Elektrokardiogram a umelá inteligencia

ROBERT HATALA

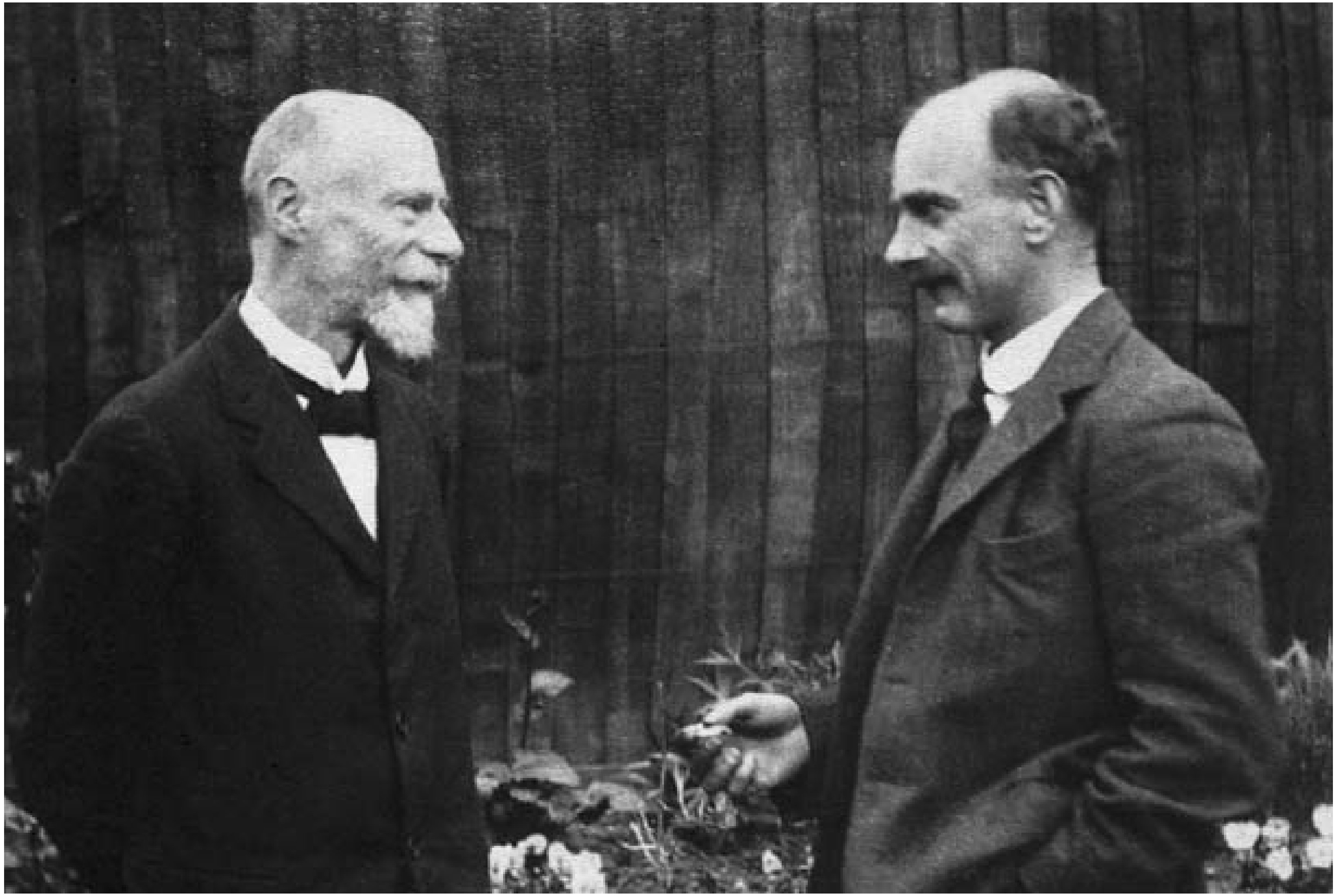
Klinika kardiológie a angiológie

NÚSCH a.s. a LF SZU Bratislava

Deklarace konfliktu zájmů

	Nemám konflikt zájmů	Mám konflikt zájmů	Specifikace konfliktu (vyjmenujte subjekty, firmy či instituce, se kterými Vaše spolupráce může vést ke konfliktu zájmů)
Zaměstnanecký poměr	X		
Vlastník / akcionář	X		
Konzultant	X		
Přednášková činnost	X		
Člen poradních sborů (advisory boards)	X		
Podpora výzkumu / granty	X		
Jiné honoráře (např. za klinické studie či registry)	X		

Willem Einthoven and Thomas Lewis
Leiden, April 10th 1921



120 years of electrocardiography

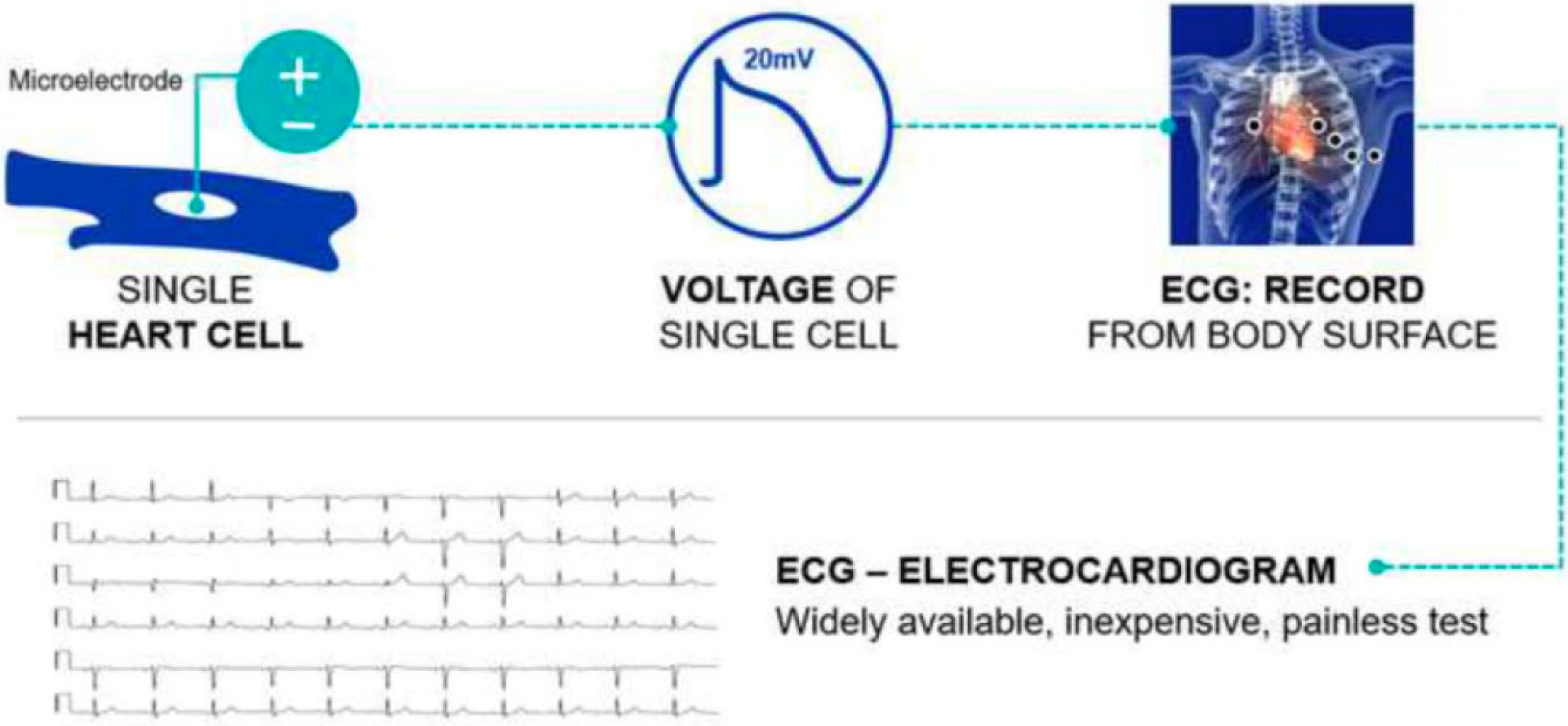
ECG – ubiquitous diagnostic tool in clinical medicine

- low cost, rapid, simple to obtain
- available at point-of-care

Inherent contradiction within electrocardiography

- Acquisition is standardized and highly reproducible
- Interpretation is highly variable - according to variable human expertise

EKG - bohatý zdroj fyziologických informácií, ktoré reflektujú stav srdca i iných systémov



Attia Z et al. Eur Heart J. 2021;ehab649. doi:10.1093/eurheartj/ehab649

Aims to eliminate the varability of ECG interpretation are not new

- **Computer based interpretation**
  - Applying predefined rules based on previous experience derived from experimental and clinical observation

- **Artificial intelligence**
  - Deep learning - neural networks
  - CNNs – **convolutional neural networks - „image recognition“**

ČÍM VIAC INFORMÁCII O ELEKTRICKOM POLI SRDCA MÁME, TÝM LEPŠIE MÔŽEME DIAGNOSTIKOVAŤ KARDIÁLNE OCHORENIA.

ALE: ODKIAĽ ČERPAŤ INFORMÁCIE?

EXTENZÍVNY VERSUS INTENZÍVNY PRÍSTUP

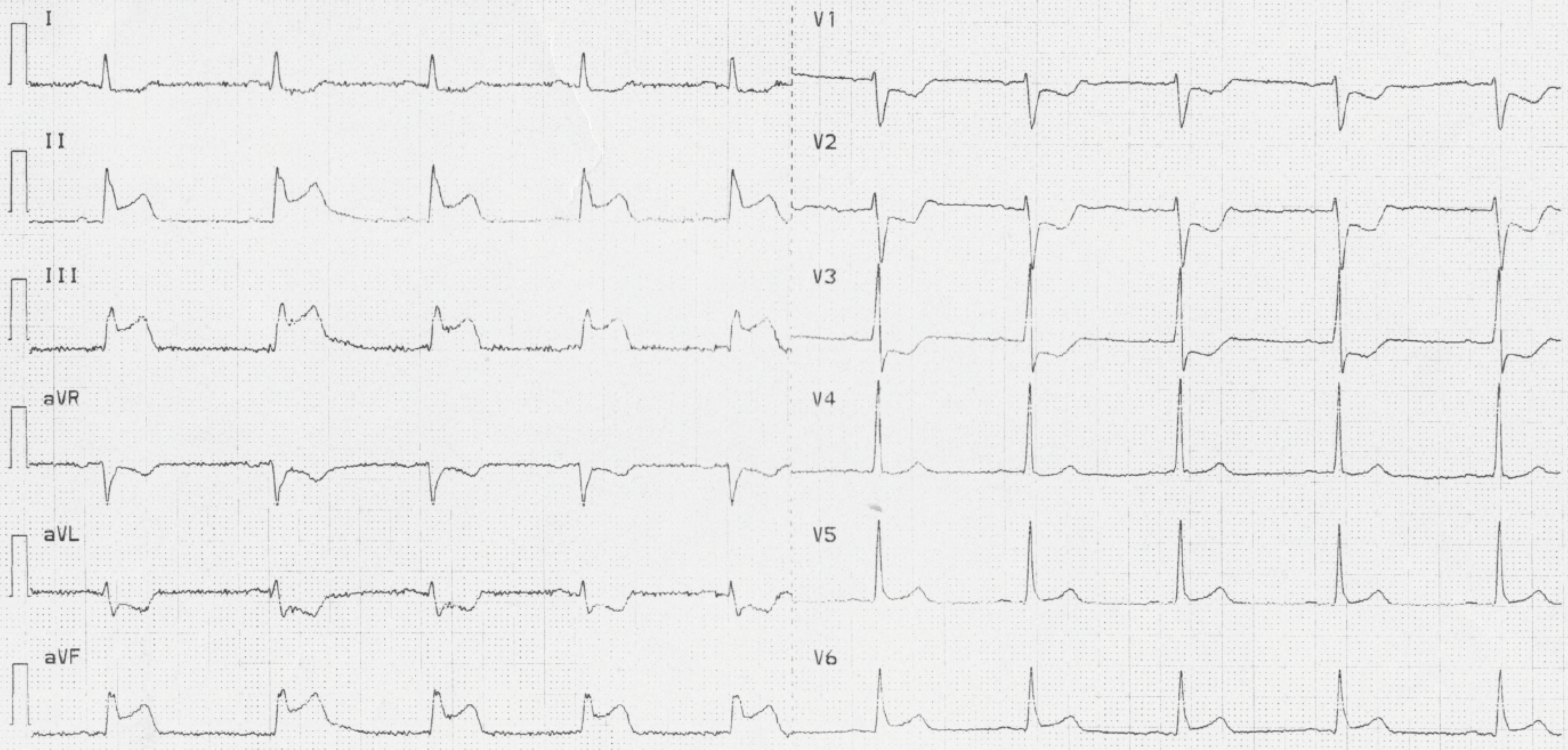
Computers for ECG interpretation

1. Mimicking human interpretation by applying predefined **rules** (traditional computer interpretation) = i.e. computer searches for digital counterparts of visible ecg changes.
2. **Artificial intelligence (AI**) - extracting information beyond the level of recognition by humans
3. **Expanding the number of leads** to increase precision.

Vent. Rate:	60 bpm
RR Interval:	988 ms
PR Interval:	168 ms
QRS Duration:	116 ms
QT Interval:	406 ms
QTc Interval:	406 ms
QT Dispersion:	56 ms
P-R-T AXIS: -18°	66° 98°

SINUS RHYTHM
** INTERPRETATION MADE WITHOUT KNOWING PATIENT'S GENDER/AGE
  Low maximum QRS spatial velocity
  Broad QRS in (V1 or V2) and (V5 or V6)
INCOMPLETE LEFT BUNDLE BRANCH BLOCK
  Inferior ST elevation
CONSIDER ACUTE INFERIOR INFARCTION
  Anterolateral ST-T changes
STRONGLY SUGGESTS MYOCARDIAL INJURY/ISCHEMIA

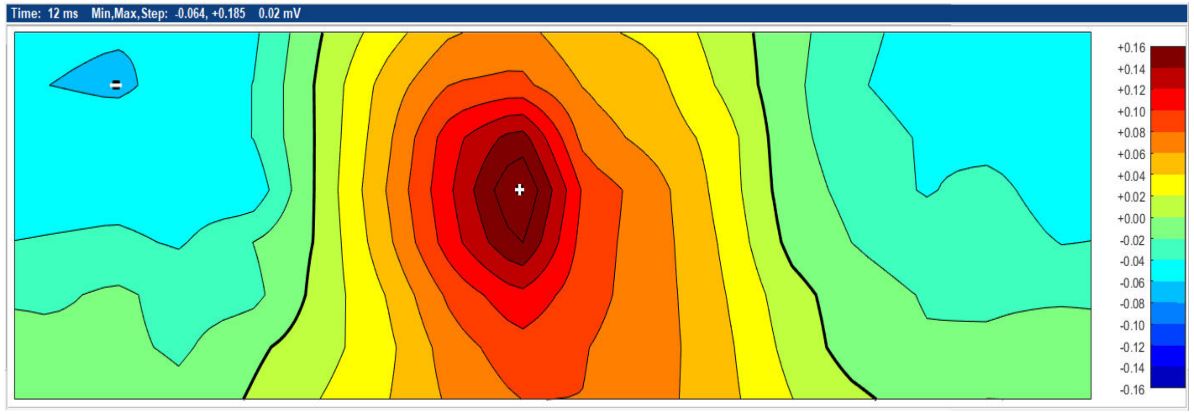
Summary: ABNORMAL ECG   * Unconfirmed Analysis



L: 10 mm/mV
C: 10 mm/mV
QTc=Hodges
NUSCH koronarna jednotka
25 mm/s
STABLE 40 Hz

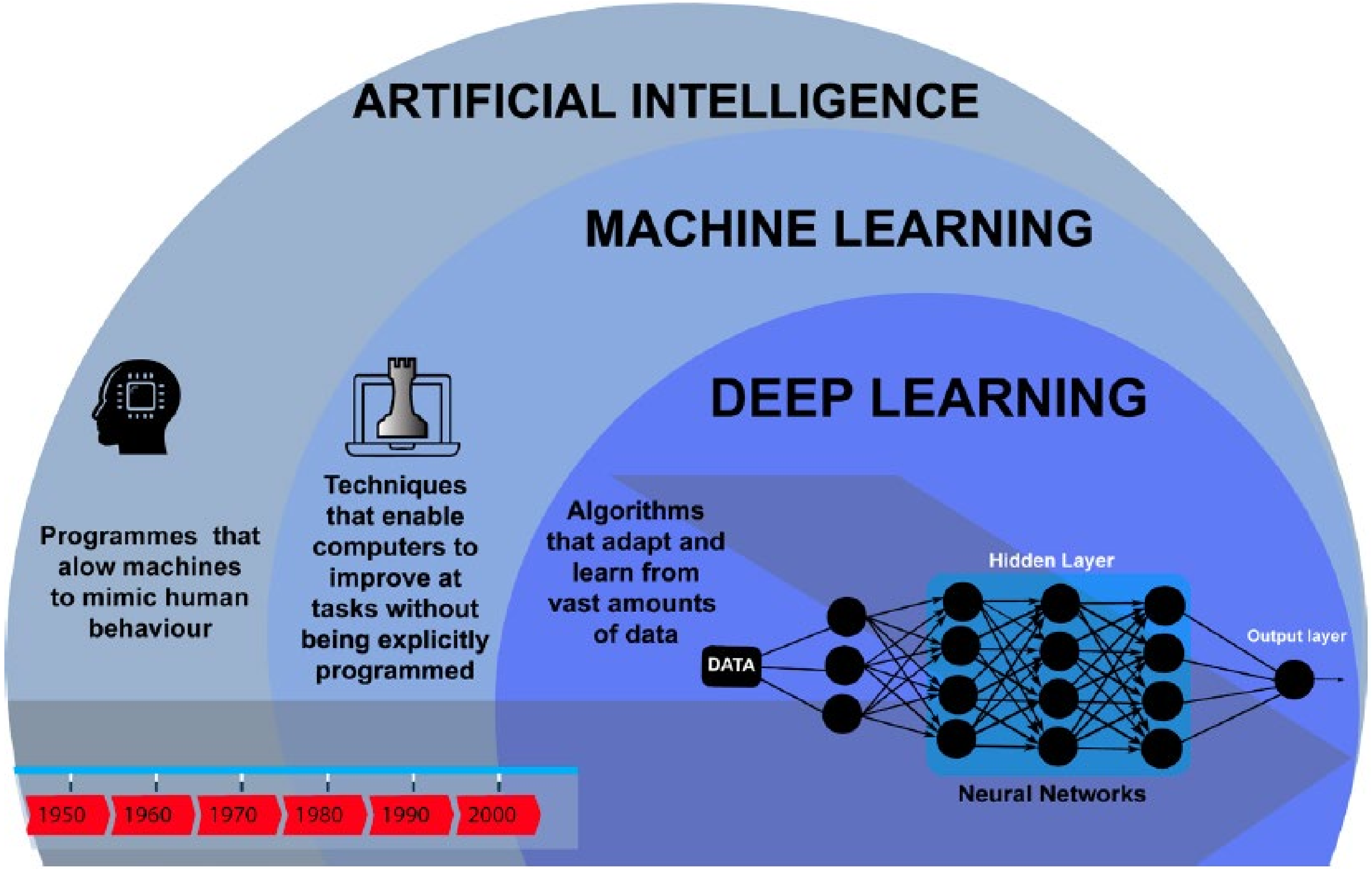
Noninvasive PVC localization

- Patient P034 with implanted pacemaker. During spontaneous activity the PVC focus could be localizaed in the basal lateral segment of the left ventricle.



