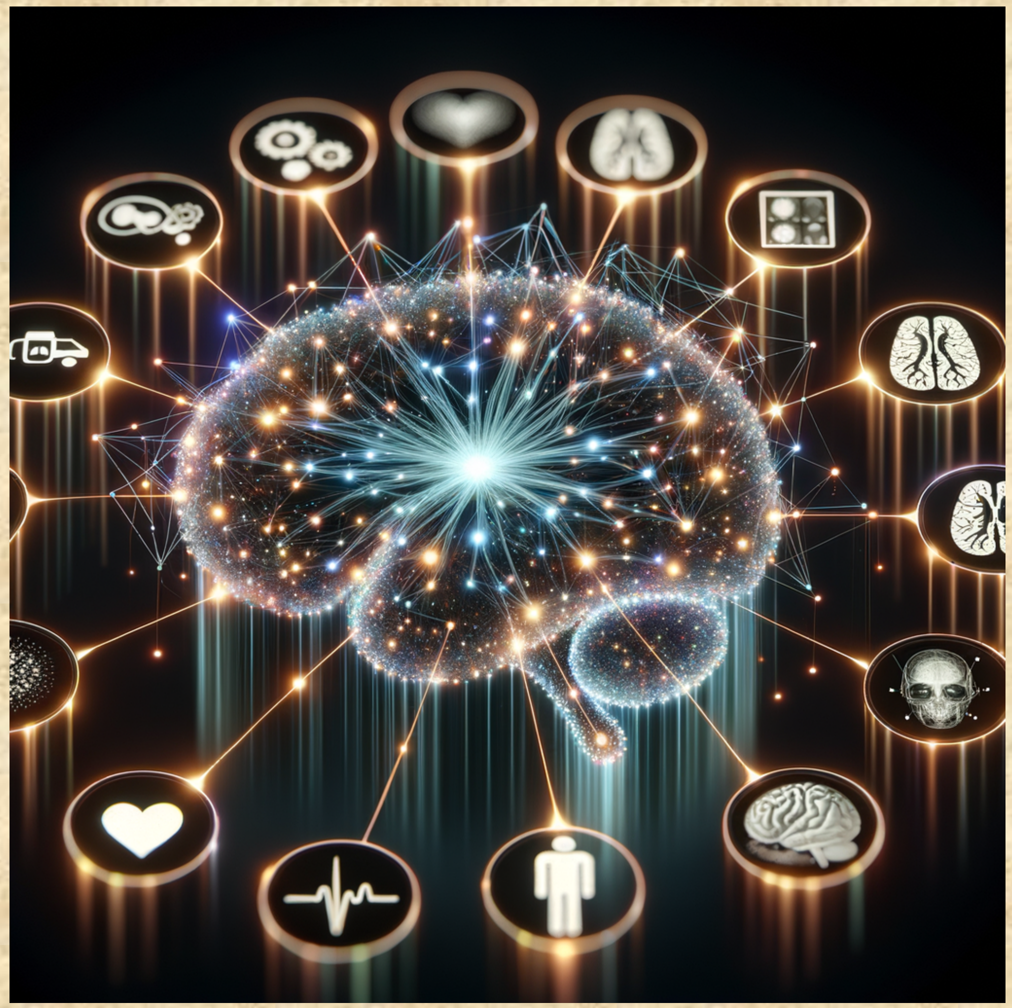
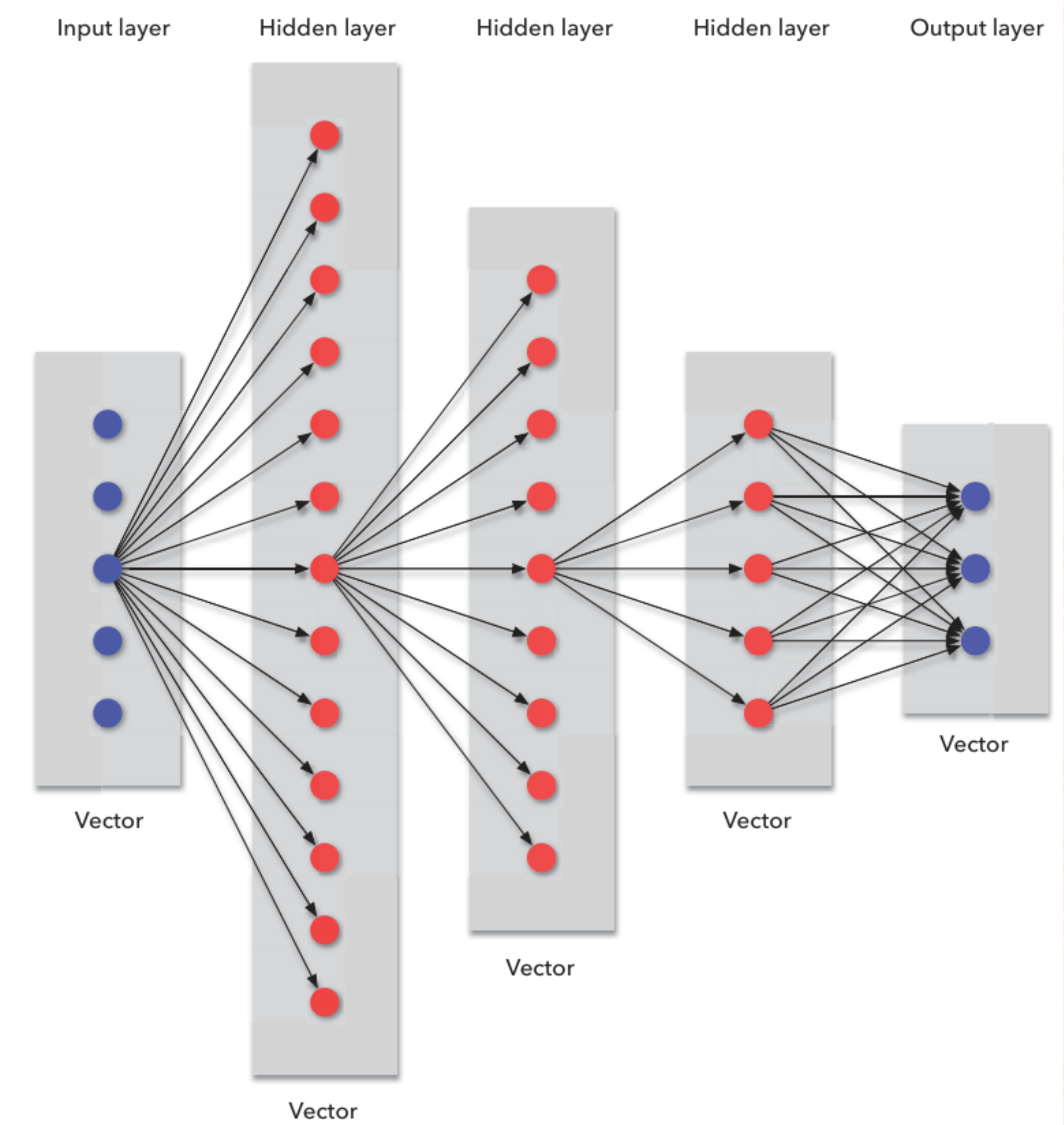
Inteligencia Artificial y Modelos de Lenguaje en Medicina

