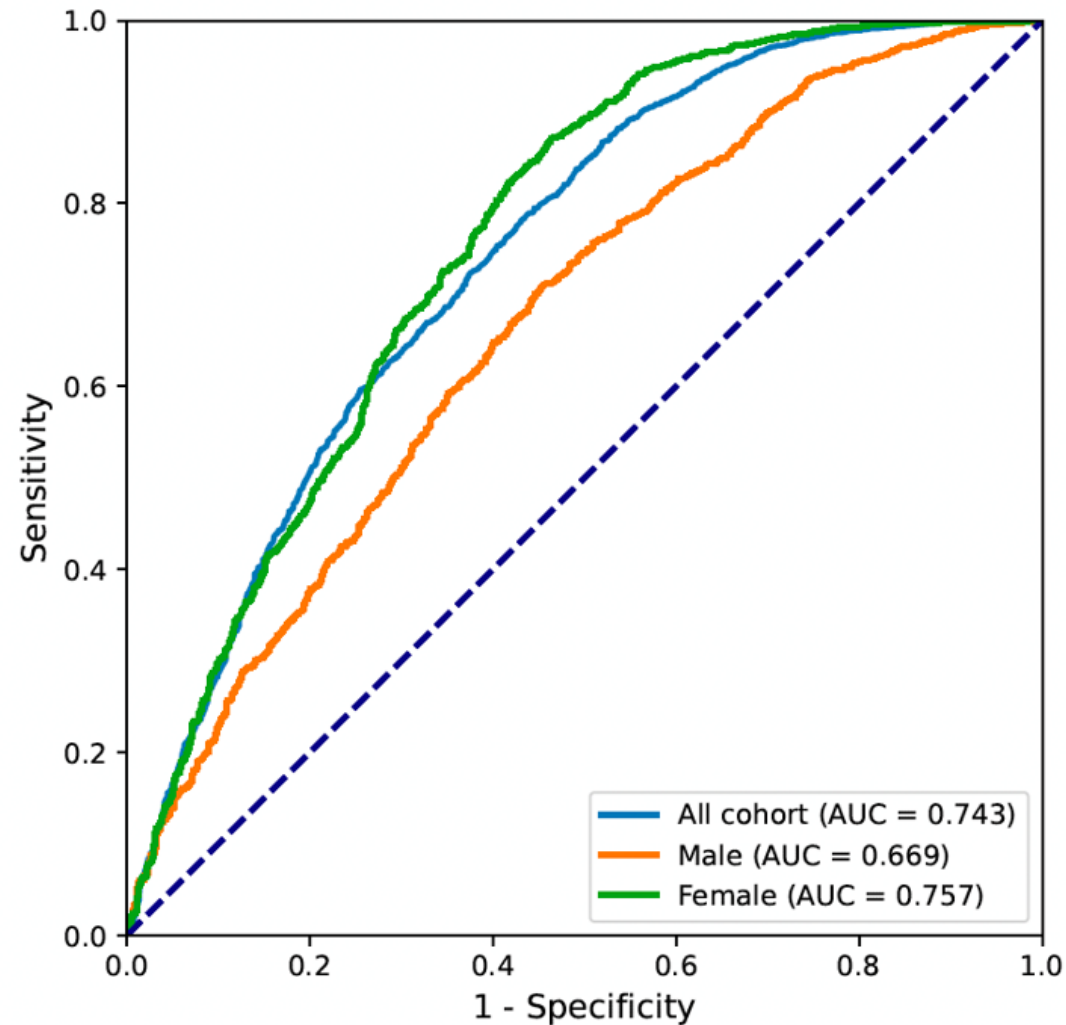




Prediction of presence of OSA (AHI of >5/hour) based on 12-lead ECG

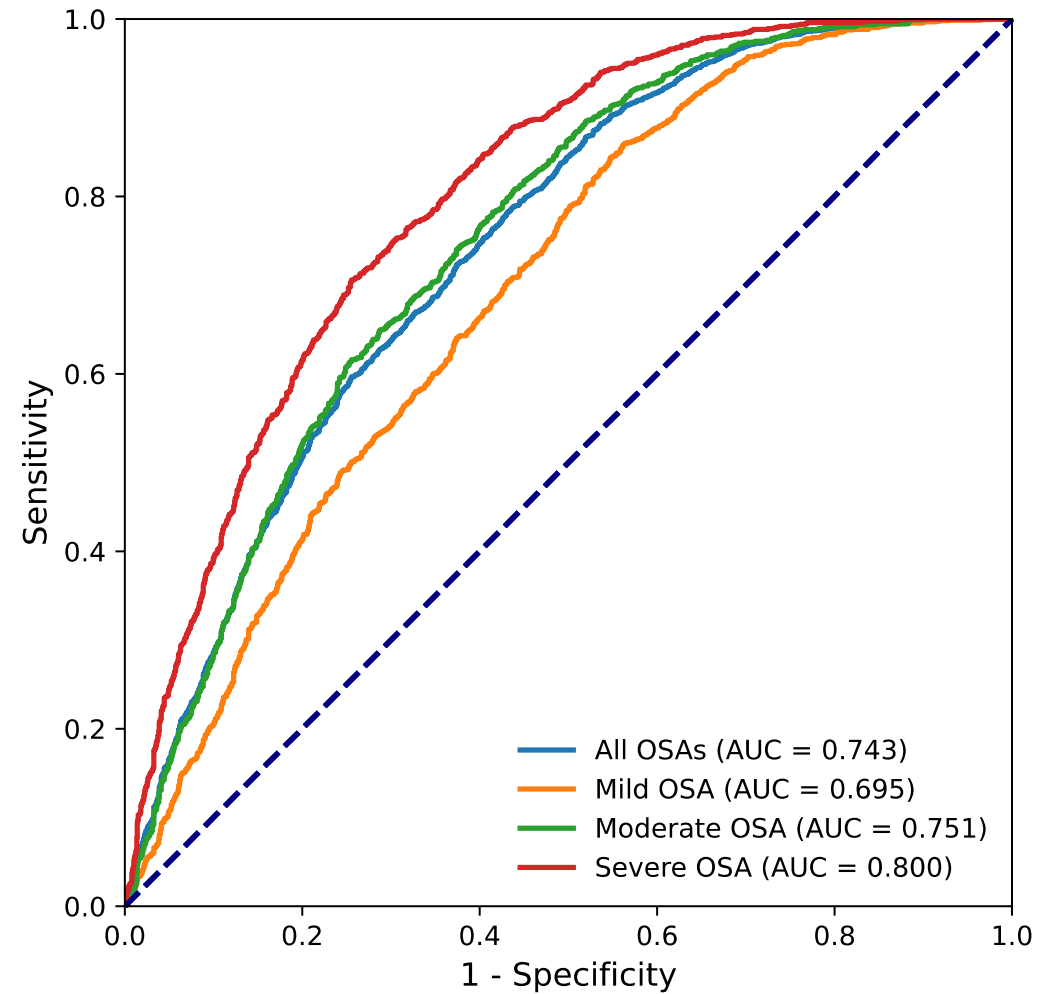
(Liu et al, 2023)

Receiver Operating Characteristic



Prediction Accuracy of different severities of OSA based on AHI (Liu et al, 2023)

Receiver Operating Characteristic



Summary

Deep neural networks provide accurate assessments of age, sex, and risks of premature aging disorders, left ventricular dysfunction, HCM, AS, atrial fibrillation and OSA from analysis of the 12-lead standard ECG. This is an evolving field with enormous implications for patient screening and health care economics.

***An A.I.-Generated Picture
Won an Art Prize. Artists
Aren't Happy.***

"I won, and I didn't break any rules," the artwork's creator says.



Jason Allen's AI-generated work, titled "Théâtre D'opéra Spatial," took first place in the digital category at the Colorado State Fair. via Jason Allen