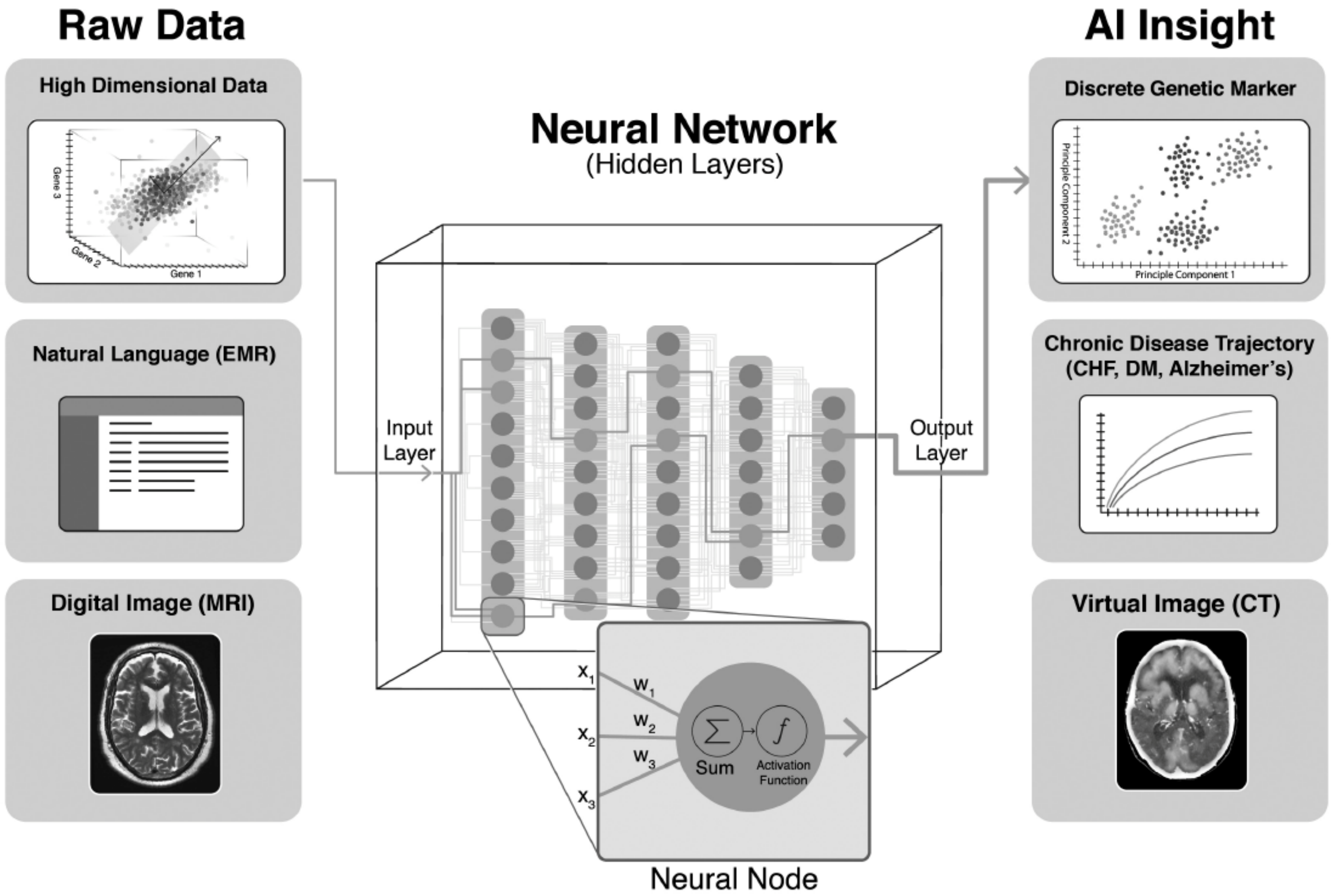
The PVC focus was localized from a BSPM 12 ms after the PVC onset.

SVET UMELEJ INTELIGENCIE



de Marvao A. et al. Heart 2020;106:399–400.

Machine learning (AI) by an artificial neural network



Miller DD Cardiology in Review 2020;28: 53–64

Artificial intelligence

- ML aims to characterise **relationships among multiple variables** or features within data sets that are not readily discernible to humans and diffcult to discover using traditional biostatistical methods
- ML can only yield **associations and correlations**; currently it cannot make definitive cause−effect inferences.
- The principal tasks of ML comprise: **<u>classification</u>** (e.g. distinguishing disease from non-disease); **<u>prediction</u>** (or regression) (e.g. estimating risk of future clinical events); and **<u>discovery</u>** (e.g. a new use for a drug or a new disease phenotype).

ECG = ideal target for applying AI and deep learning

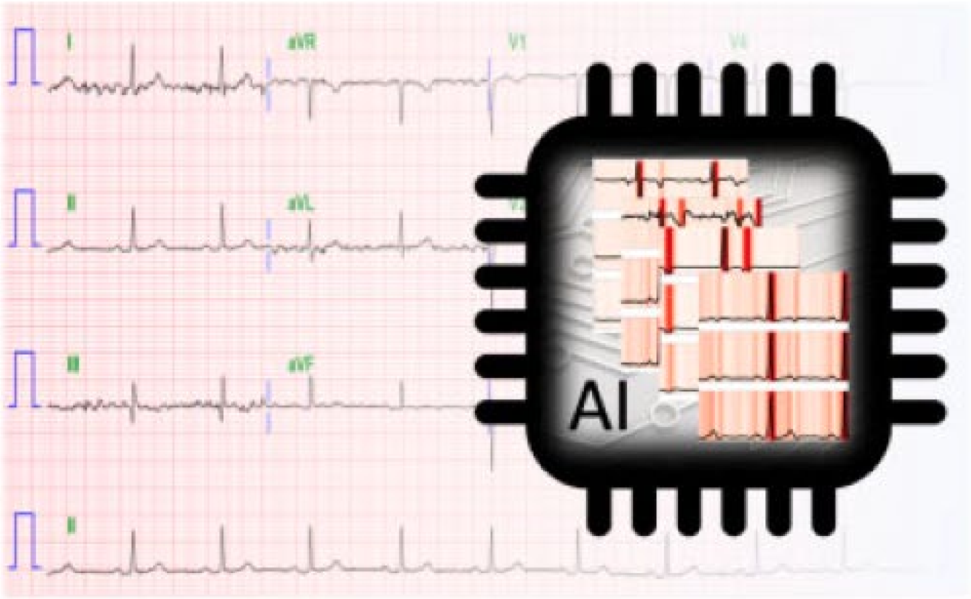
- Widely available digital data
- Easily stored and transfered
- Huge datasets available
- Powerful computing readily available

STROJOVÉ UČENIE (MACHINE LEARNING)

- Strojové učenie, jeden z druhov umelej inteligencie, funguje na základe identifikácie vzorov v dostupných údajoch a následného uplatnenia týchto znalostí na nové údaje . Čím väčší je súbor údajov, tým ľahšie je možné odhaliť aj nepatrné súvislosti.

- Významné pokroky v týchto technológiách sa dosiahli použitím **veľkých súborov údajov ("big data") a nevídanej výpočtovej sily.**

Umelá inteligencia v elektrokardiografii



Diagnosis
-Left ventricular systolic dysfunction
-Heart failure with preserved ejection fraction
-Aortic valve stenosis
-Mitral valve regurgitation
-Pulmonary hypertension
-Left ventricular hypertrophy
-Myocardial infarction with or without ST elevation
-Arrhythmia
-Hyperkalemia
-Anemia

Prediction
-Paroxysmal atrial fibrillation
-Patient deterioration and cardiac arrest
-Aortic valve stenosis
-Heart failure with preserved ejection fraction
-Mitral valve regurgitation

Kwn J-M et al. Eur Heart J 2021: 42, 2896–2898 doi:10.1093/eurheartj/ehab090

Agreement Between Artificial Neural Networks and Experienced Electrocardiographer on Electrocardiographic Diagnosis of Healed Myocardial Infarction

BO HEDÉN, MD, MATTIAS OHLSSON, PhD, RALF RITTNER, MSc, OLLE PAHLM, MD, PhD, WESLEY K. HAISTY, Jr., MD,* CARSTEN PETERSON, PhD, LARS EDENBRANDT, MD, PhD

Lund, Sweden and Winston-Salem, North Carolina

Objectives. The purpose of this study was to compare the diagnoses of healed myocardial infarction made from the 12-lead electrocardiogram (ECG) by artificial neural networks and an experienced electrocardiographer.

Background. Artificial neural networks have proved of value in pattern recognition tasks. Studies of their utility in ECG interpretation have shown performance exceeding that of conventional ECG interpretation programs. The latter present verbal statements, often with an indication of the likelihood for a certain diagnosis, such as "possible left ventricular hypertrophy." A neural network presents its output as a numeric value between 0 and 1; however, these values can be interpreted as Bayesian probabilities.

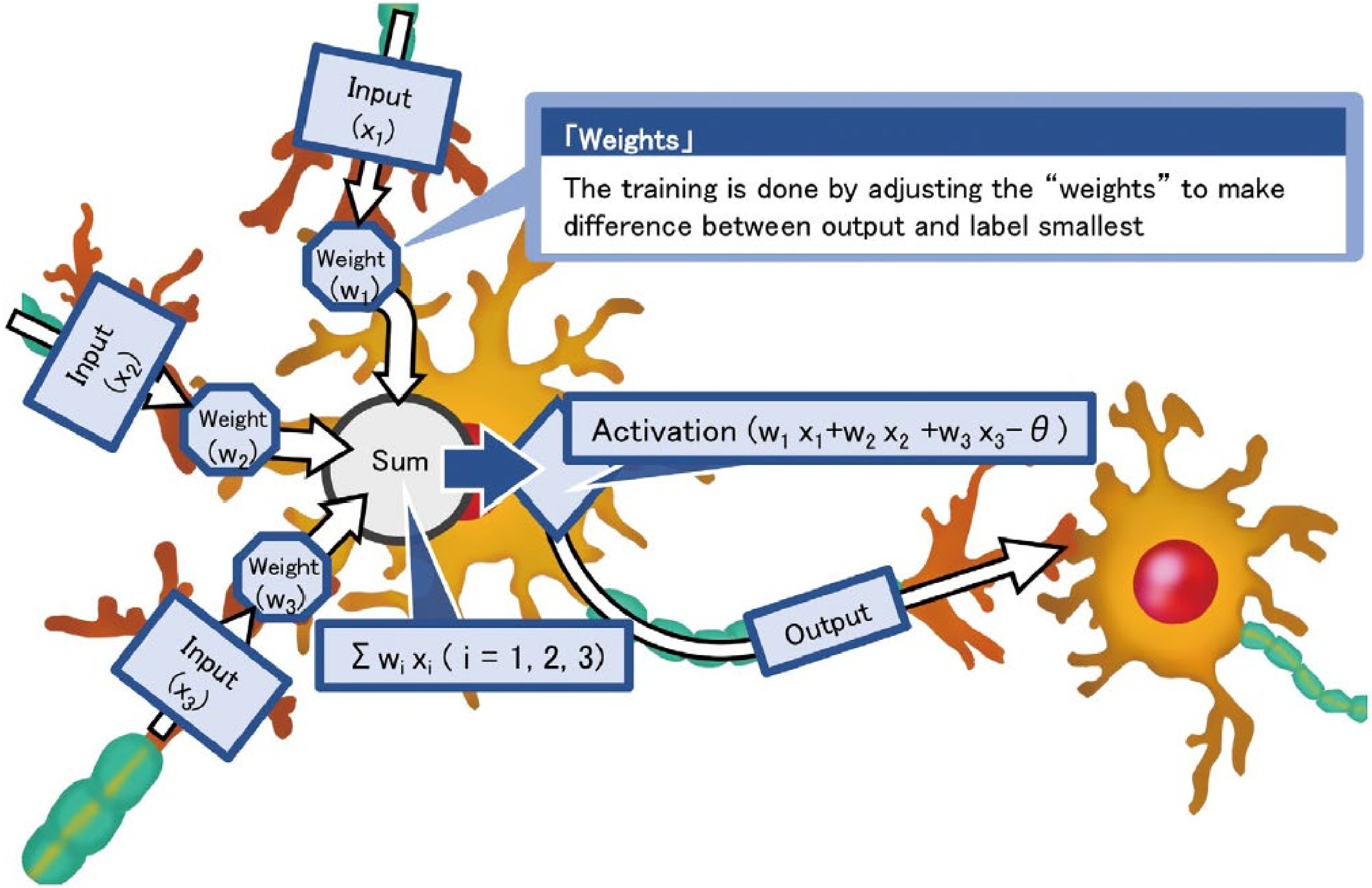
Methods. The study was based on 351 healthy volunteers and 1,313 patients with a history of chest pain who had undergone diagnostic cardiac catheterization. A 12-lead ECG was recorded in each subject. An expert electrocardiographer classified the ECGs in five different groups by estimating the probability of anterior myocardial infarction. Artificial neural networks were trained and tested to diagnose anterior myocardial infarction. The network outputs were divided into five groups by using the output values and four thresholds between 0 and 1.

Results. The neural networks diagnosed healed anterior myocardial infarctions at high levels of sensitivity and specificity. The network outputs were transformed to verbal statements, and the agreement between these probability estimates and those of an expert electrocardiographer was high.

Conclusions. Artificial neural networks can be of value in automated interpretation of ECGs in the near future.

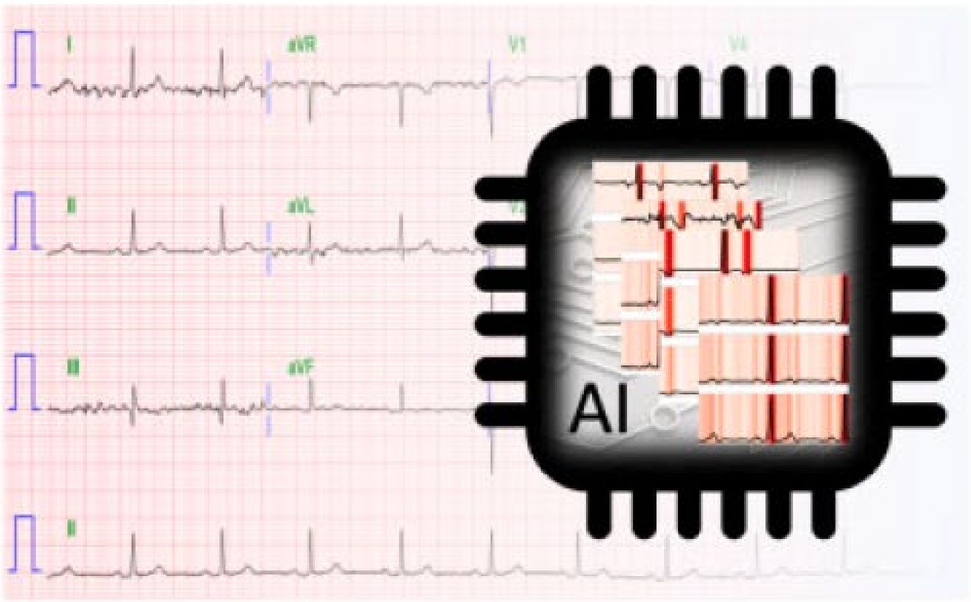
(J Am Coll Cardiol 1996;28:1012–6)

Neural network is constructed by multiple units of statistical model called “neuron” that simulates the function of neuron cells



Goto S, Goto S. Circ Rep. 2019 Nov 2;1(11):481-486. doi: 10.1253/circrep.CR-19-0096