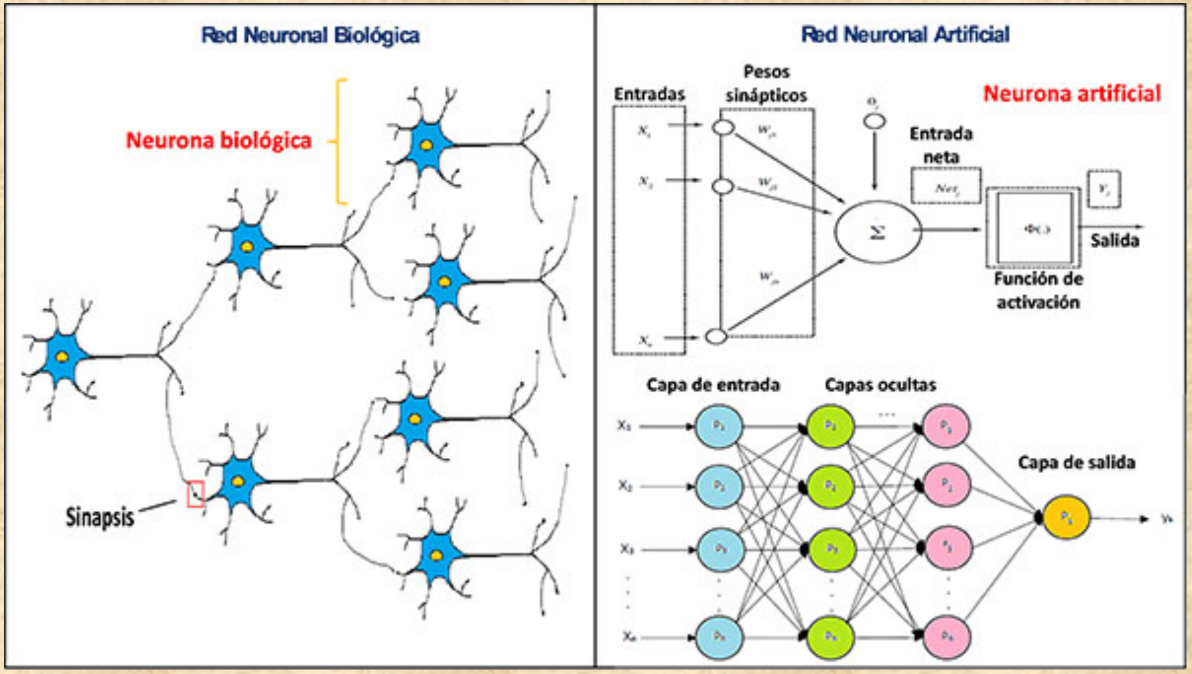


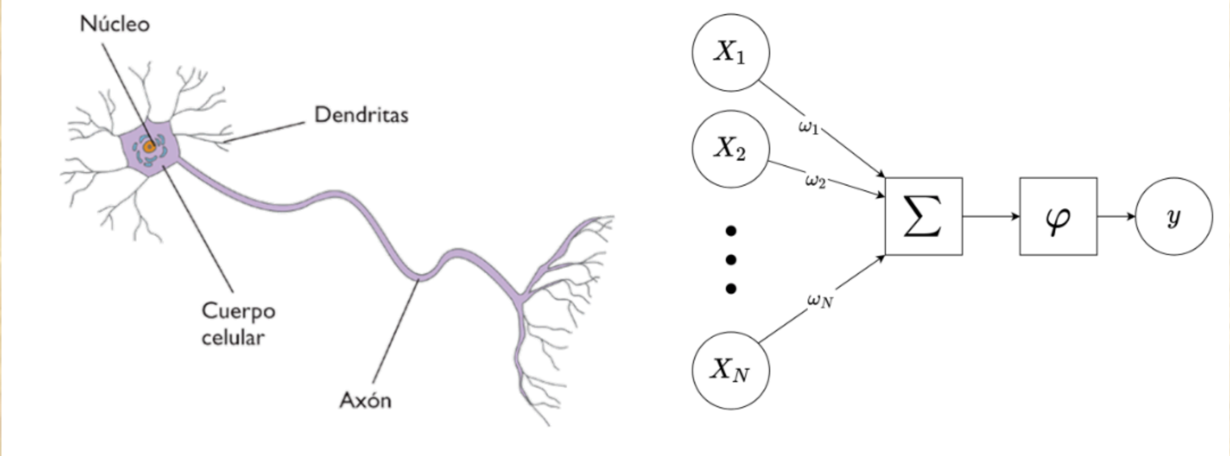
Ángel Martínez
Servicio de Medicina Interna
CAULE
11 Octubre 2024