Umelá inteligencia v elektrokardiografii



Diagnosis
- -Left ventricular systolic dysfunction
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- -Aortic valve stenosis
- -Mitral valve regurgitation
- -Pulmonary hypertension
- -Left ventricular hypertrophy
- -Myocardial infarction with or without ST elevation
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Prediction
- -Paroxysmal atrial fibrillation
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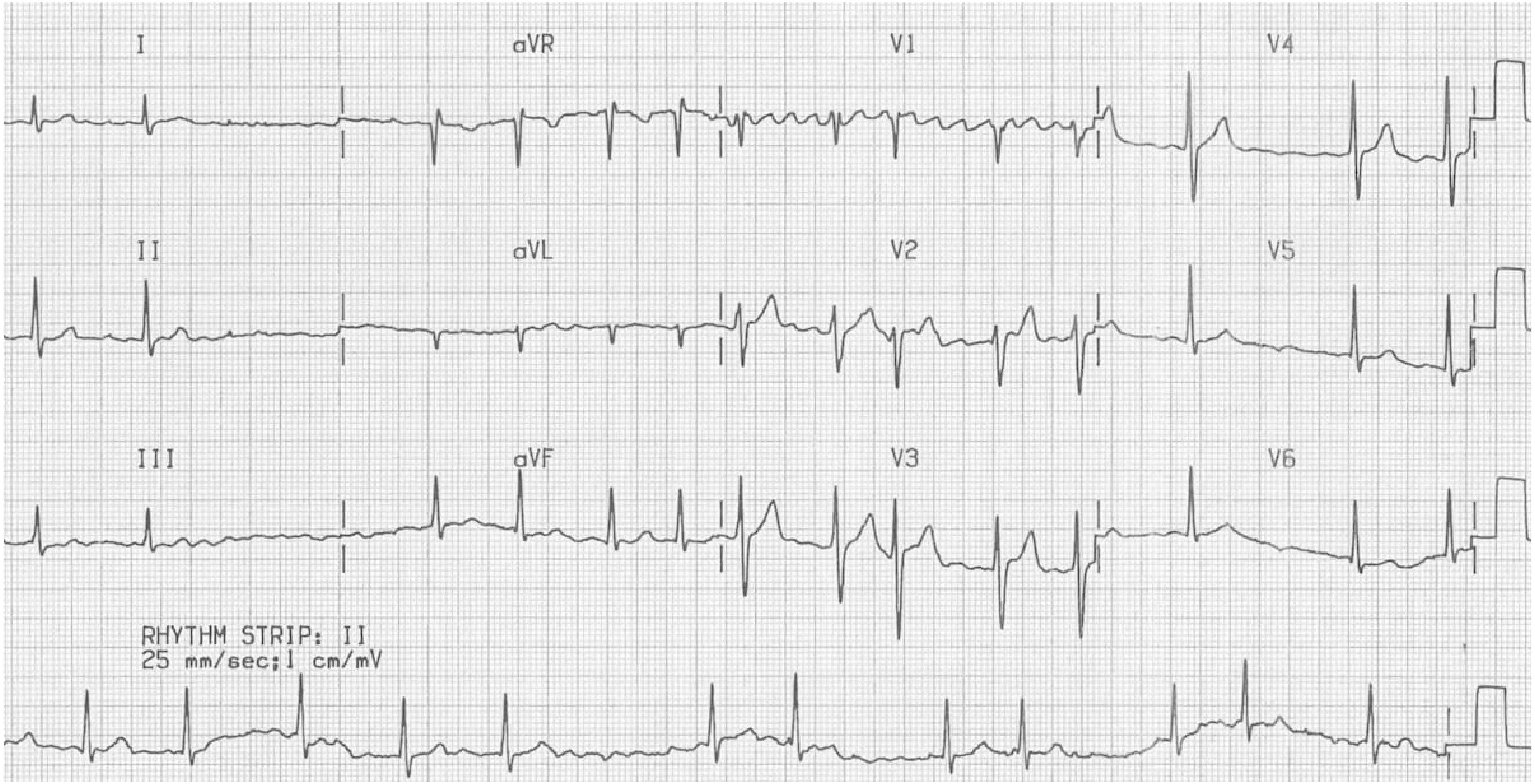
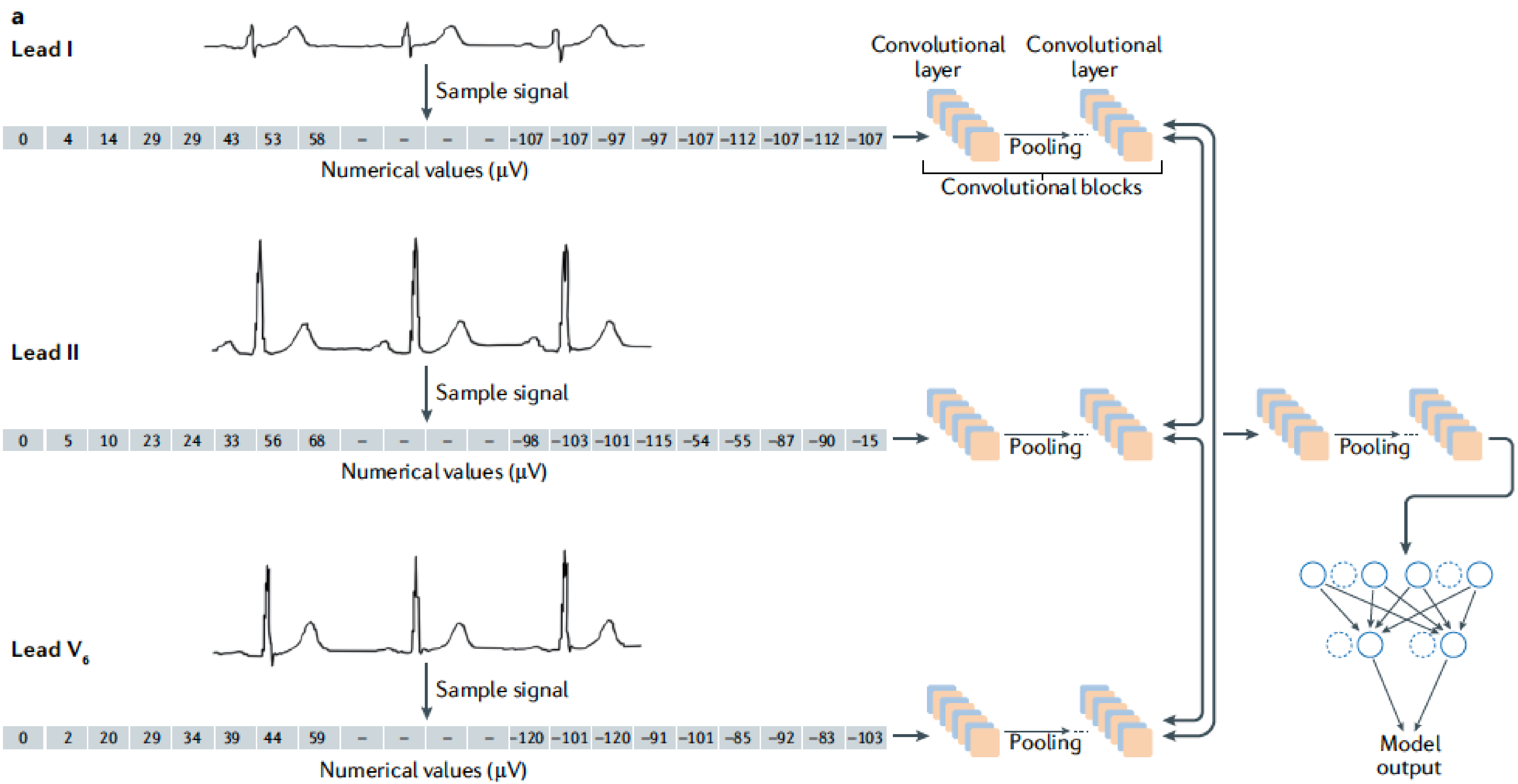
- -Mitral valve regurgitation

Kwn J-M et al. Eur Heart J 2021: 42, 2896–2898 doi:10.1093/eurheartj/ehab090

ELEKTRICKÉ OCHORENIA SRDCA

ATRIAL FIBRILLATION





Siontis KC et al. Nat Rev Cardiol. 2021 Feb 1:1–14. doi: 10.1038/s41569-020-00503-2.

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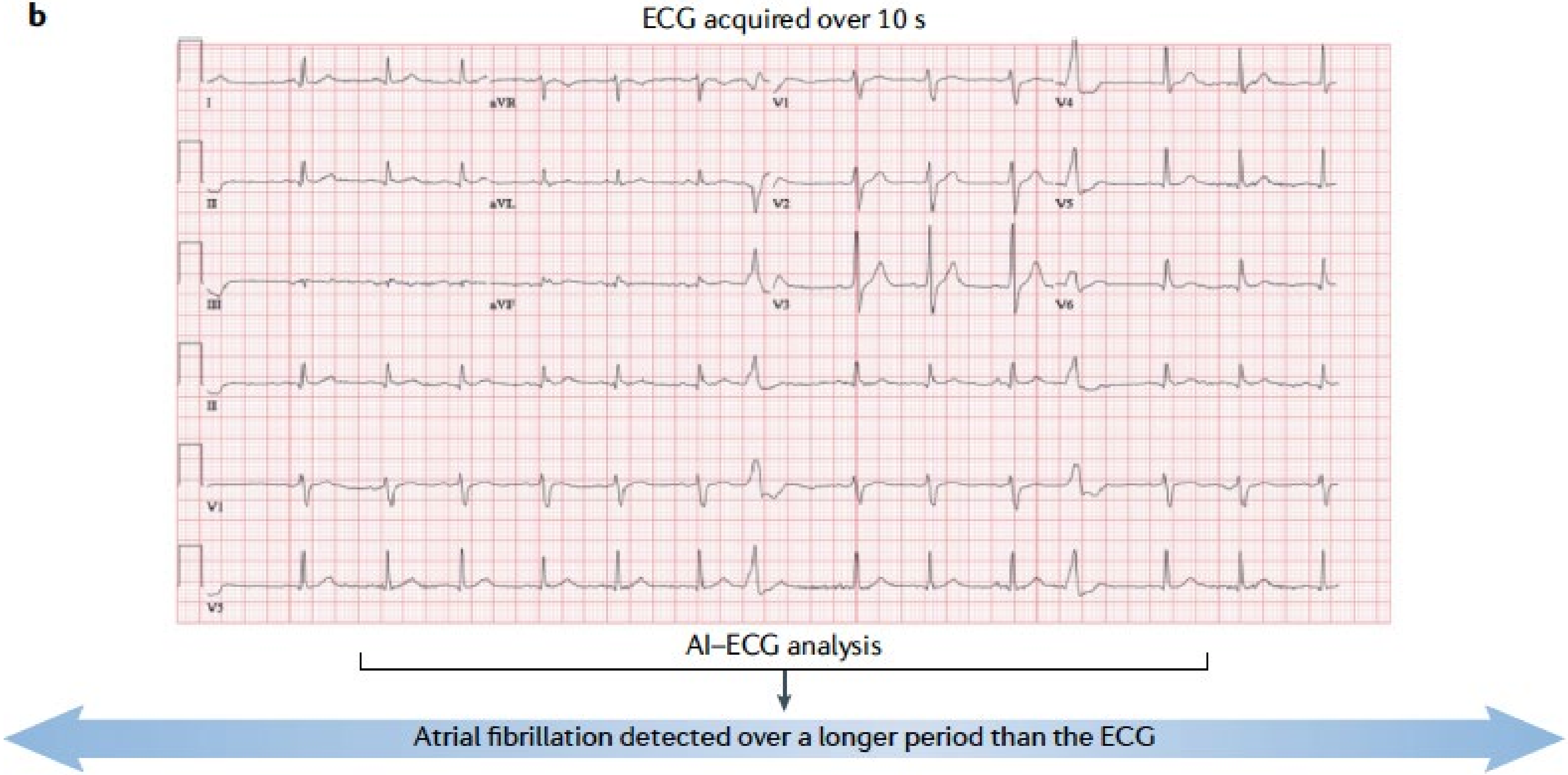
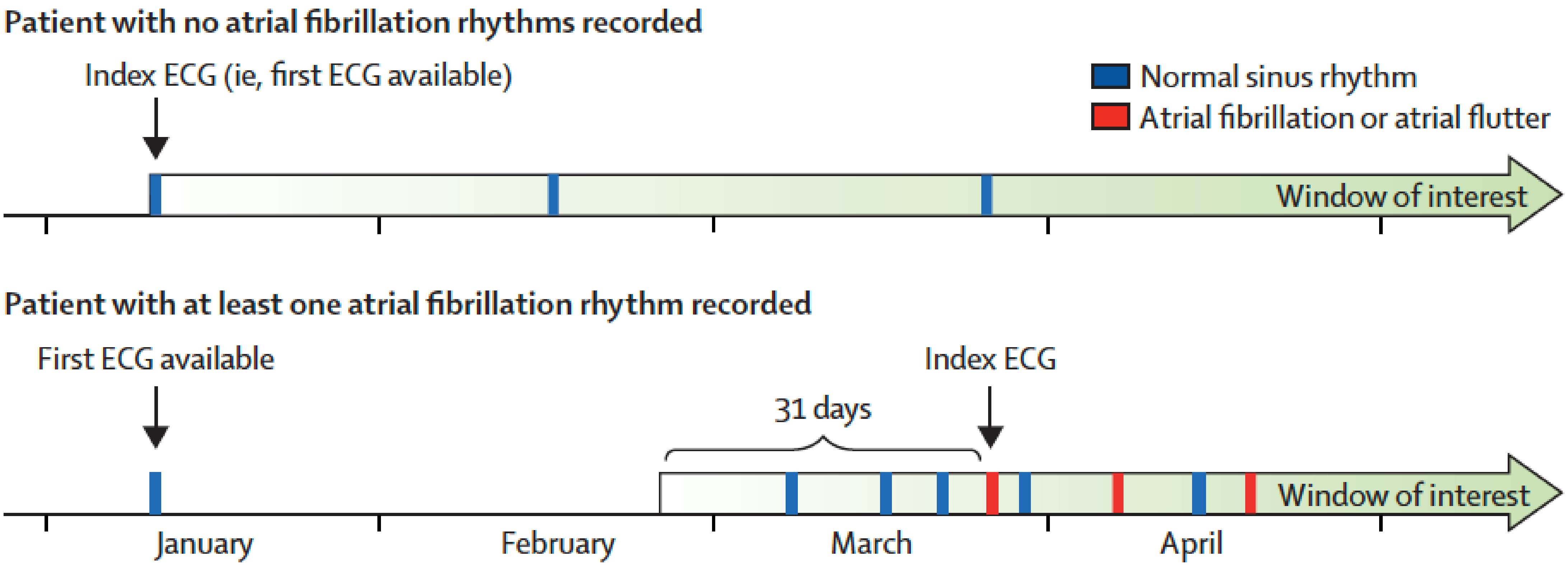


Siontis KC et al. Nat Rev Cardiol. 2021 Feb 1:1–14. doi: 10.1038/s41569-020-00503-2.

An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction

Zachi I Attia, Peter A Noseworthy*, Francisco Lopez-Jimenez, Samuel J Asirvatham, Abhishek J Deshmukh, Bernard J Gersh, Rickey E Carter, Xiaoxi Yao, Alejandro A Rabinstein, Brad J Erickson, Suraj Kapa, Paul A Friedman*



Attia ZI et al. Lancet. 2019 Sep 7;394(10201):861-867. doi: 10.1016/S0140-6736(19)31721-0.

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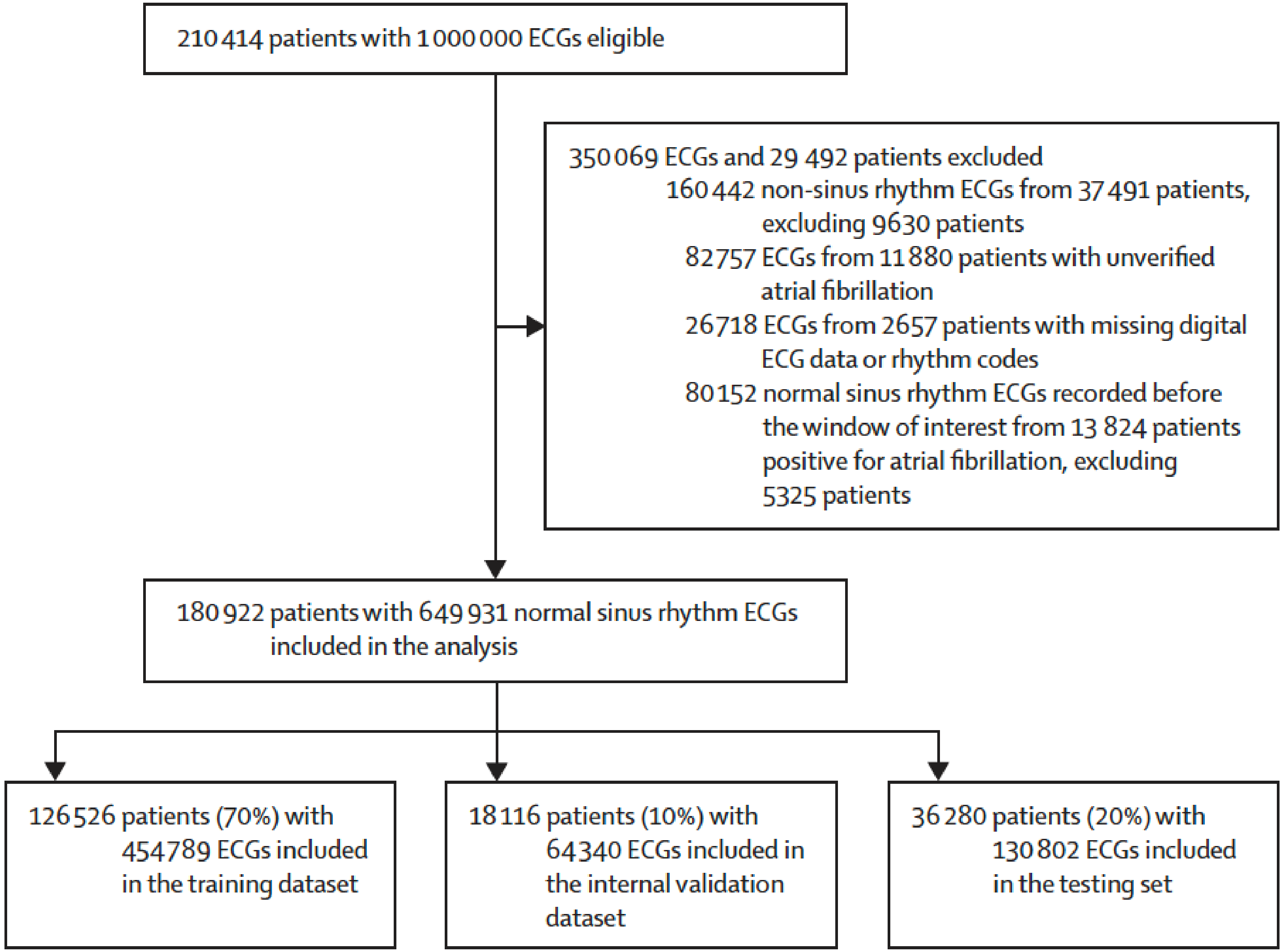

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	AUC	Sensitivity	Specificity	F1 score	Accuracy
Main analysis	0·87 (0·86–0·88)	79·0% (77·5–80·4)	79·5% (79·0–79·9)	39·2% (38·1–40·3)	79·4% (79·0–79·9)
Secondary analysis	0·90 (0·90–0·91)	82·3% (80·9–83·6)	83·4% (83·0–83·8)	45·4% (44·2–46·5)	83·3% (83·0–83·7)

Data in parentheses are 95% CIs. In the main analysis, only the score of the first normal sinus rhythm ECG in the window of interest was used. In the secondary analysis, the highest score for all ECGs done in the first month of the window of interest was used. AUC=area under the curve. ECG=electrocardiograph.

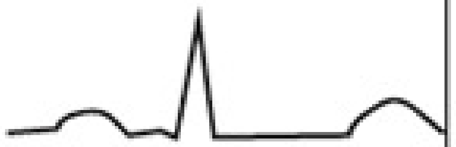
Attia ZI et al. Lancet. 2019 Sep 7;394(10201):861-867. doi: 10.1016/S0140-6736(19)31721-0.

“Torsade de Points” Tachycardia in long QT syndrome

Gabel A et al., Am J Cardiol 1999

LONG QT SYNDROME

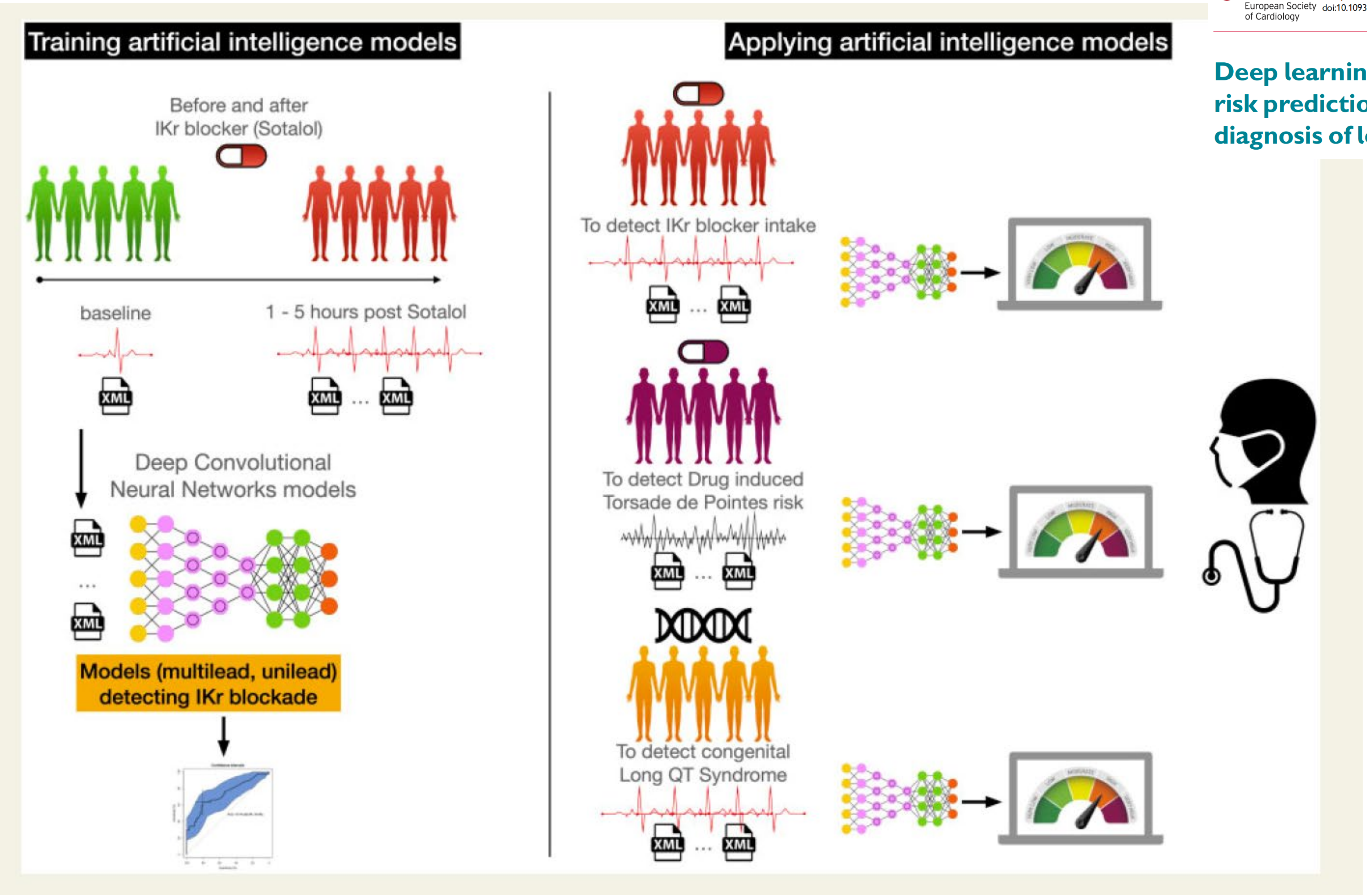
Figure 2: Characteristics of LQTS 1–3

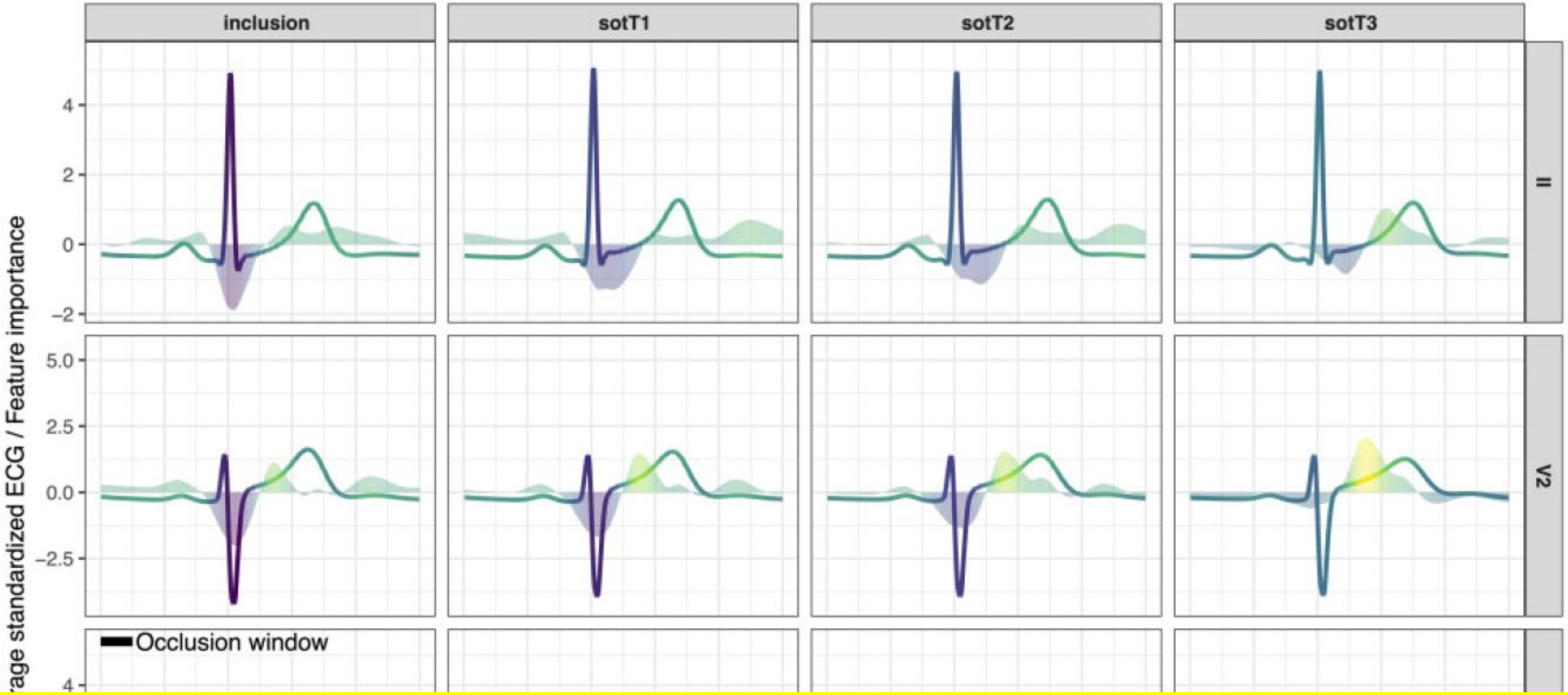
Type	Current	Functional Effect	Frequency Among LQTS	ECG	Triggers Lethal Cardiac Event	Penetrance*
LQTS1	K	↓	30%-35%		Exercise (68%) Emotional stress (14%) Sleep, response (9%) Others (19%)	62%
LQTS2	K	↓	25%-30%		Exercise (29%) Emotional stress (49%) Sleep, response (22%)	75%
LQTS3	Na	↑	5%-10%		Exercise (4%) Emotional stress (12%) Sleep, response (64%) Others (20%)	90%

Source: Adapted from Rev Esp Cardiol. 2007;60(7):739-5. Published with permission of Elsevier España.

ESC
European Society of Cardiology
European Heart Journal (2021) **42**, 3948–3961
doi:10.1093/eurheartj/ehab588
CLINICAL RESEARCH
Arrhythmias

Deep learning analysis of electrocardiogram for risk prediction of drug-induced arrhythmias and diagnosis of long QT syndrome





Profil významnosti jednotlivých charakteristík pre identifikáciu ekg stopy sotalolu (feature importance profile)

CNN sa "naučila" rozoznávať ekg zmeny (často subtílne, presahujúce schopnosť ľudského posúdenia) indukované sotalolom ako modelom blokády kanála Ikr. To je rozhodujúci mechanizmus predĺženia intervalu QT, čo predisponuje ku vzniku TdP.

Mapa senzitivity pre určenie ekg segmentu rozhodujúceho pre dg. aortálnej stenózy

Kwon JM et al. J Am Heart Assoc. 2020;9(7):e014717. doi:10.1161/JAHA.119.014717

JAMA Cardiology | Original Investigation

Use of Artificial Intelligence and Deep Neural Networks in Evaluation of Patients With Electrocardiographically Concealed Long QT Syndrome From the Surface 12-Lead Electrocardiogram

J. Martijn Bos, MD, PhD; Zachi I. Attia, PhD; David E. Albert, MD; Peter A. Noseworthy, MD; Paul A. Friedman, MD; Michael J. Ackerman, MD, PhD

- the AI-ECG was found to distinguish patients with electrocardiographically concealed LQTS
- provide a nearly 80% accurate **pregenetic** test anticipation of LQTS genotype status.
- For a cut-off of QTc > 500ms, a strong diagnostic and risk marker for the likelihood of LQTS, the area under the curve (AUC) was 0.97, with sensitivity and specificity of 80.0%, and 94.4%, respectively, indicating strong utility as a **screening method**.

Bos JM et al. JAMA Cardiol. 2021 May 1;6(5):532-538. doi: 10.1001/jamacardio.2020.7422

DYSFUNKCIA ĽAVEJ KOMORY

A QRS SCORING SYSTEM FOR ASSESSING LEFT VENTRICULAR FUNCTION AFTER MYOCARDIAL INFARCTION

SEBASTIAN T. PALMERI, M.D., DAVID G. HARRISON, M.D., FREDERICK R. COBB, M.D., KENNETH G. MORRIS, M.D., FRANK E. HARRELL, PH.D., RAYMOND E. IDEKER, M.D., PH.D., RONALD H. SELVESTER, M.D., AND GALEN S. WAGNER, M.D.

Abstract A QRS scoring system for estimating the size of a myocardial infarct was evaluated in 55 patients who did not have left ventricular hypertrophy or conduction abnormalities. Serial 12-lead surface electrocardiograms were scored according to a 29-point system based on the duration of Q and R waves and on the ratios of R-to-Q amplitude and R-to-S amplitude. The scores were proportional to the severity of wall-motion abnormalities, which was determined by radionuclide blood-pool scanning and which correlated inversely with the radionuclide-determined left ventricular ejection fraction (LVEF). A score >3 was 93 per cent sensitive and 88 per cent specific for both severe regional dyssynergy and major depression of the global LVEF. The following equation was used to estimate the LVEF from the QRS score: LVEF (%) = 60 – (3 × QRS score).

After acute myocardial infarction, an electrocardiogram can provide important indirect quantitative information about left ventricular function. (N Engl J Med. 1982; 306:4-9.)

COHORT OF 84 PATIENTS

N Engl J Med. 1982 Jan 7;306(1):4-9. doi: 10.1056/NEJM198201073060102

Table 1. Criteria for Determining Point Score in the QRS Scoring System.[9]

Lead	Criteria (No. of Points)		Maximum Points
	Duration	Amplitude Ratio	
I	Q ≥30 msec (1)	R/Q ≤1 (1)	2
II	Q ≥40 msec (2) Q ≥30 msec (1)		2
aVL	Q ≥30 msec (1)	R/Q ≤1 (1)	2
aVF	Q ≥50 msec (3) Q ≥40 msec (2) Q ≥30 msec (1)	R/Q ≤1 (2) R/Q ≤2 (1)	5
V_1	Any Q (1) R ≥50 msec (2) R ≥40 msec (1)	 R/S ≥1 (1)	4
V_2	Any Q or R ≤20 msec (1) R ≥60 msec (2) R ≥50 msec (1)	 R/S ≥1.5 (1)	4
V_3	Any Q or R ≤30 msec (1)		1
V_4	Q ≥20 msec (1)	R/Q or R/S ≤0.5 (2) R/Q or R/S ≤1 (1)	3
V_5	Q ≥30 msec (1)	R/Q or R/S ≤1 (2) R/Q or R/S ≤2 (1)	3
V_6	Q ≥30 msec (1)	R/Q or R/S ≤1 (2) R/Q or R/S ≤3 (1)	3

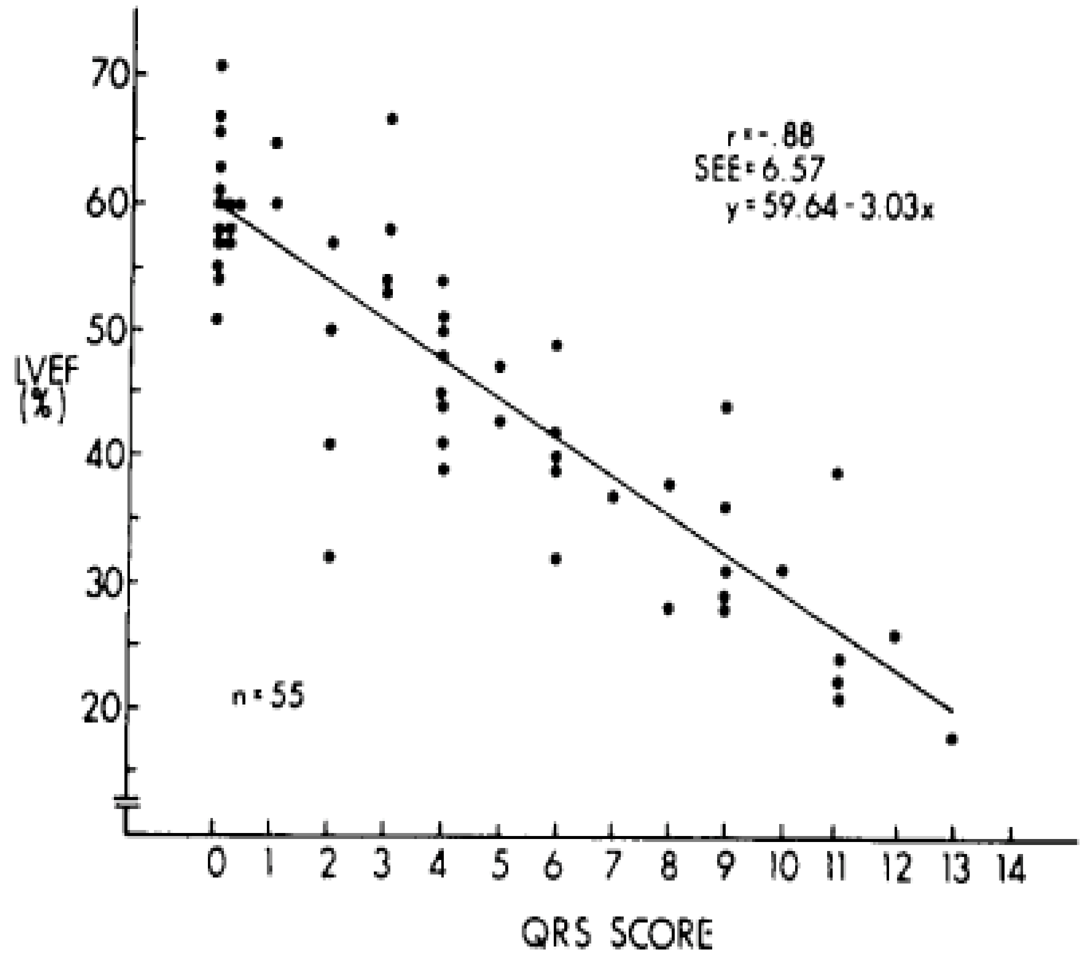
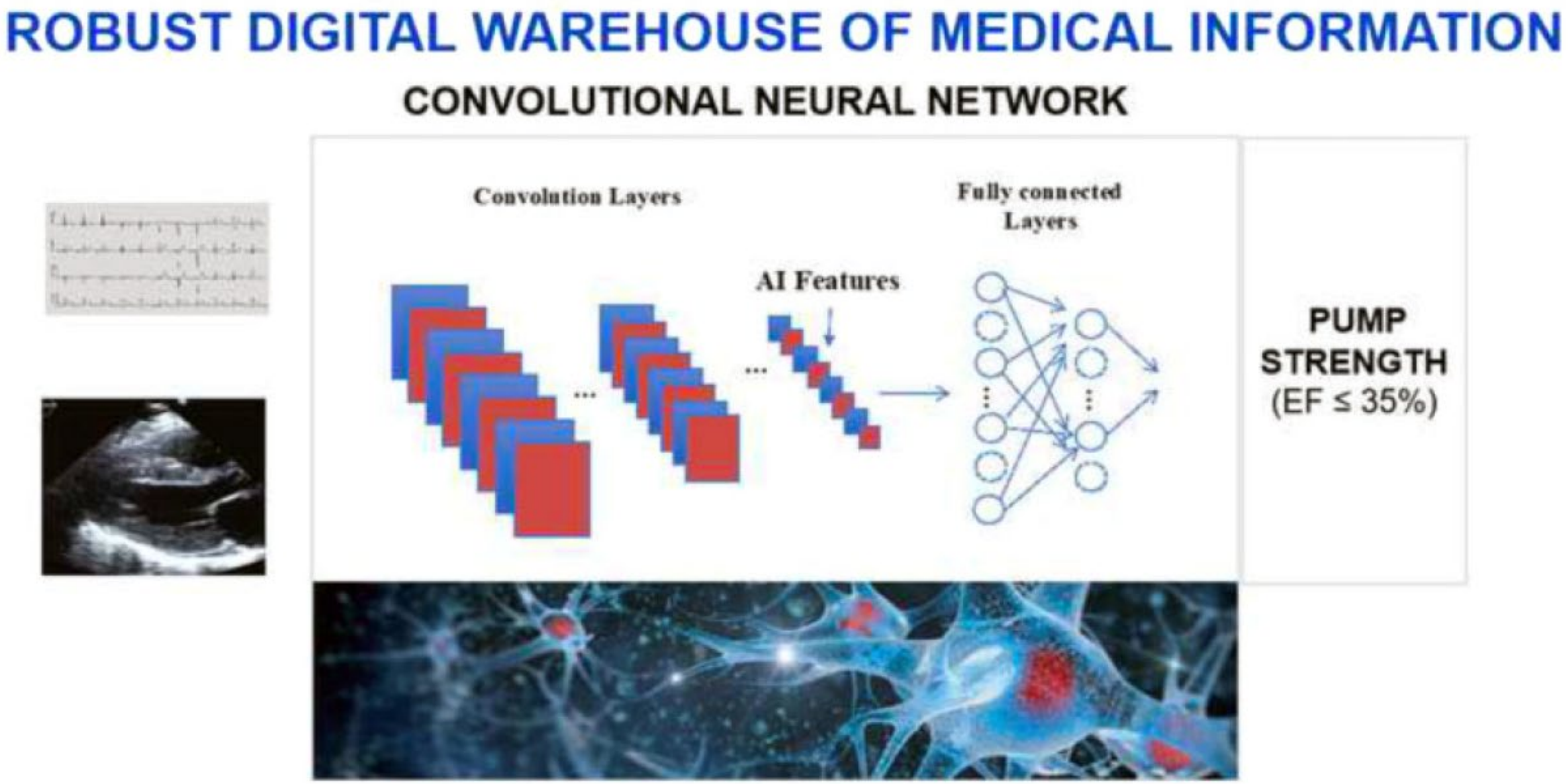


Figure 1. Correlation between QRS Score and LVEF (Determined by Radionuclide Angiography) Three Weeks after Infarction.