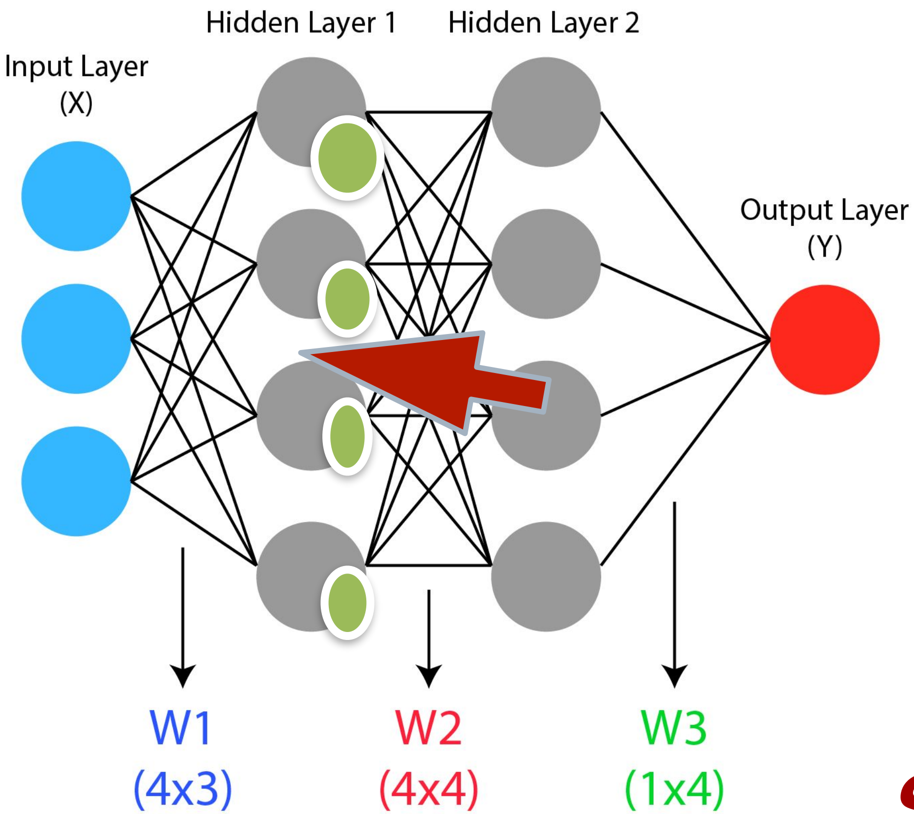
REDES NEURONALES



DE LA NEURONA A LA RED ARTIFICIAL







$$Y = \overbrace{f(W3 * \underbrace{f(W2 * \overbrace{f(W1 * \underset{\text{Input Layer}}{X} + B1)}^{\text{Hidden Layer 1}} + B2)}_{\text{Hidden Layer 2}} + B3)}^{\text{Output layer (Y)}}$$

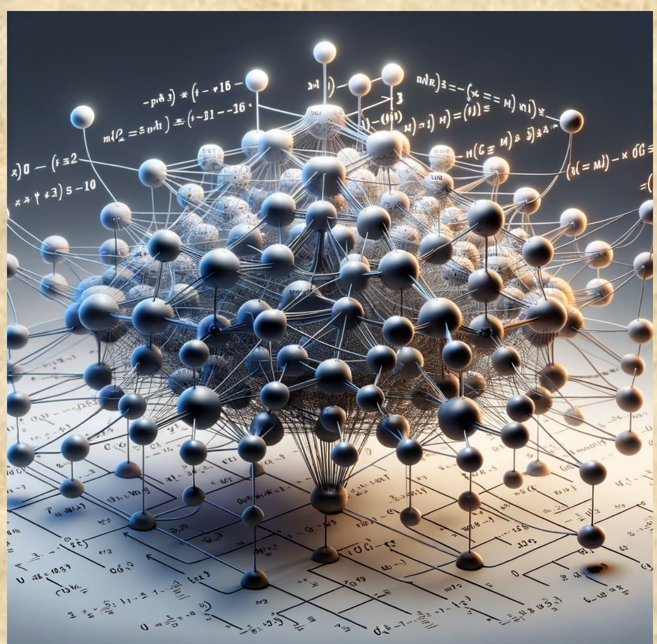
FUNCIÓN DE ACTIVACIÓN F(W)

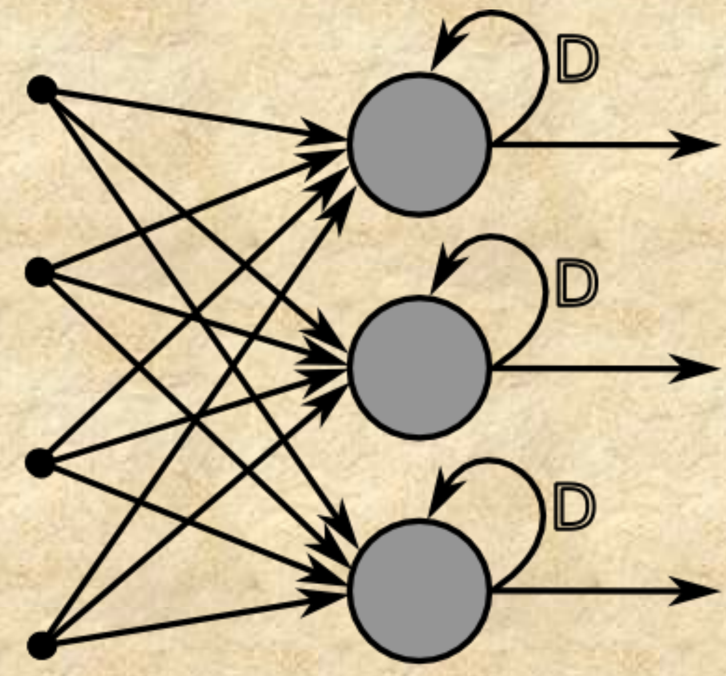
SESGO

RETROPROPAGACIÓN

APRENDIZAJE AUTOMÁTICO

- **Minimizan una función de pérdida (probabilística)**
- **Autoatención: Detectan relaciones sutiles entre los elementos de una secuencia (MODELOS TRANSFORMADORES: CHAT GPT)**
- **El desceso de gradientes (BLACKPROPAGATION) refuerza ciertas vías**
- **LA PROGRESIÓN A TRAVÉS DE LAS CAPAS REFINA LA PREDICCIÓN O LA CATEGORIZACIÓN**





Pitt y McCullogh 1943

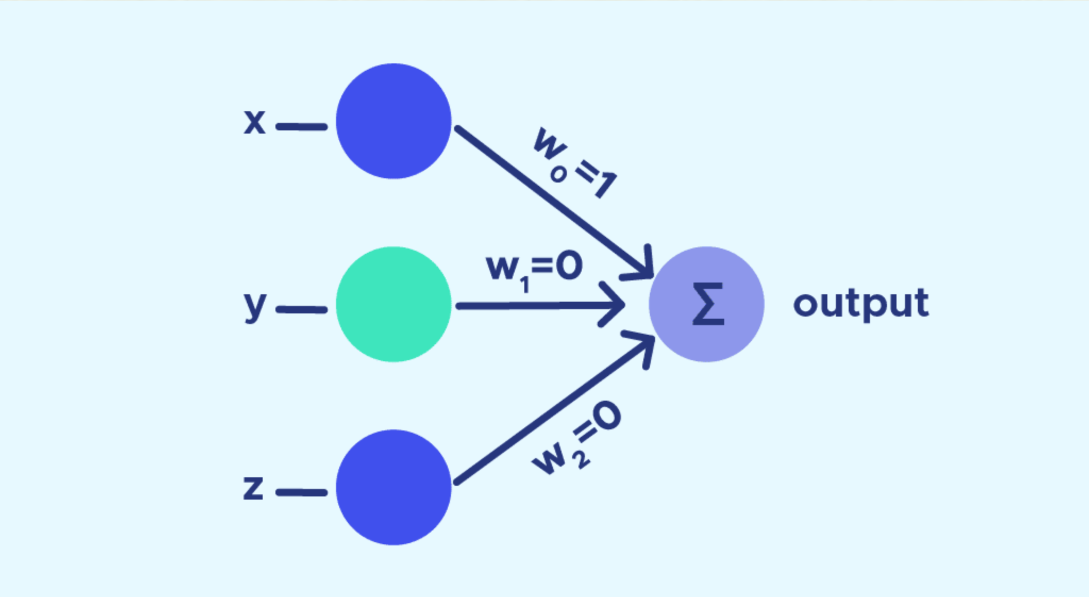
Warren McCulloch y Walter Pitt, "Un Cálculo Lógico de Ideas Immanent en Actividad Nerviosa", 1943, Boletín de Biofísica Matemática