Konvolučná neuronálna sieť (CNN) s “učením pod dohľadom” (supervised learning)

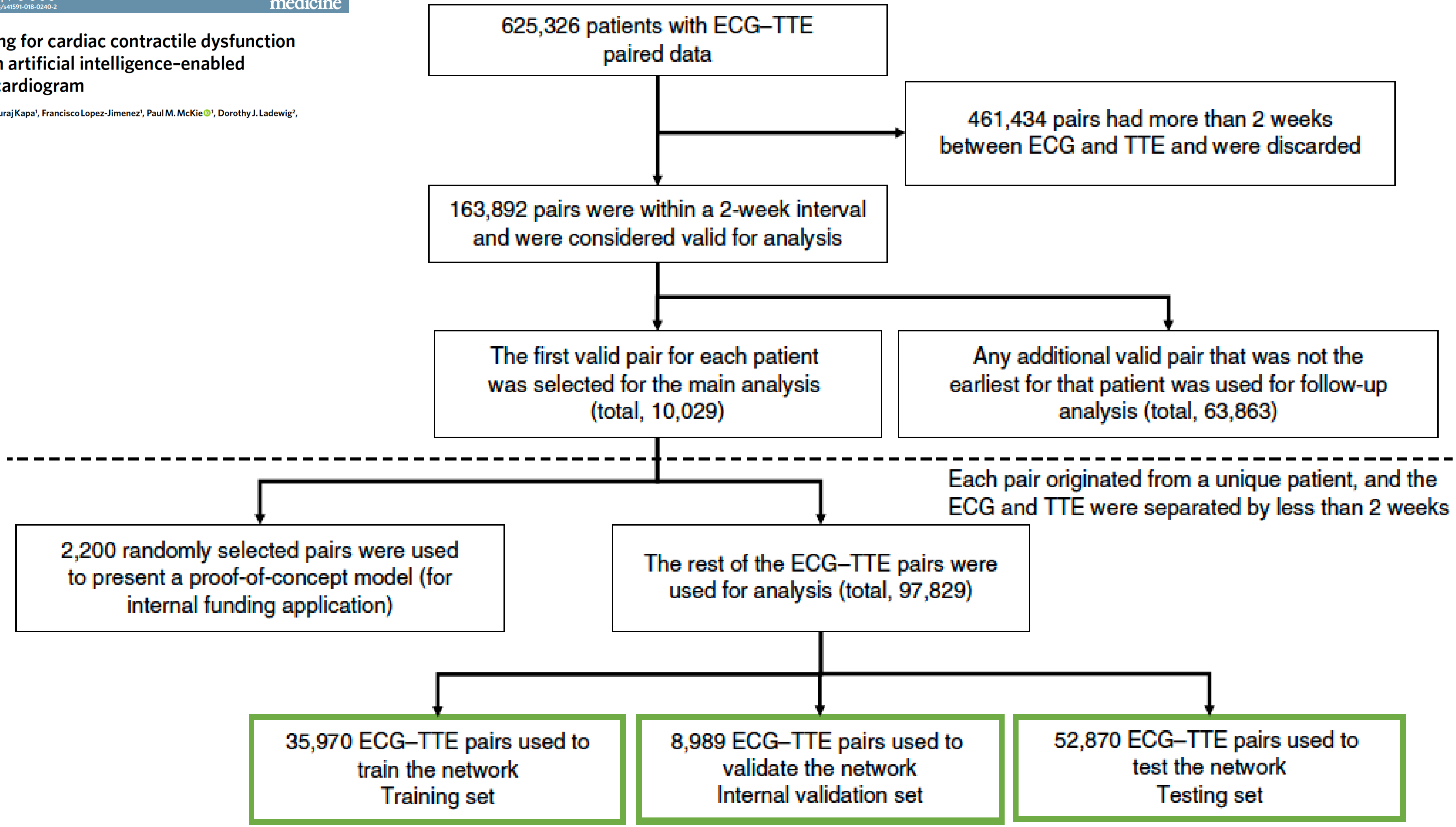


Attia Z et al. Eur Heart J. 2021;ehab649. doi:10.1093/eurheartj/ehab649

LETTERS | FOCUS
https://doi.org/10.1038/s41591-018-0240-2
nature medicine

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

Zachi I. Attia[1], Suraj Kapa[1], Francisco Lopez-Jimenez[1], Paul M. McKie[1], Dorothy J. Ladewig[2],



Attia ZI et al. Nat Med. 2019 Jan;25(1):70-74. doi: 10.1038/s41591-018-0240-2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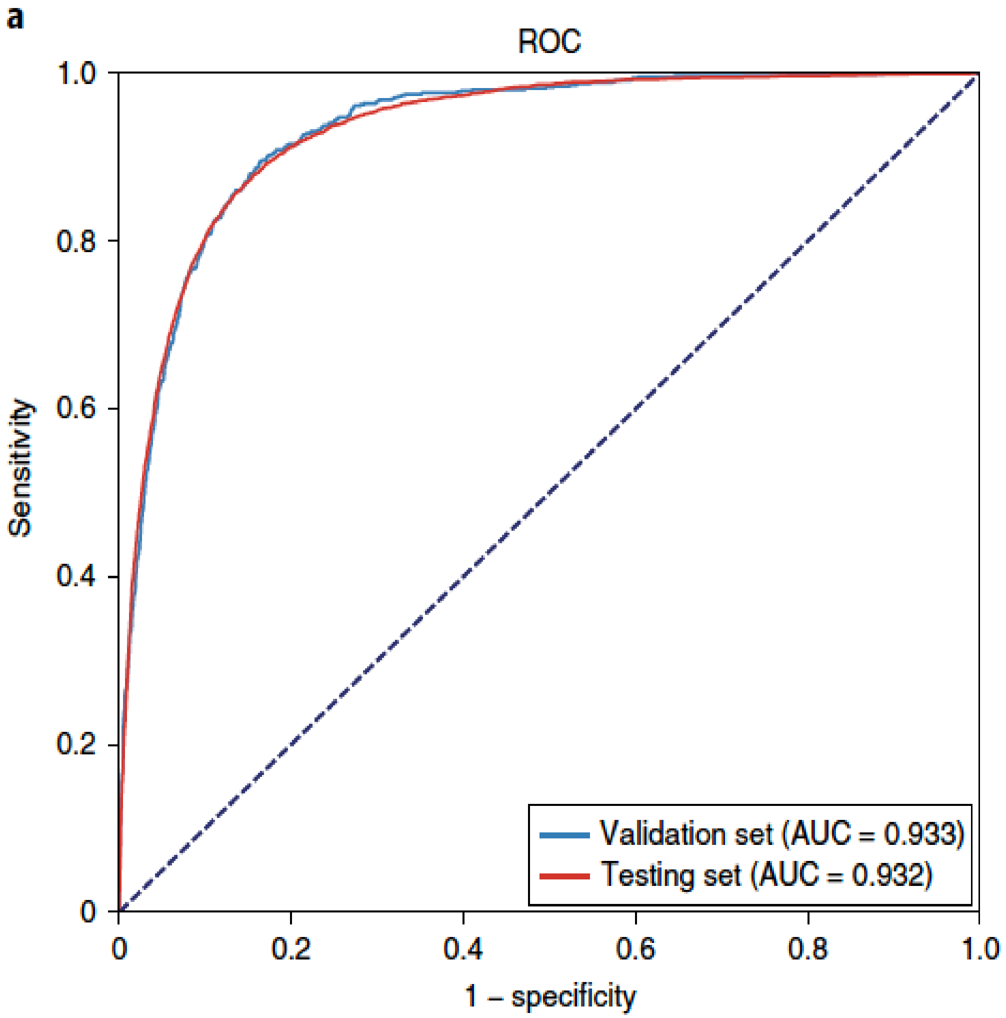

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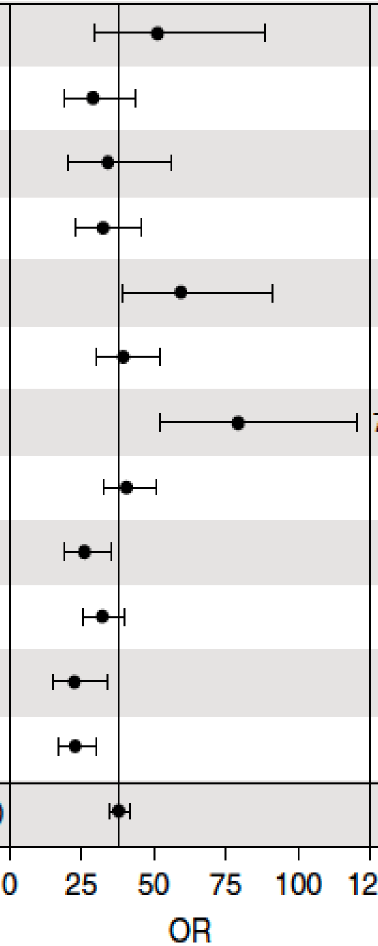
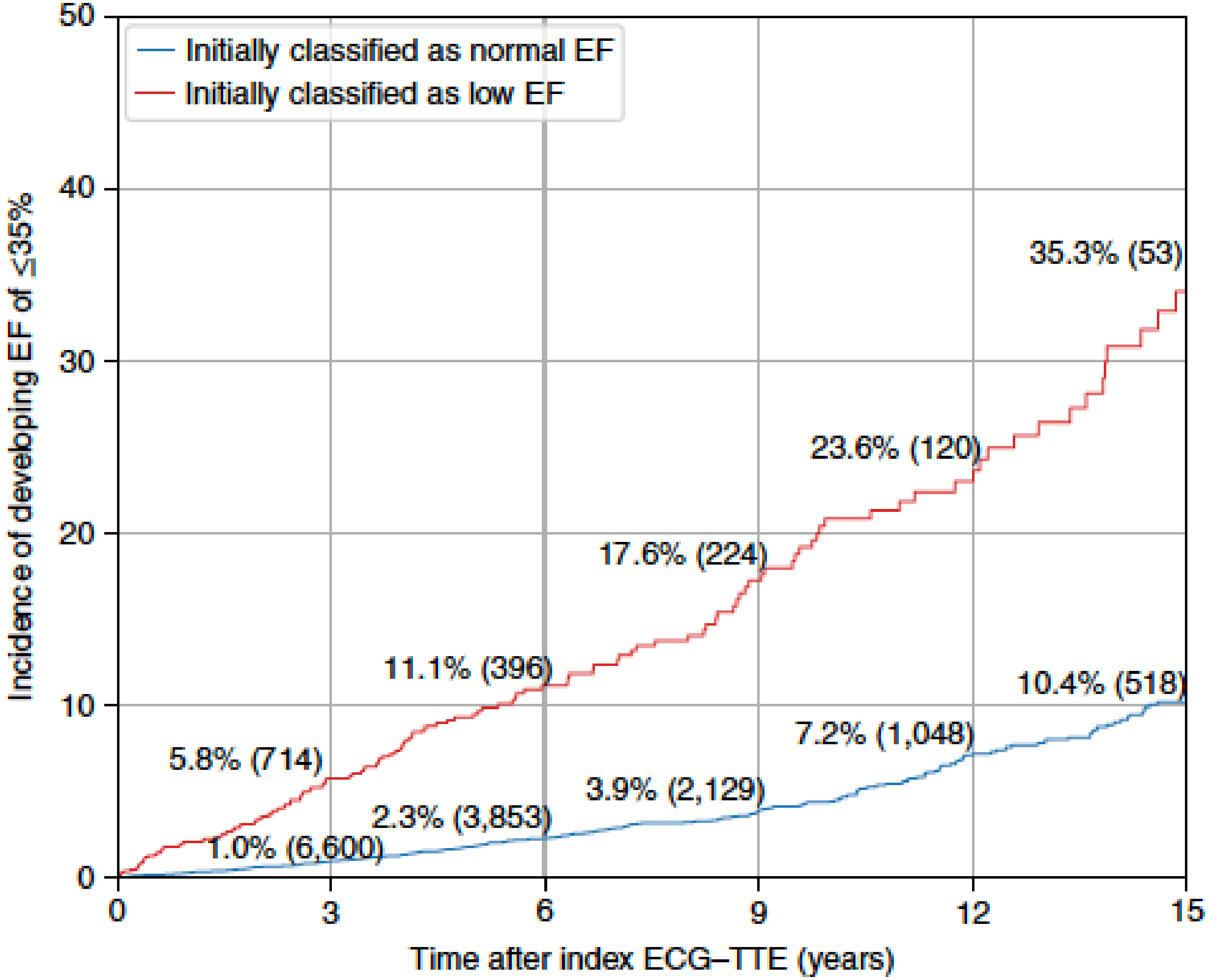
Group	Sensitivity	Specificity	OR (95% CI)
Female <40	74 (53/72)	95 (2,895/3,053)	51.11 (29.55–88.41)
Male <40	72 (86/120)	92 (2,405/2,616)	28.83 (18.92–43.93)
Female 40–49	74 (63/85)	92 (2,300/2,495)	33.78 (20.35–56.07)
Male 40–49	80 (178/223)	89 (2,491/2,796)	32.31 (22.81–45.75)
Female 50–59	85 (150/177)	91 (3,286/3,593)	59.46 (38.83–91.06)
Male 50–59	86 (390/455)	87 (4,440/5,116)	39.41 (29.94–51.87)
Female 60–69	90 (235/260)	89 (4,207/4,707)	79.09 (51.83–120.69)
Male 60–69	89 (722/815)	84 (5,762/6,867)	40.48 (32.32–50.71)
Female 70–79	80 (228/284)	86 (4,230/4,897)	25.82 (19.06–34.98)
Male 70–79	90 (843/936)	78 (5,014/6,433)	32.03 (25.65–40.00)
Female ≥80	84 (156/186)	81 (2,350/2,895)	22.42 (15.00–33.50)
Male ≥80	89 (463/518)	73 (2,382/3,271)	22.56 (16.88–30.14)
Overall	86 (3,567/4,131)	86 (41,762/48,739)	37.86 (34.52–41.52)



Attia ZI et al. Nat Med. 2019 Jan;25(1):70-74. doi: 10.1038/s41591-018-0240-2

Long-term incidence of developing an EF of ≤35% in patients with an initially normal EF stratified by AI classification



HR for developing low LVEF with abnormal AI-ECG = 4.1 (CI 3.3-5.0)

Applying AI permits the ECG to serve as a powerful tool:

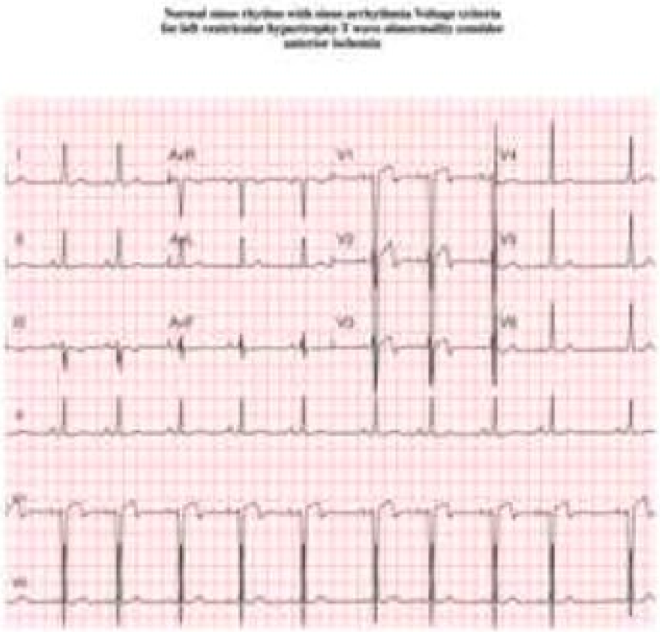
- **to screen for heart failure with LV dysfunction**
- **to identify individuals at increased risk for its development in the future.**