Lo que el ojo de la Rana de dice al cerebro de la Rana" (1959)

APRENDIZAJE DE HEBB (Psicólogo: 1948)

sugerencia de Turing, que el córtex humano infantil es lo que llamaba «máquina desorganizada» (también conocido como «máquina Turing Tipo B»

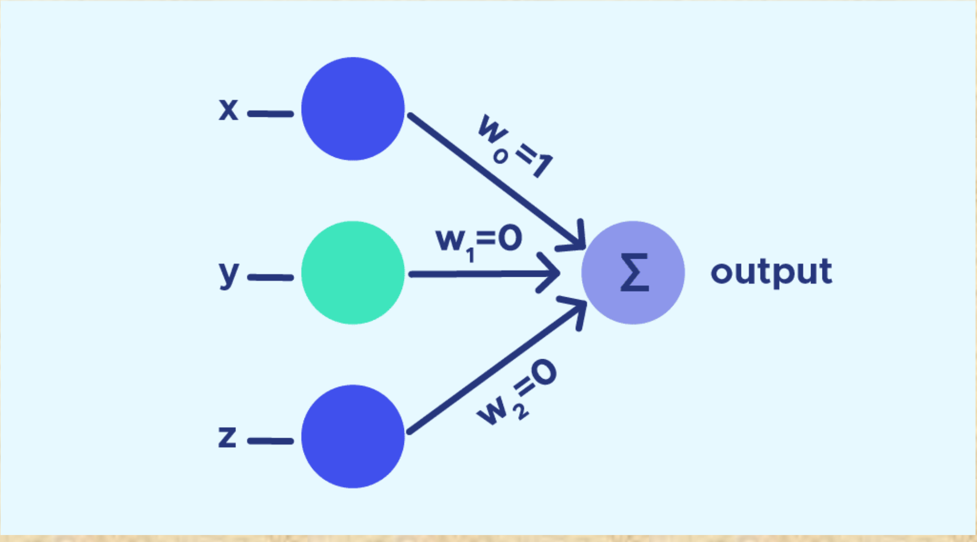
1957 Frank Rosenblatt (Cornell): Perceptrón (neurona artificial)

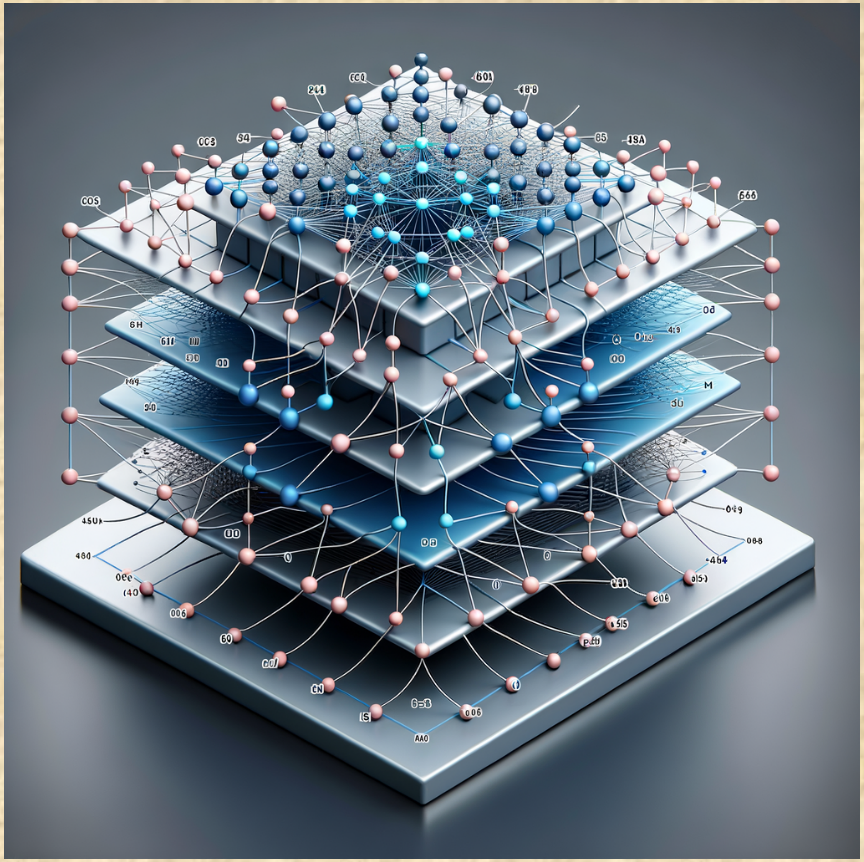


En realidad **el perceptrón es una función matemática**. Los datos de entrada (x) se multiplican por los coeficientes de peso (w). El resultado es un valor.

Ese **valor puede ser positivo o negativo**. La neurona artificial se activa si el valor es positivo. Solo se activa si el peso calculado de los datos de entrada supera un umbral determinado.

El **resultado predicho se compara con el resultado conocido**. En caso de diferencia, el error se retropropaga para permitir ajustar los pesos.

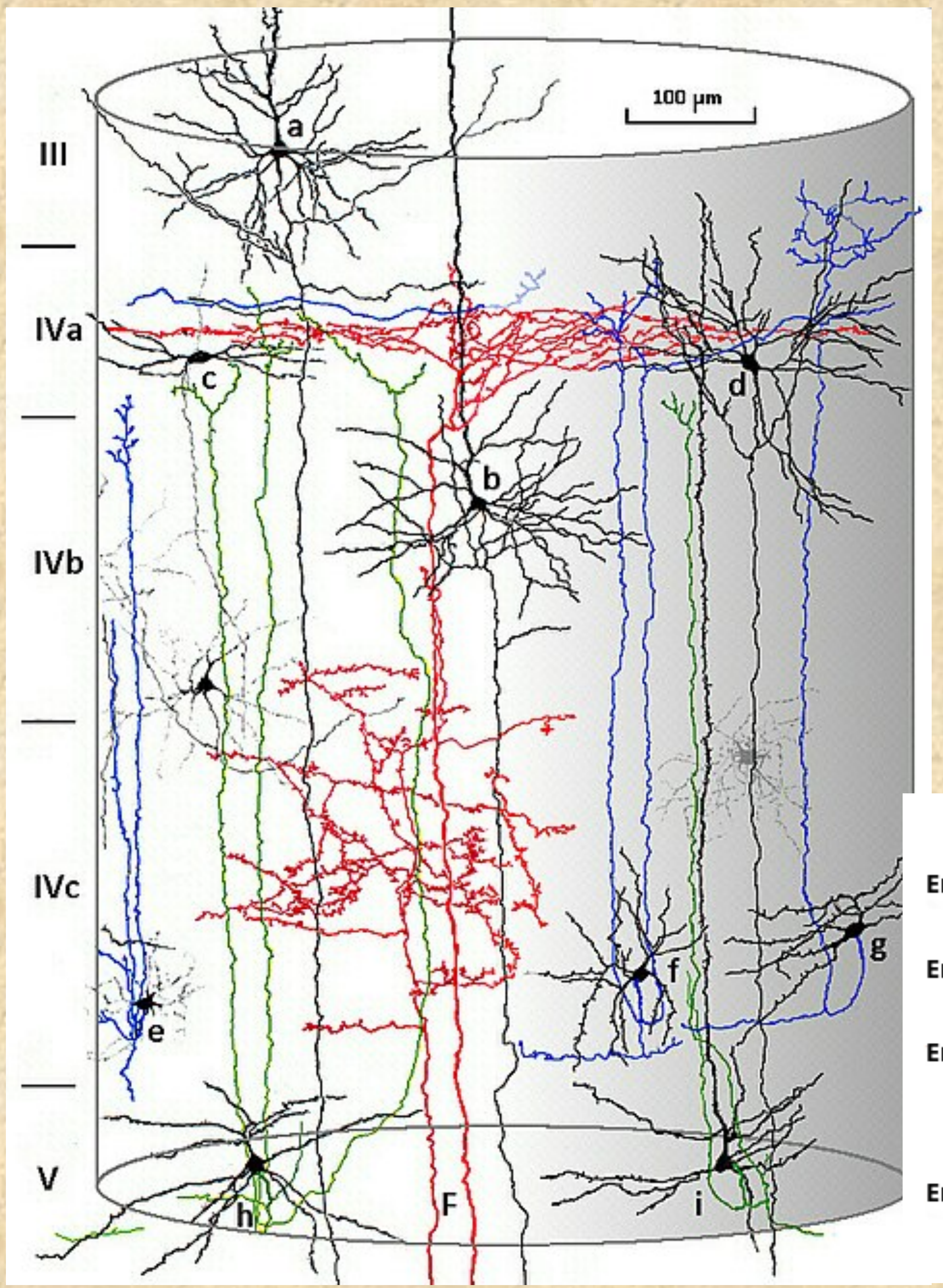




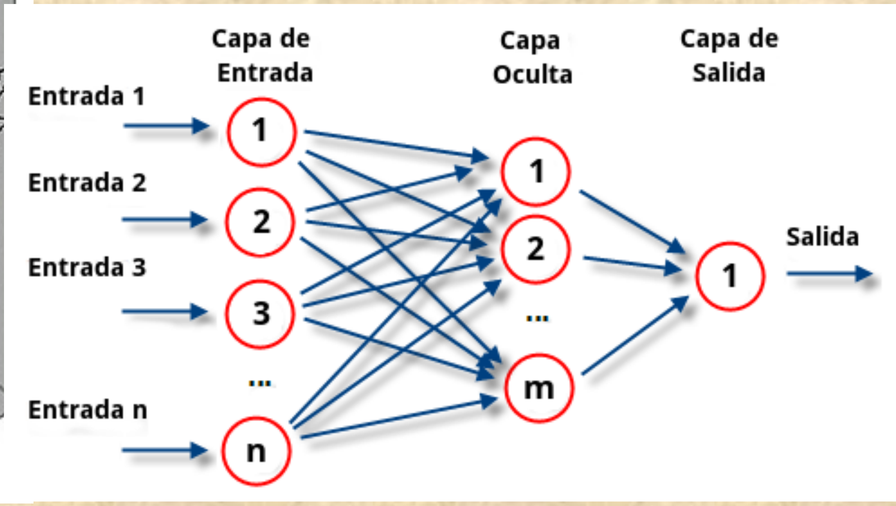
Se trata de un **algoritmo para el aprendizaje supervisado** de clasificadores binarios. Ese algoritmo es el que permite que las neuronas artificiales aprendan y traten los elementos de una serie de datos.

El perceptrón desempeña un **papel esencial en los proyectos de Machine Learning**. Se utiliza en gran medida para clasificar datos, o como algoritmo que permite simplificar o supervisar las capacidades de aprendizaje de los clasificadores binarios.

Recordemos que el aprendizaje supervisado consiste en **enseñar a un algoritmo a hacer predicciones**. Para conseguirlo, se alimenta el algoritmo con ayuda de datos que ya están etiquetados correctamente.



El cortex visual es un perceptrón multicapa (Hubel y Viesel, 1959) Red convolucional