Attia ZI et al. Nat Med. 2019 Jan;25(1):70-74. doi: 10.1038/s41591-018-0240-2

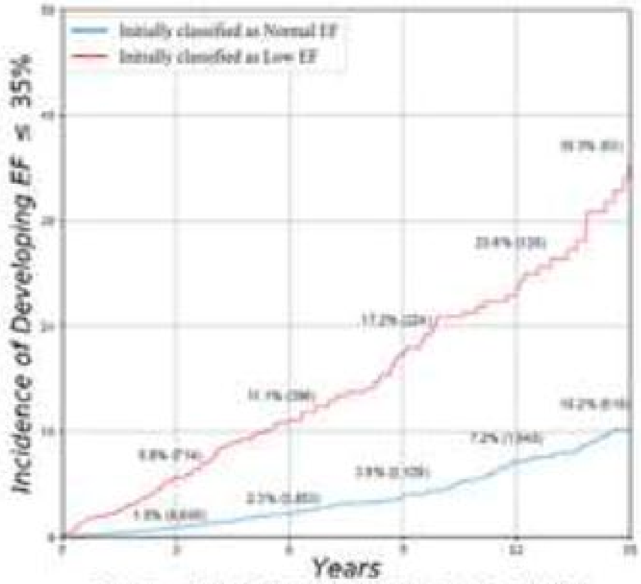
AI ECG: Positive for Low EF

Echo Ejection Fraction: 50%
Apparent False Positive

AI ECG: Positive for Low EF



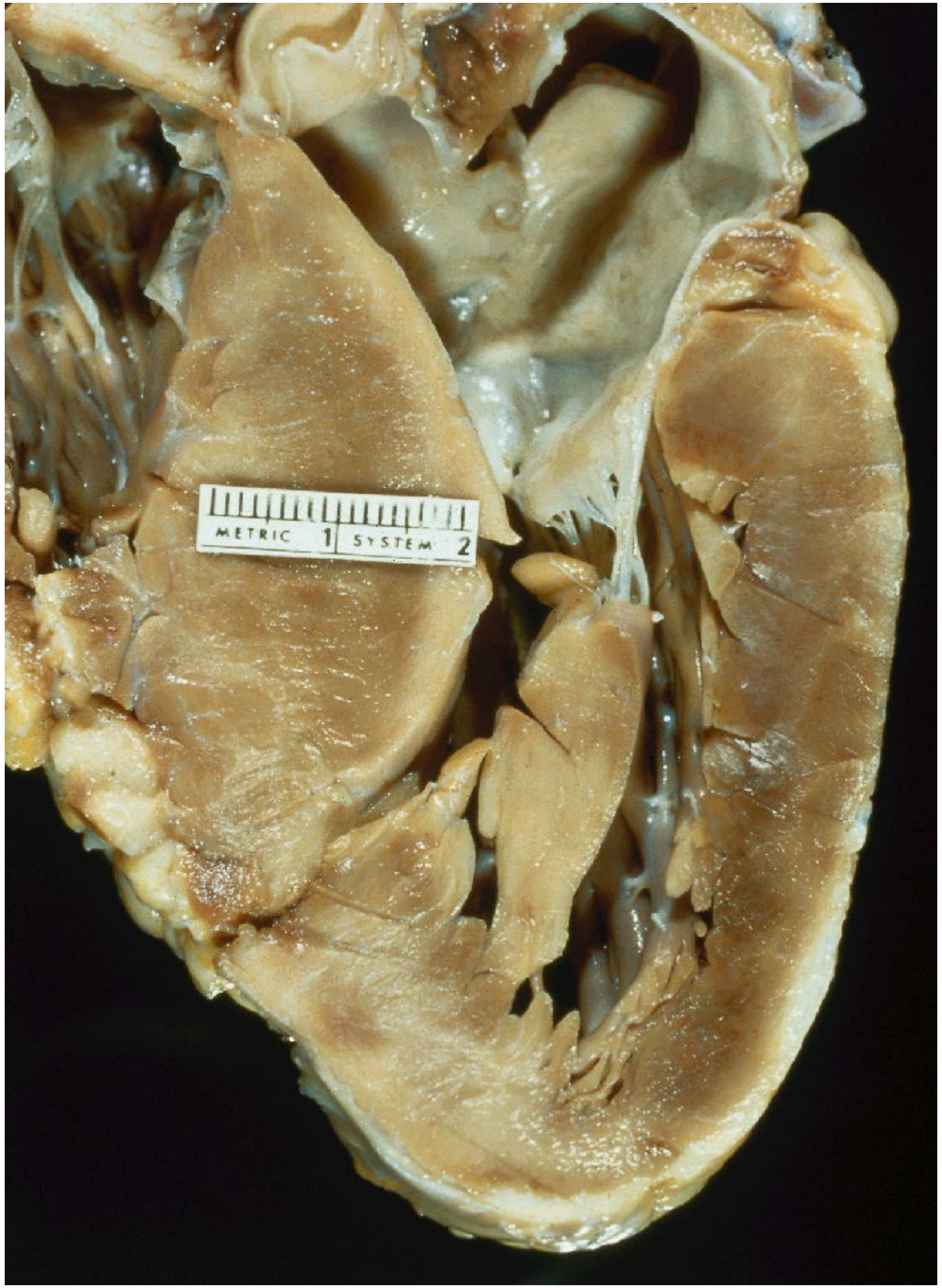
Echo Ejection Fraction 5 years later (age 33) : 31%