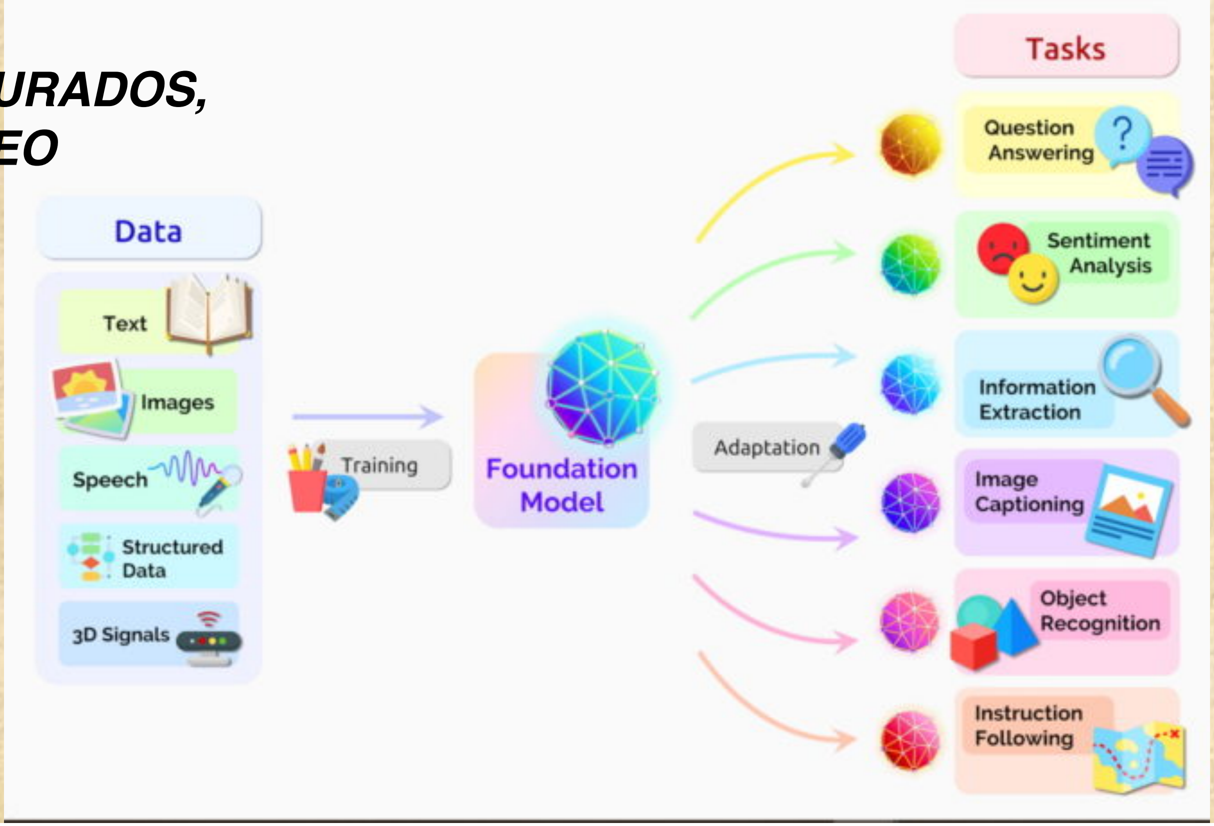


Entre 2009 y 2012, las redes neuronales recurrentes y redes neuronales profundas feedforward desarrollados en el grupo de investigación de Jürgen Schmidhuber en el laboratorio suizo de IA IDSIA han ganado ocho concursos internacionales de reconocimiento de patrones y aprendizaje automático. Por ejemplo, la memoria bidireccional y multidimensional de largo a corto plazo (LSTM) de Alex Graves ha ganado tres competiciones en el reconocimiento de escritura conectada en Conferencia Internacional sobre Análisis de documentos y Reconocimiento (ICDAR) del 2009, sin ningún conocimiento previo acerca de los tres idiomas diferentes que se pueden aprender

MODELOS TRANSFORMADORES

modelo transformer es una red neuronal que aprende contexto y, por lo tanto, significado mediante el seguimiento de relaciones en datos secuenciales como las palabras de esta oración.

DATOS NO ESTRUCTURADOS, IMAGEN O VÍDEO



Cualquier aplicación que utilice datos de texto, imagen o video secuenciales es un candidato para los modelos de transformers.

LLM: LARGE LANGUAJE MODELS

- Capaces de entrenarse sin supervisión,
- Una explicación más precisa es que los transformadores llevan a cabo un autoaprendizaje.
- Es a través de este proceso que aprenden a entender la gramática, los idiomas y los conocimientos

REVIEWS

Check for updates

Artificial intelligence-enhanced electrocardiography in cardiovascular disease management

Konstantinos C. Siontis, Peter A. Noseworthy, Zachi I. Attia and Paul A. Friedman

NATURE REVIEWS | CARDIOLOGY VOLUME 18 | JULY 2021 | 467

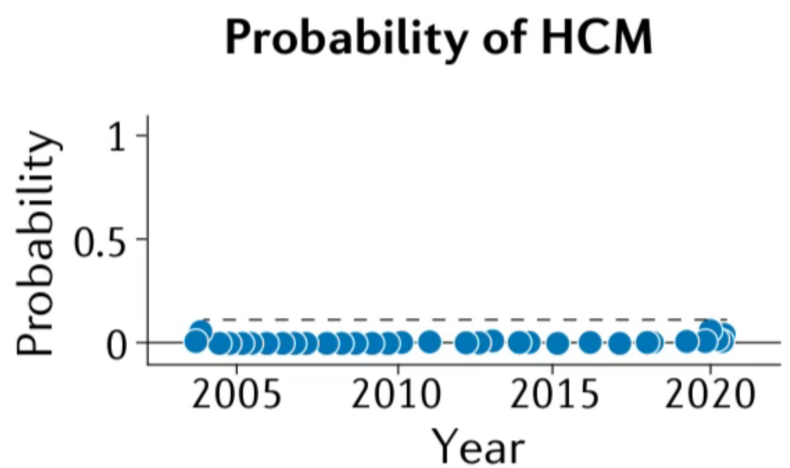
Key points

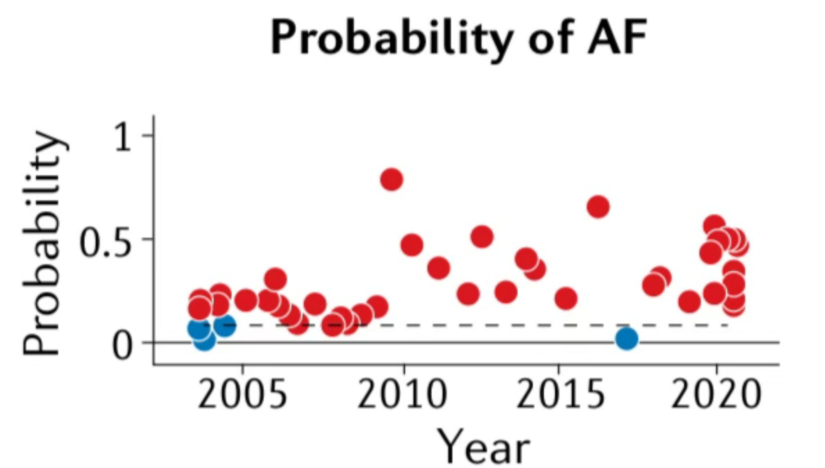
- The feasibility and potential value of the application of advanced artificial intelligence methods, particularly deep-learning convolutional neural networks (CNNs), to the electrocardiogram (ECG) have been demonstrated.
- CNNs developed with the use of large numbers of digital ECGs linked to rich clinical datasets might be able to perform accurate and nuanced, human-like interpretation of ECGs.
- CNNs have also been developed to detect asymptomatic left ventricular dysfunction, silent atrial fibrillation, hypertrophic cardiomyopathy and an individual's age, sex and race on the basis of the ECG alone.
- CNNs to detect other cardiac conditions, such as aortic valve stenosis and amyloid heart disease, are in active development.
- These approaches might be applicable to the standard 12-lead ECG or to data obtained from single-lead or multilead mobile or wearable ECG technologies.
- Evidence on patient outcomes, as well as the challenges and potential limitations from the real-world implementation of the artificial intelligence-enhanced ECG, continues to emerge.

Results (screenshot from AI–ECG Dashboard)

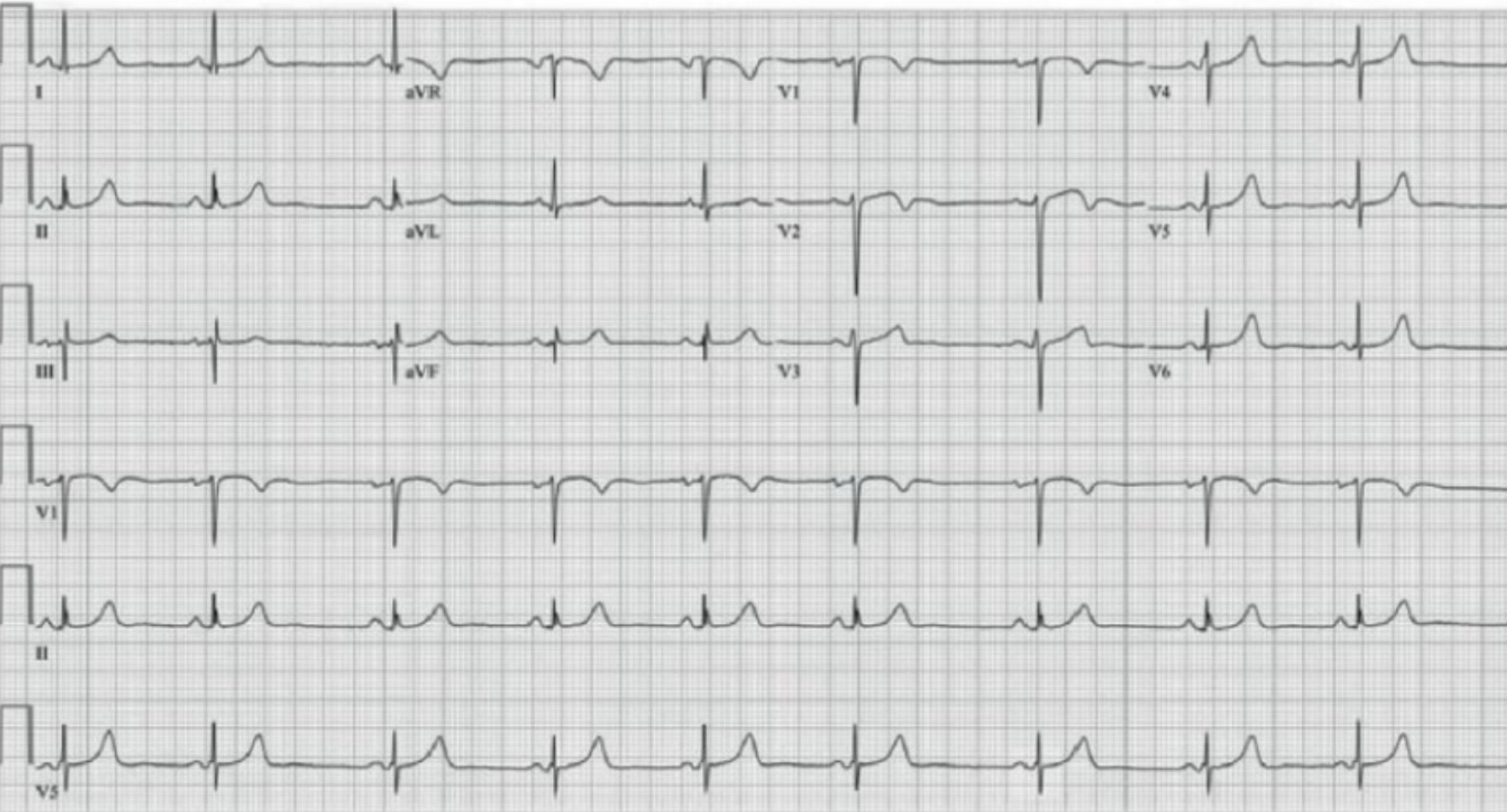
Compare ECGs | Print Report | Download Results

ECG Date	Main Rhythm	Heart Rate	QT/QTc	Real Age	ECG Age	P of Male (%)	P of Low EF (%)	P of AF (%)	P of HCM (%)
XX/XX/2019	Atrial flutter	116	326/453	92.2	72.0	17.42%	0.59%	65.63%	0.01%
XX/XX/2019	Sinus tachycardia	109	356/477	92.2	79.7	16.35%	0.93%	43.52%	0.01%
XX/XX/2019	Normal sinus rhythm	79	426/488	92.1	79.7	7.77%	0.39%	92.94%	0.03%
XX/XX/2019	Sinus rhythm	92	398/492	92.1	75.7	7.55%	1.87%	78.84%	0.22%
XX/XX/2014	Normal sinus rhythm	69	434/465	86.7	81.5	1.04%	1.11%	65.15%	0.10%
XX/XX/2007	Normal sinus rhythm	63	456/466	79.7	72.9	0.57%	0.75%	10.56%	0.18%
XX/XX/2006	Normal sinus rhythm	69	436/463	78.6	74.9	2.94%	1.77%	10.28%	0.08%
XX/XX/2004	Normal sinus rhythm	63	448/454	76.6	75.3	2.99%	0.63%	10.71%	0.18%
XX/XX/2003	Normal sinus rhythm	68	436/460	75.5	75.0	0.13%	0.57%	1.75%	0.35%
XX/XX/2002	Normal sinus	65	436/449	74.5	76.9	2.39%	0.59%	18.00%	0.04%





AI–ECG probability of HCM 72.6%



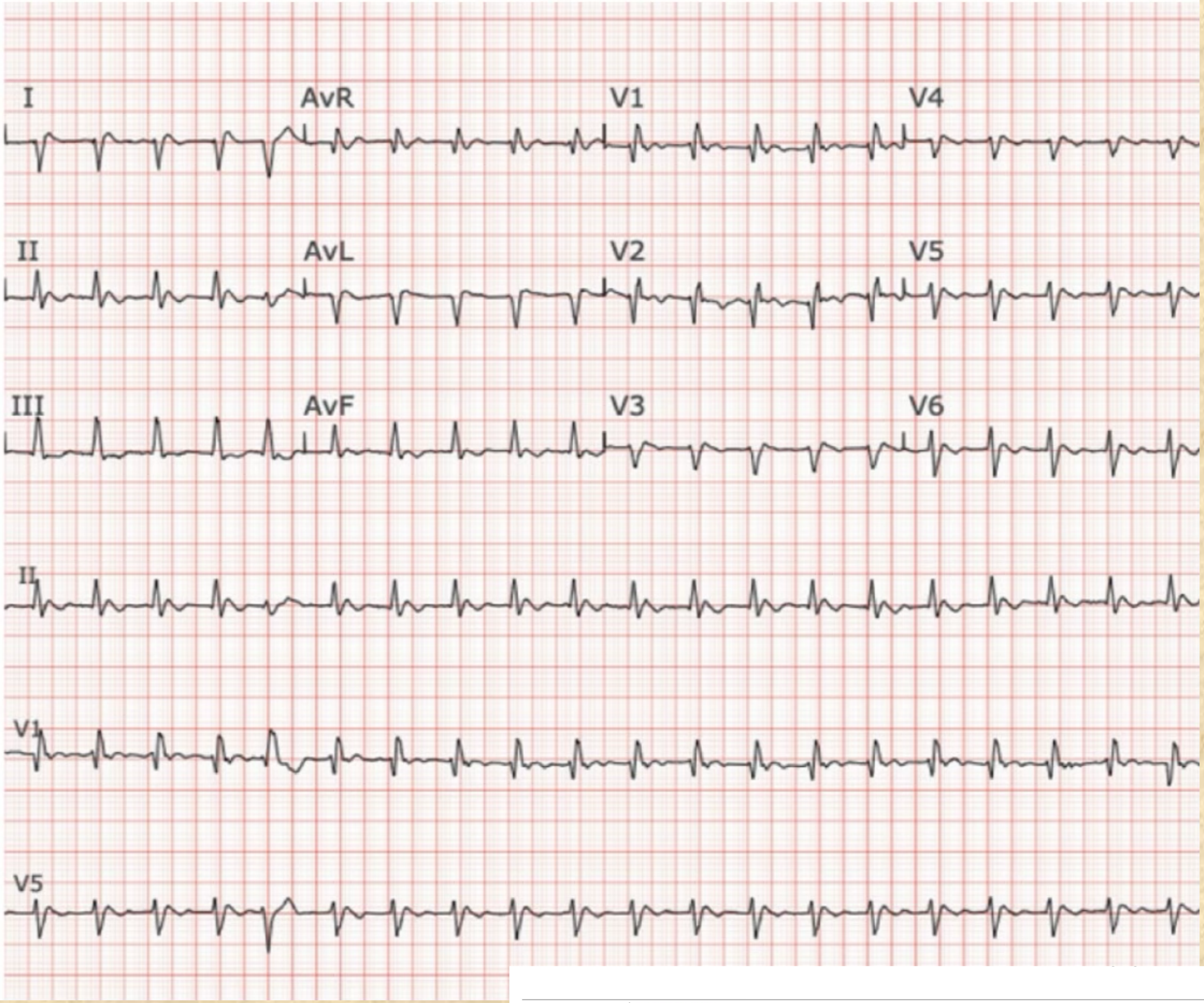
- **6% de la población asintomática tiene FE<50%**
- **Estudio C. Mayo: 45.000 pacientes: se entrenó el modelo con los datos de sus ECG y de sus ecocardiogramas**