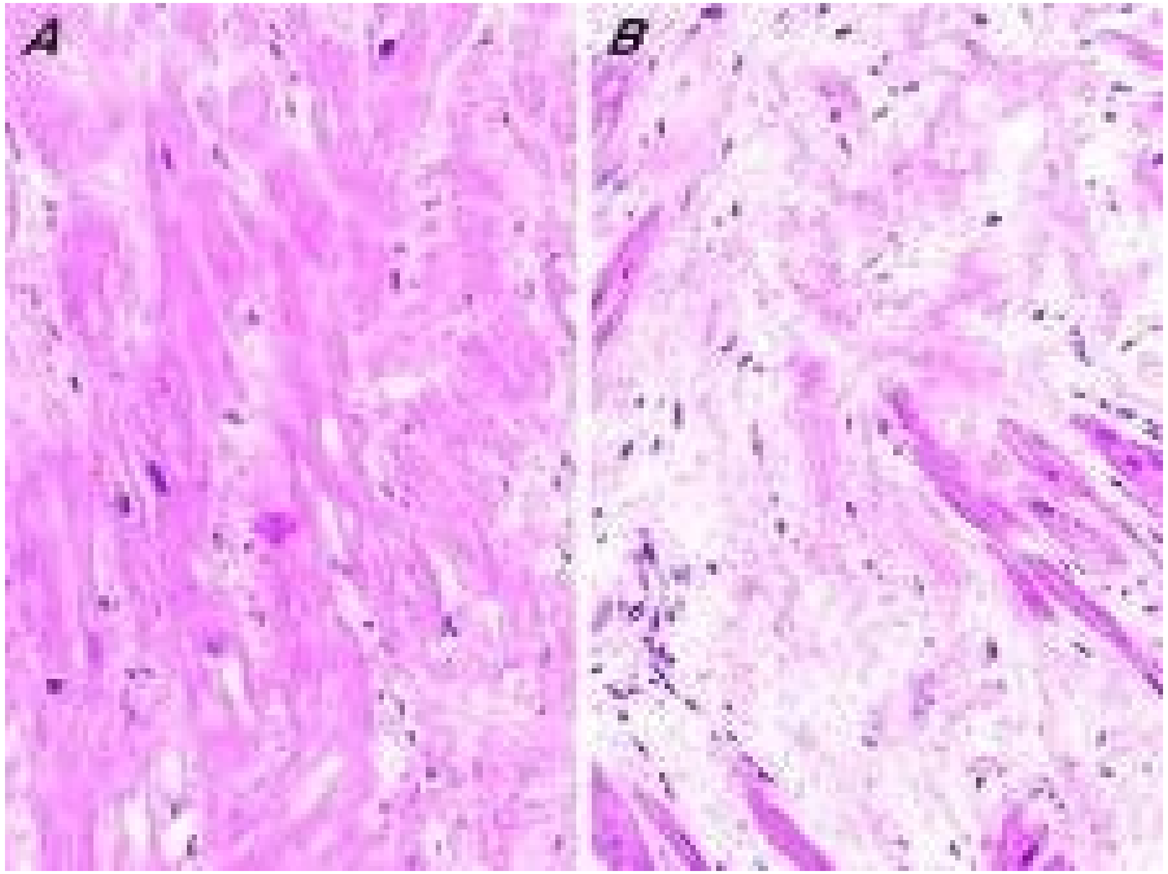
Attia….Friedman Nature Medicine 2019

AI disease "previvor:" disease detected before manifest

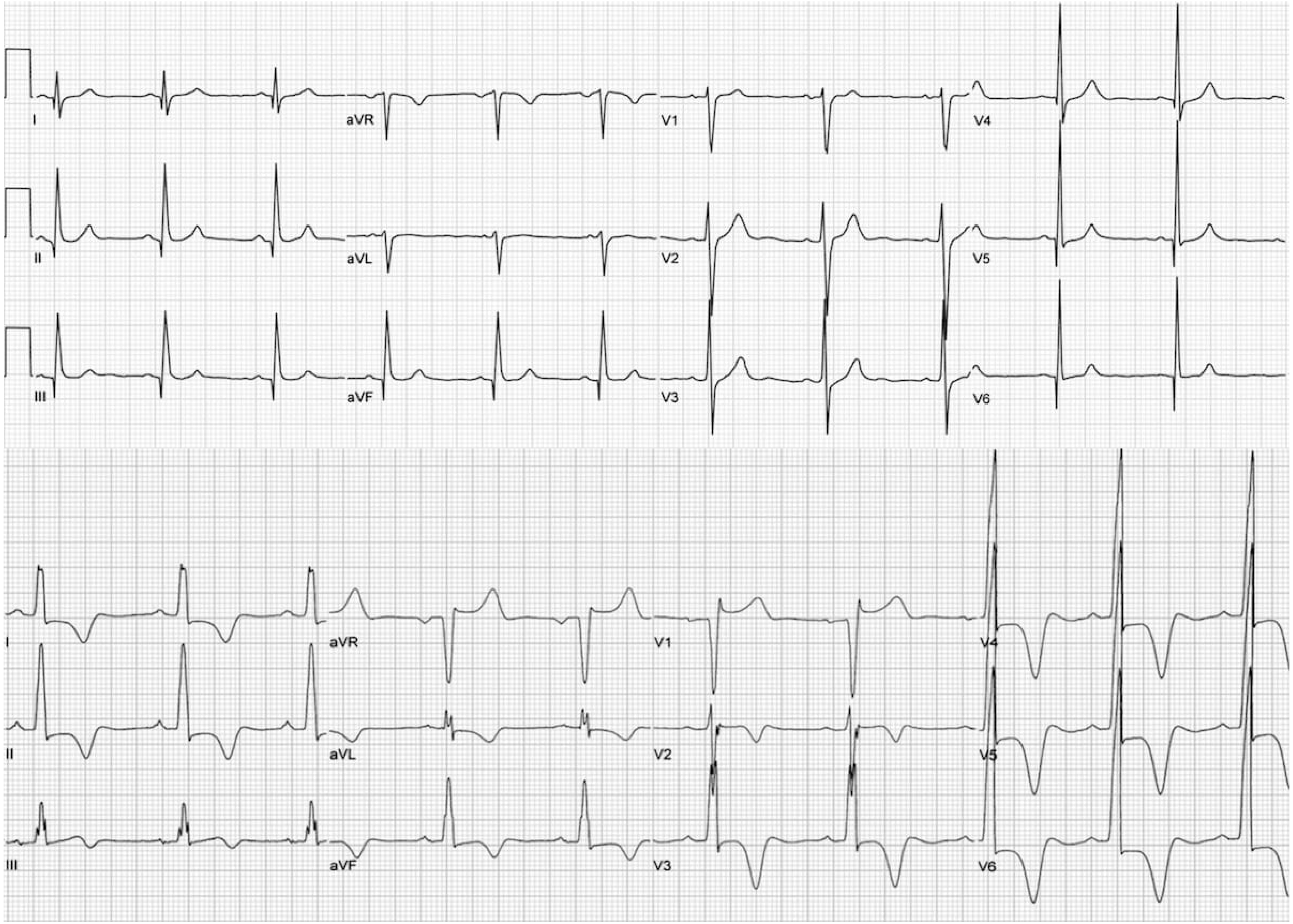
ŠTRUKTURÁLNE OCHORENIA SRDCA



Patologic findings in HCMP

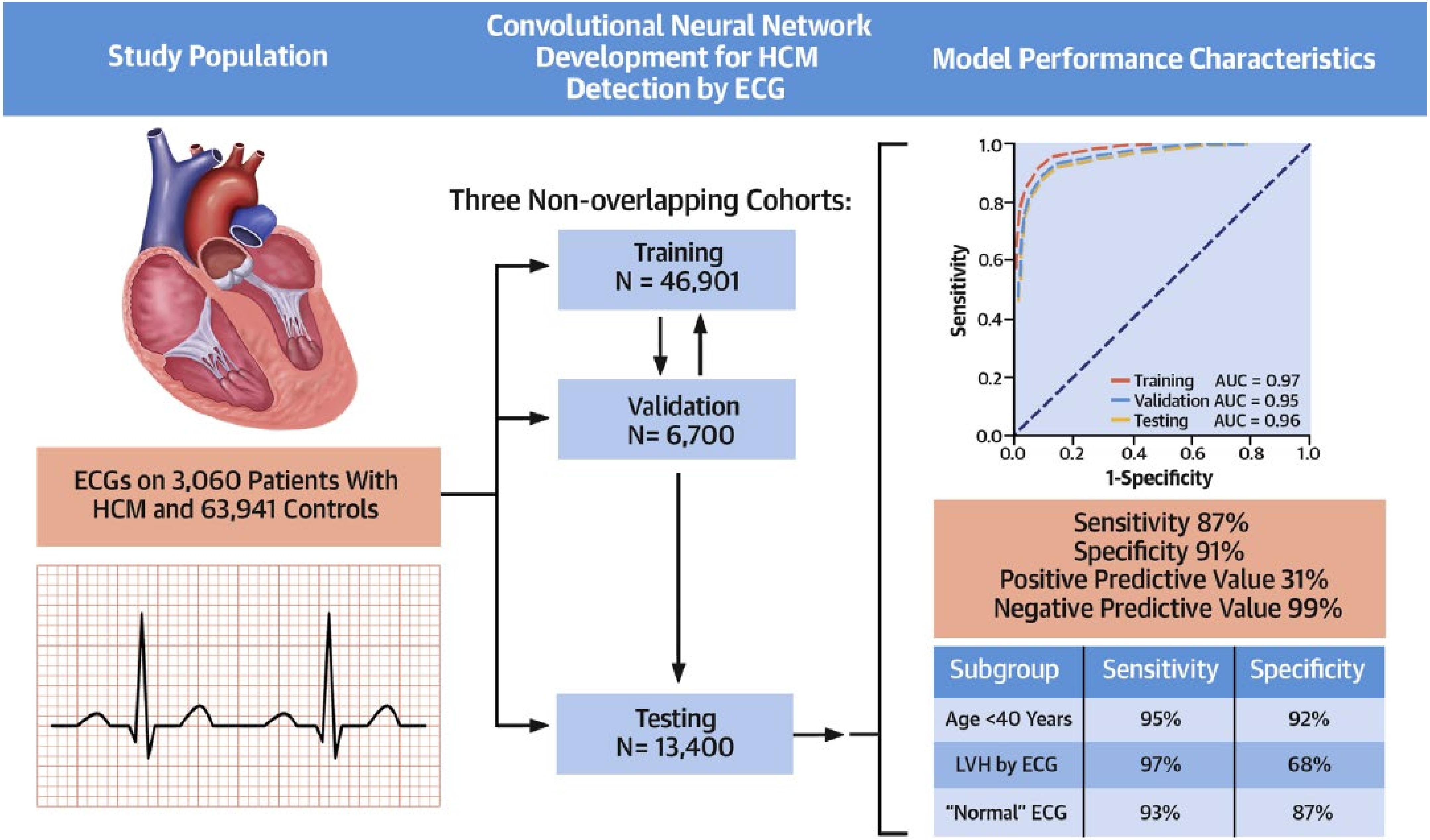


Maron BJ et al. NEJM 1987

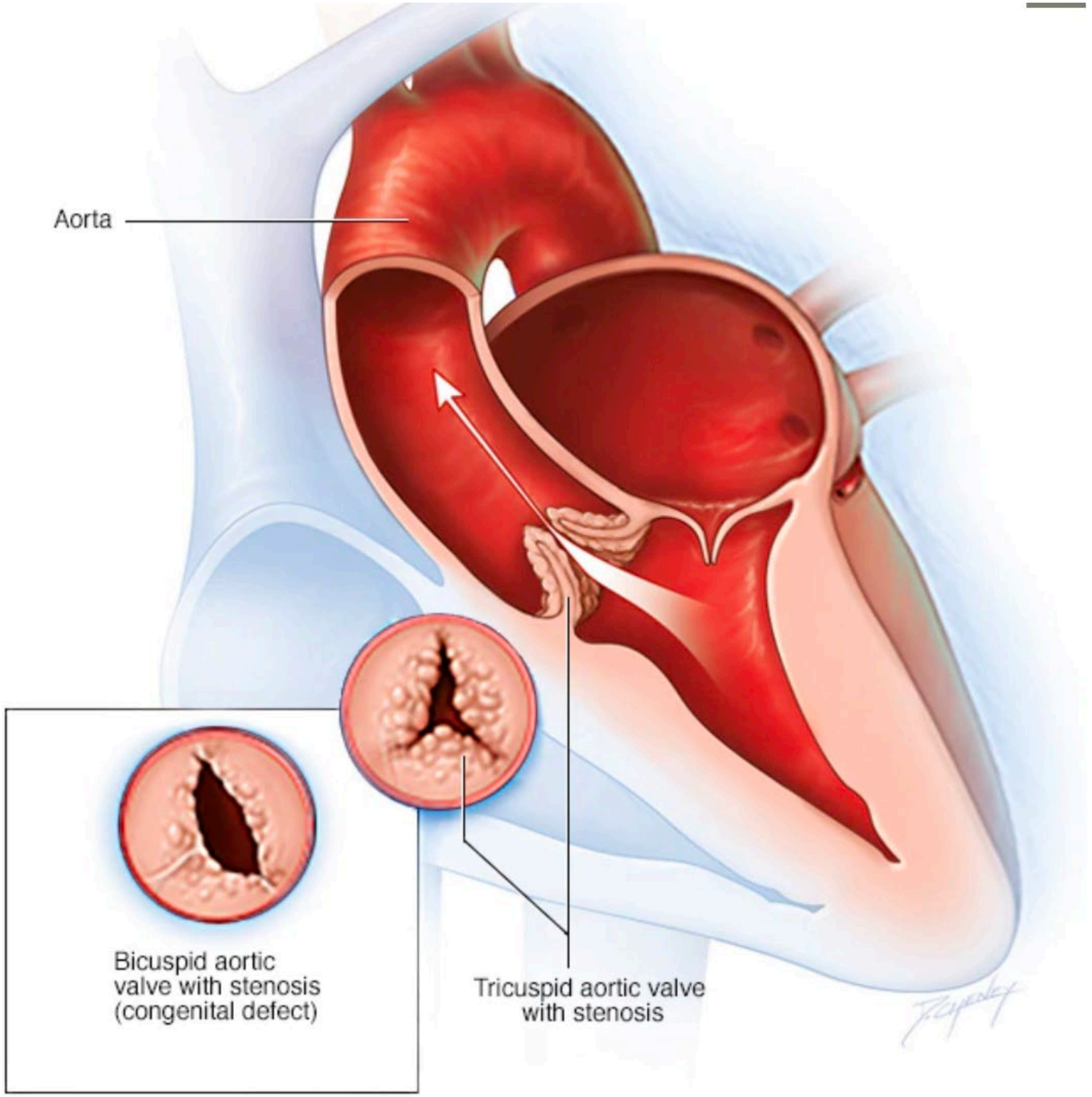


ECG in HCMP

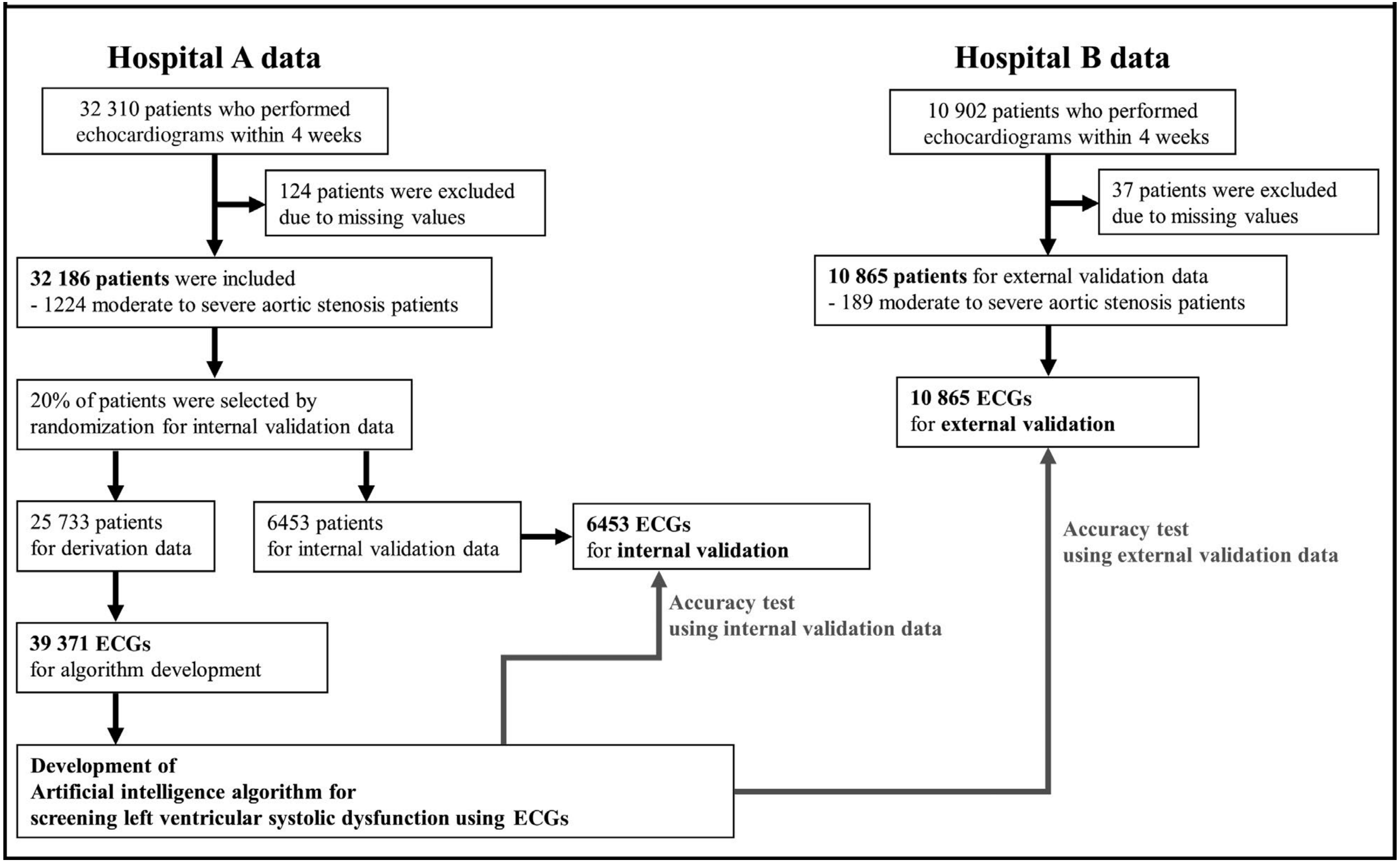
Buttner R, Burns E https://litfl.com/hypertrophic-cardiomyopathy-hcm-ecg-library/

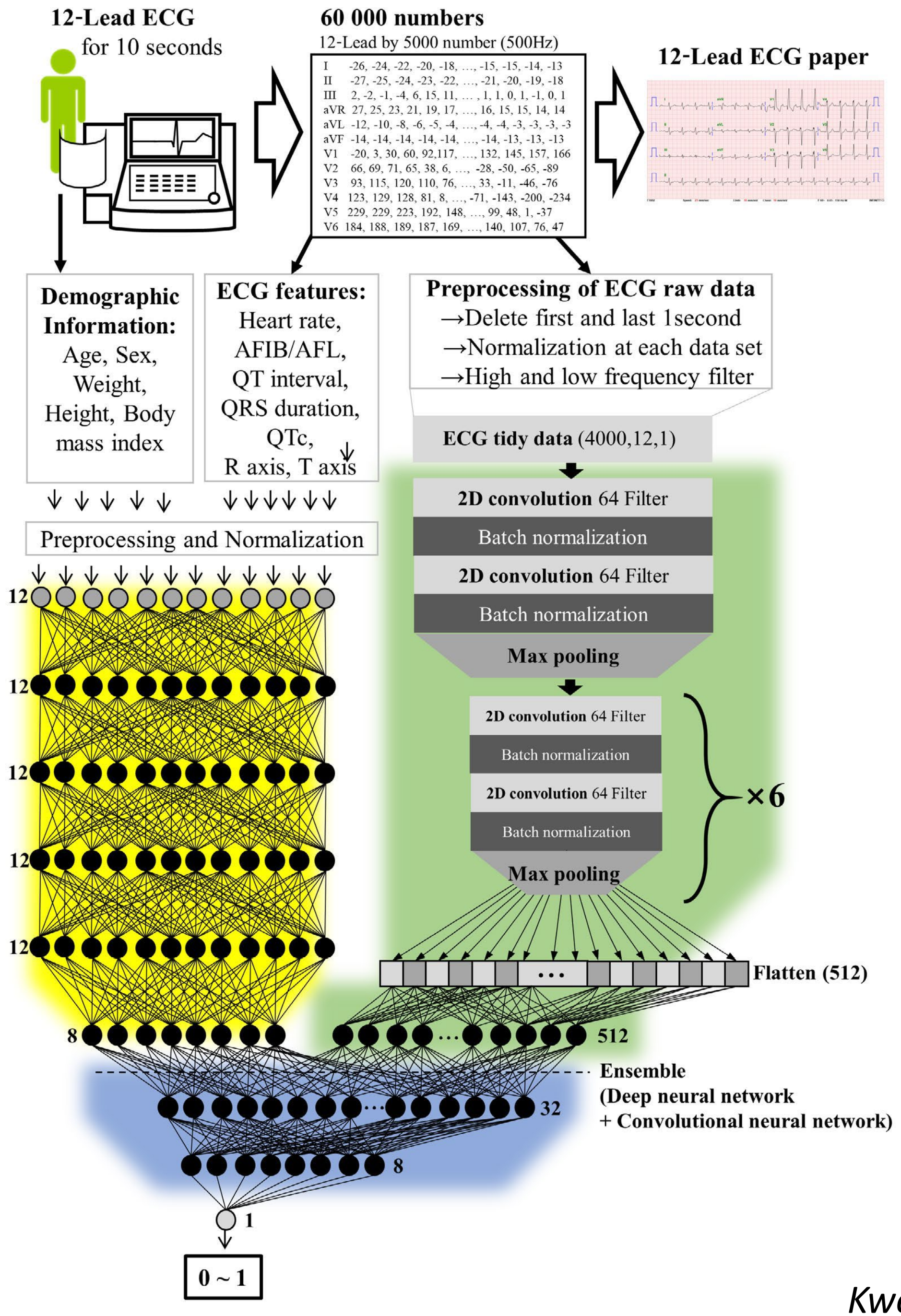


Ko, W.-Y. et al. J Am Coll Cardiol. 2020;75(7):722-33.



AORTIC STENOSIS


Hospital A data
32 310 patients who performed echocardiograms within 4 weeks
124 patients were excluded due to missing values
32 186 patients were included
- 1224 moderate to severe aortic stenosis patients
20% of patients were selected by randomization for internal validation data
25 733 patients for derivation data
6453 patients for internal validation data
6453 ECGs for internal validation
39 371 ECGs for algorithm development
Accuracy test using internal validation data
Development of Artificial intelligence algorithm for screening left ventricular systolic dysfunction using ECGs
Hospital B data
10 902 patients who performed echocardiograms within 4 weeks
37 patients were excluded due to missing values
10 865 patients for external validation data
- 189 moderate to severe aortic stenosis patients
10 865 ECGs for external validation
Accuracy test using external validation data



Journal of the American Heart Association

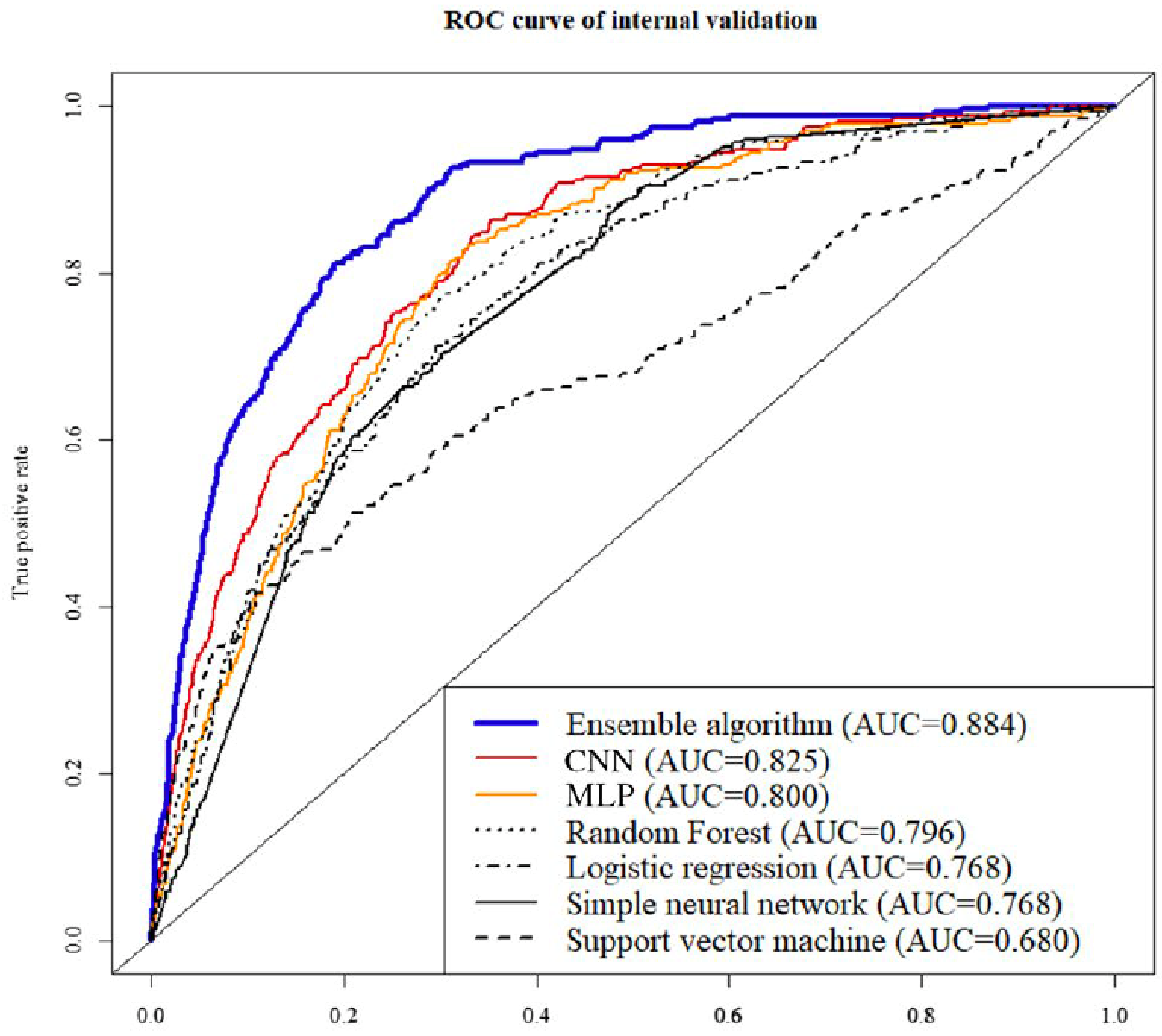
ORIGINAL RESEARCH

Deep Learning–Based Algorithm for Detecting Aortic Stenosis Using Electrocardiography

Joon-Myoung Kwon, MD, MS*; Soo Youn Lee, MD, MS*; Ki-Hyun Jeon, MD, MS; Yeha Lee, PhD; Kyung-Hee Kim, MD, PhD; Jinsik Park, MD, PhD; Byung-Hee Oh, MD, PhD; Myong-Mook Lee, MD, PhD

Algoritmus AI a EKG

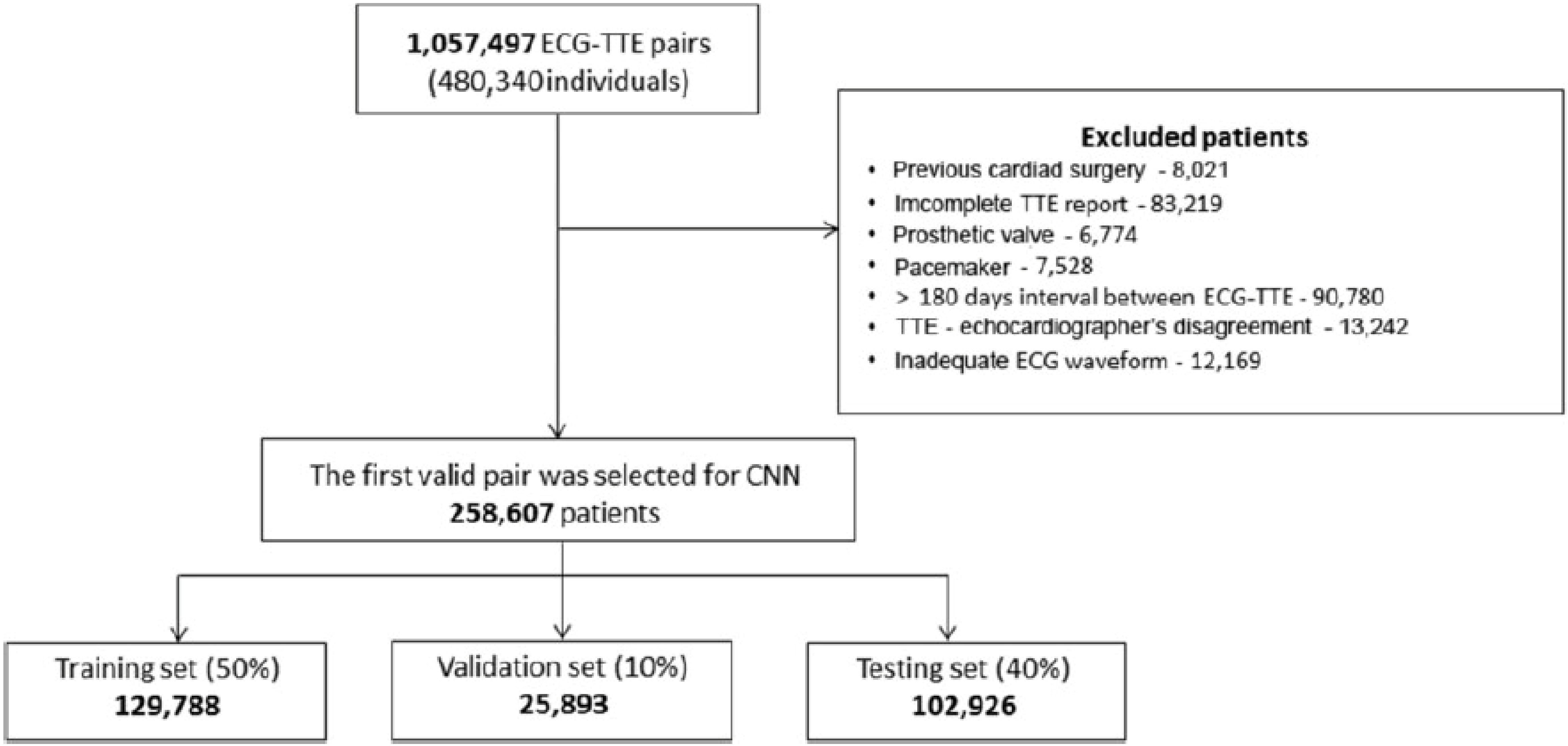
Kwon JM et al. J Am Heart Assoc. 2020;9(7):e014717. doi:10.1161/JAHA.119.014717



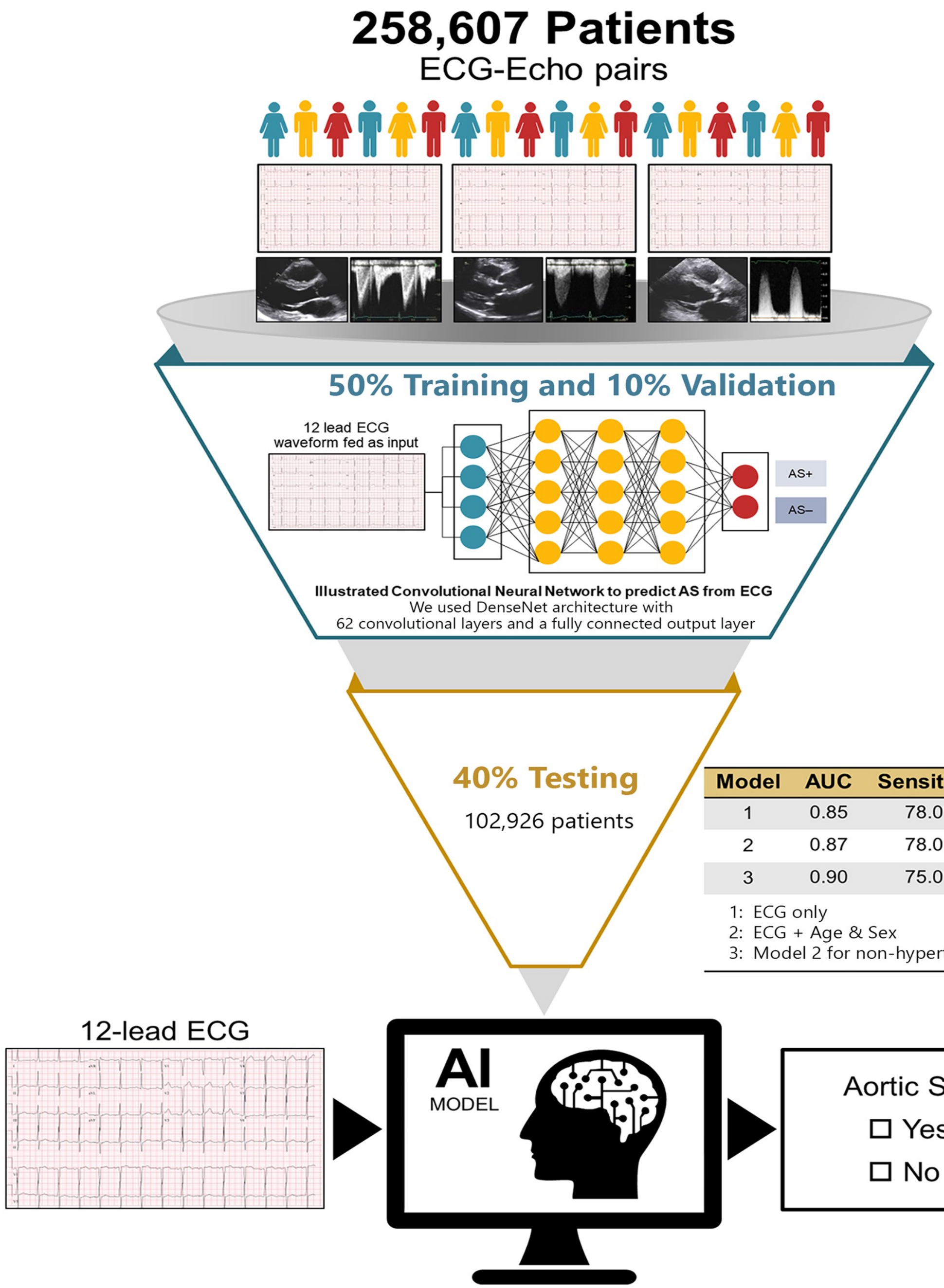
Výkon algoritmu AI pre detekciu aortálnej stenózy

ROC krivka je graf, ktorý popisuje kvalitu bináreho klasifikátora v závislosti na nastavení jeho klasifikačního prahu.

Kwon JM et al. J Am Heart Assoc. 2020;9(7):e014717. doi:10.1161/JAHA.119.014717



Eur Heart J, Volume 42, Issue 30, 7 August 2021, Pages 2885–2896, https://doi.org/10.1093/eurheartj/ehab153

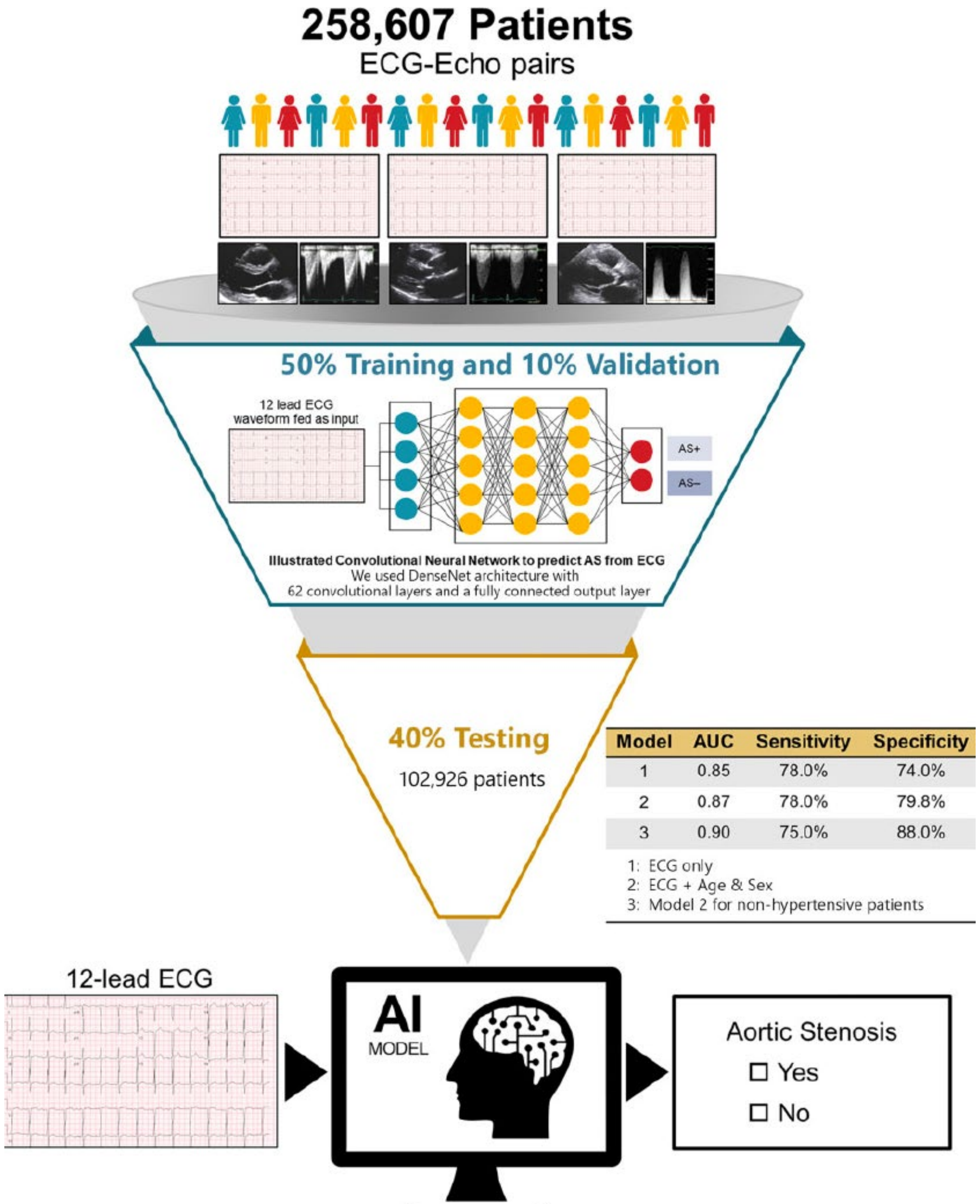


Model	AUC	Sensitivity	Specificity
1	0.85	78.0%	74.0%
2	0.87	78.0%	79.8%
3	0.90	75.0%	88.0%

1: ECG only
2: ECG + Age & Sex
3: Model 2 for non-hypertensive patients

AI-ECG pre skríning aortálnej stenózy pomocou konvolučných neuronálnych sietí (CNN)

Eur Heart J, Volume 42, Issue 30, 7 August 2021, Pages 2885–2896, https://doi.org/10.1093/eurheartj/ehab153



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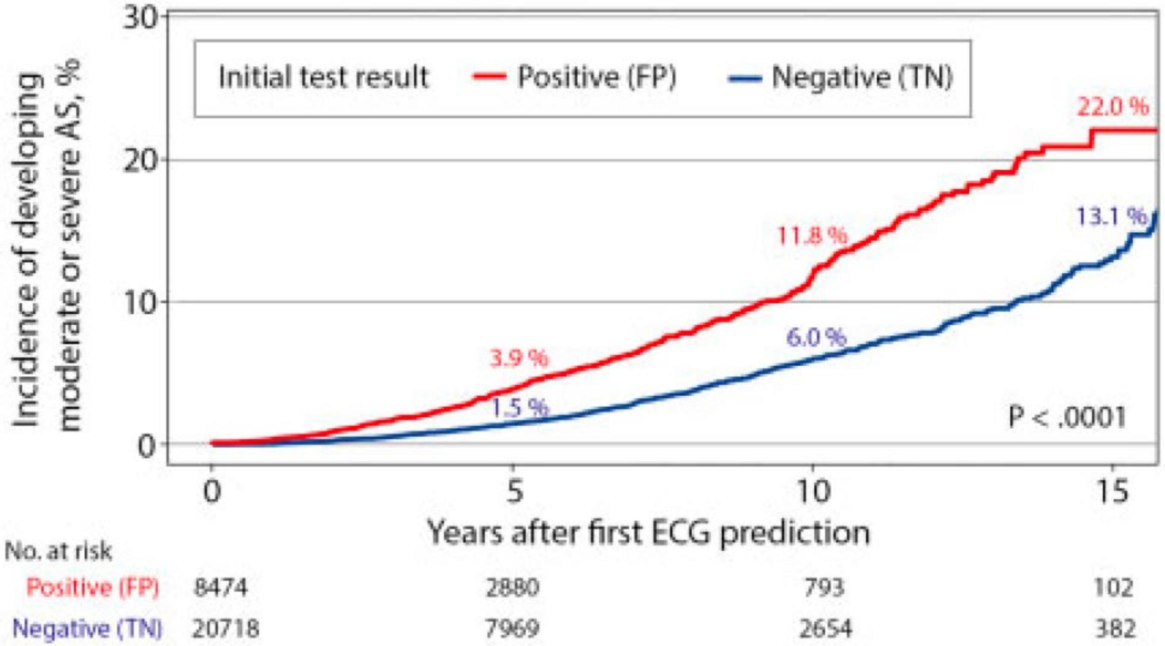
ESC European Society of Cardiology
European Heart Journal (2021) **00**, 1–12
doi:10.1093/eurheartj/ehab153
CLINICAL RESEARCH
Valvular heart disease

Electrocardiogram screening for aortic valve stenosis using artificial intelligence

Michal Cohen-Shelly [1], Zachi I. Attia [1], Paul A. Friedman[1], Saki Ito[1],



Positive predictive value was low at 10.5%, but negative predictive value was 98.9%.

NEKARDIÁLNE OCHORENIA

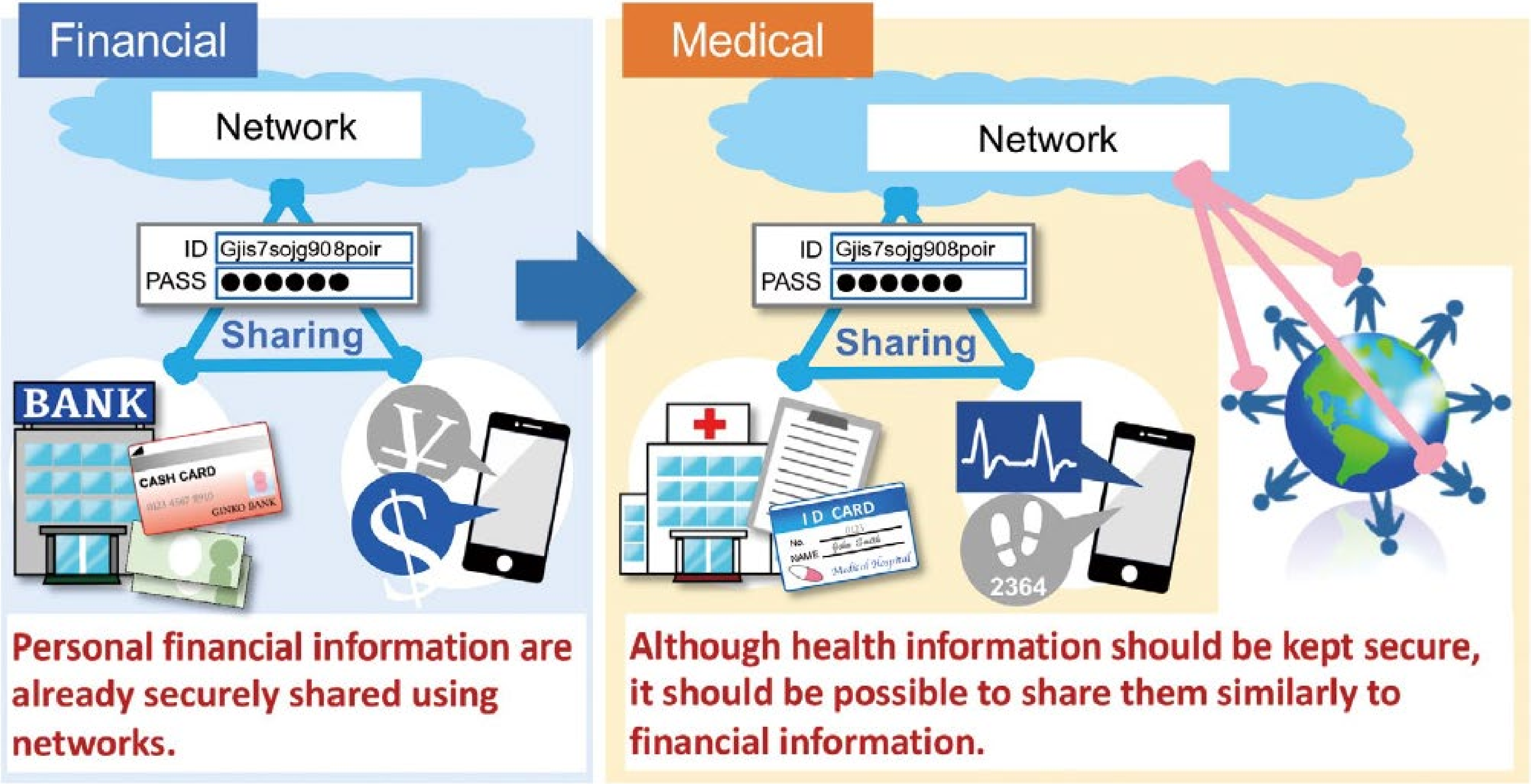
JAMA Cardiology | Original Investigation

Development and Validation of a Deep-Learning Model to Screen for Hyperkalemia From the Electrocardiogram

Conner D. Galloway, MSc; Alexander V. Valys, BS; Jacqueline B. Shreibati, MD; Daniel L. Treiman, BS;
Frank L. Petterson, PhD; Vivek P. Gundotra; David E. Albert, MD; Zachi I. Attia, MSc; Rickey E. Carter, PhD;
Samuel J. Asirvatham, MD; Michael J. Ackerman, MD, PhD; Peter A. Noseworthy, MD;
John J. Dillon, MD; Paul A. Friedman, MD

- Using 2 leads of an ECG acquired from patients with chronic kidney disease, a DL detected elevated potassium with an AUC of 0.853 to 0.883 and a sensitivity of 88.9% to 91.3%.
- The application of AI to the ECG may enable screening for hyperkalemia (HR for death with hyperkalemia as high as 13!)

AI and personal data protection

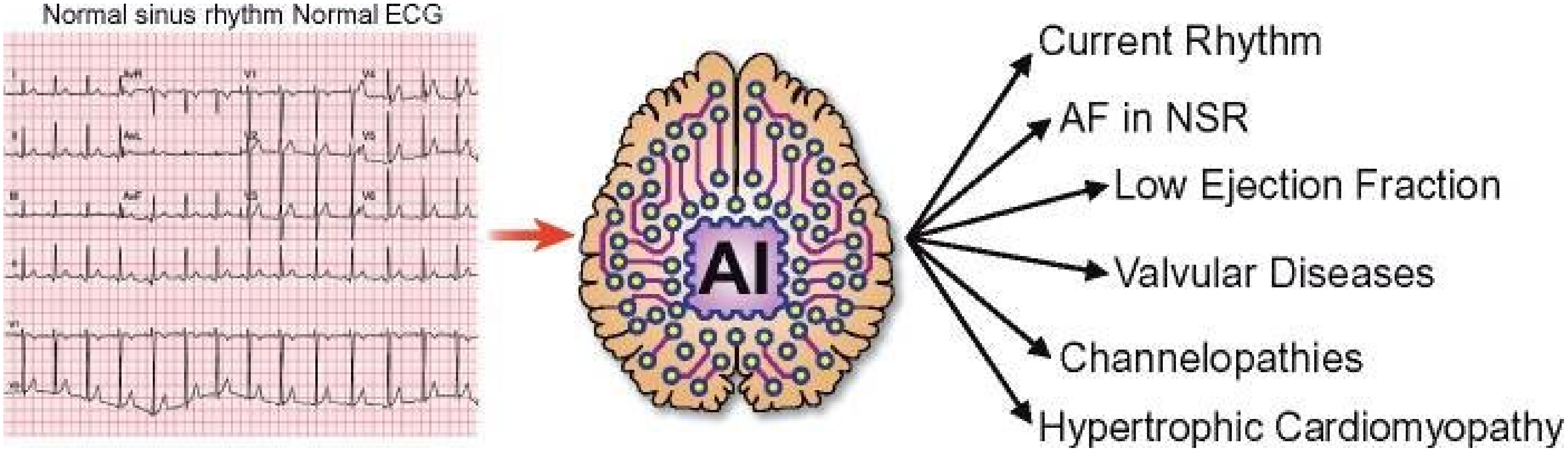


Goto S, Goto S. Circ Rep. 2019 Nov 2;1(11):481-486. doi: 10.1253/circrep.CR-19-0096

AI heralds a new era in expanding the role of ECG

- **ECG is rich** on relevant pathophysiologic information which remained largely undiscovered
- **Deep learning** allows for identifying both ”**visible and invisible**” contents of the ECG.
- **Two important advantages offered**:
  - **compensate for lack of expertise** in ECG interpetation by non-specialist
  - **detecting early stages** of various disease processes incl. non-cardiac diseases not discernable otherwise
- **Potential to diagnose and predict**
  - later manifestatiob of the disease (aortic stenosis, AFIB, HCMP)
  - disease with intermittent phenotype manifestation (paroxysmal arrhythmias)
  - ECG as biomarker for systemic diseases (i.e. NPV for +SARS-CoV2 - 99% …)

AI V KARDIOLÓGII



Attia Z et al. Eur Heart J. 2021;ehab649. doi:10.1093/eurheartj/ehab649

Umelá inteligencia (AI) a EKG

- AI otvára pre EKG netušený, v podstate nadľudský potenciál pre diagnostiku KV ochorení
- Schopnosť učiť sa z obrovského objemu dát (bez potreby súčasnej znalosti ich biologických mechanizmov) vytvára možnosť diagnostikovať aj nekardiálne ochorenia /cirhóza pečene, COVID-19,…)
- Vzhľadom k širokej dostupnosti EKG a jeho získania pomocou "nositeľných! senzorov ("wearables") môže byť AI cestou k "demokratizácii" - t.j. univerzálnej prístupnosti pokročilej kardiovaskulárnej medicíny

A little learning is a dangerous thing;
drink **deep**, or taste not the Pierian spring:
there shallow draughts intoxicate the brain,
and drinking largely sobers us again.

Alexander Pope

"An Essay on Criticism", (1709)

ĎAKUJEM ZA POZORNOSŤ!

THANK YOU FOR YOUR TIME AND ATTENTION !