- **Testado en 53.000 pacientes**
- **AUC 0,93,   S 93%, E 86%,**
- **Predice el desarrollo de disfunción VI antes que cualquier parámetro ecográfico (a 4 años)**

NATURE REVIEWS | CARDIOLOGY VOLUME 18 | JULY 2021 | 467

Probable sinus tachycardia with first-degree AV block

Premature ventricular complexes. Right-axis deviation. Incomplete right bundle branch block. Low anterior forces. Non-specific ST and T-wave abnormalities.



Results (screenshot from AI–ECG Dashboard)

Compare ECGs | Print Report | Download Results

ECG Date	Main Rhythm	Heart Rate	QT/QTc	Real Age	ECG Age	P of Male (%)	P of Low EF (%)	P of AF (%)	P of HCM (%)
XX/XX/2020	Atrial tachycardia	95	430/537	40.4	58.8	22.89%	55.78%	18.65%	1.25%
XX/XX/2020	Junctional tachycardia	127	212/307	40.4	43.4	7.90%	85.06%	21.91%	0.48%
XX/XX/2020	Junctional tachycardia	128	310/452	40.4	59.4	42.88%	83.57%	36.26%	2.81%
XX/XX/2020	Sinus tachycardia	104	388/510	40.4	62.7	23.73%	66.18%	27.97%	0.08%
XX/XX/2020	Sinus tachycardia	107	368/491	40.4	57.3	38.91%	87.47%	47.73%	0.03%
XX/XX/2020	Atrial tachycardia	118	320/448	40.3	71.1	13.76%	48.80%	51.07%	0.47%
XX/XX/2020	Atrial tachycardia	115	350/484	40.1	43.1	20.40%	83.08%	51.82%	1.89%
XX/XX/2019	Supraventricular tachycardia	140	302/459	39.9	51.1	42.99%	86.01%	24.97%	8.47%
XX/XX/2019	Left posterior fascicular [illegible]	142	292/449	39.8	53.7	20.46%	96.27%	57.62%	0.03%
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	67.9	18.69%	95.79%	44.59%	0.12%
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	57.5	62.02%	62.84%	52.21%	1.37%
XX/XX/2019	Sinus tachycardia	121	322/457	39.6	63.4	29.47%	99.72%	42.74%	0.81%
XX/XX/2019	Sinus tachycardia	112	358/488	39.1	45.4	[illegible]	[illegible]	[illegible]	[illegible]
XX/XX/2018	Sinus tachycardia	108	336/448	38.0	33.1	[illegible]	[illegible]	[illegible]	[illegible]
XX/XX/2017	Normal sinus rhythm	93	348/432	37.9	47.3	[illegible]	[illegible]	[illegible]	[illegible]
XX/XX/2017	Normal sinus rhythm	94	354/442	37.1	39.6	[illegible]	[illegible]	[illegible]	[illegible]
XX/XX/2016	Normal sinus rhythm	90	346/423	36.1	54.2	[illegible]	[illegible]	[illegible]	[illegible]
XX/XX/2015	Normal sinus rhythm	99	352/451	35.1	46.0	11.45%	2.21%	22.40%	0.01%
XX/XX/2014	Sinus rhythm	97	310/393	34.1	38.4	16.19%	3.03%	37.29%	0.02%
XX/XX/2013	Sinus tachycardia	105	406/533	33.8	52.7	3.54%	1.61%	42.22%	0.03%
XX/XX/2013	Accelerated Junctional rhythm	104	362/476	33.1	64.9	20.88%	6.29%	24.44%	0.02%
XX/XX/2012	Normal sinus rhythm	90	352/430	32.5	37.7	25.20%	1.49%	52.82%	0.00%
XX/XX/2012	Normal sinus rhythm	91	354/435	32.1	39.3	7.32%	0.30%	25.22%	0.00%
...	...	...	...	...	...	...	...	...	...
XX/XX/2003	Sinus tachycardia	113	292/398	23.5	52.3	87.18%	99.87%	16.13%	0.06%

29% P (sexo masculino)

90% P (Disf. SISTÓLICA V. IZDO)

HIPERPOTASEMIA

ESTENOSIS AÓRTICA

AMILOIDOSIS

FIBRILACIÓN AURICULAR SILENTE

IMC, SEXO… PROBABILIDAD DE MUERTE

DISFUNCIÓN SISTÓLICA V. IZDO

- **Puede excluir el sd. respiratorio severo por Covid 19 (AUC 0,78, VPN 99,2%)**

Attia, Rapid Exclusion of COVID Infection With the Artificial Intelligence Electrocardiogram. Mayo Clin. Proc. 2021, 96, 2081–2094.

- **Screening de anemia y cirrosis**

multicentre study. Lancet Digit. Health 2020

nature medicine

Article https://doi.org/10.1038/s41591-023-02396-3

Machine learning for ECG diagnosis and risk stratification of occlusion myocardial infarction

Received: 24 January 2023

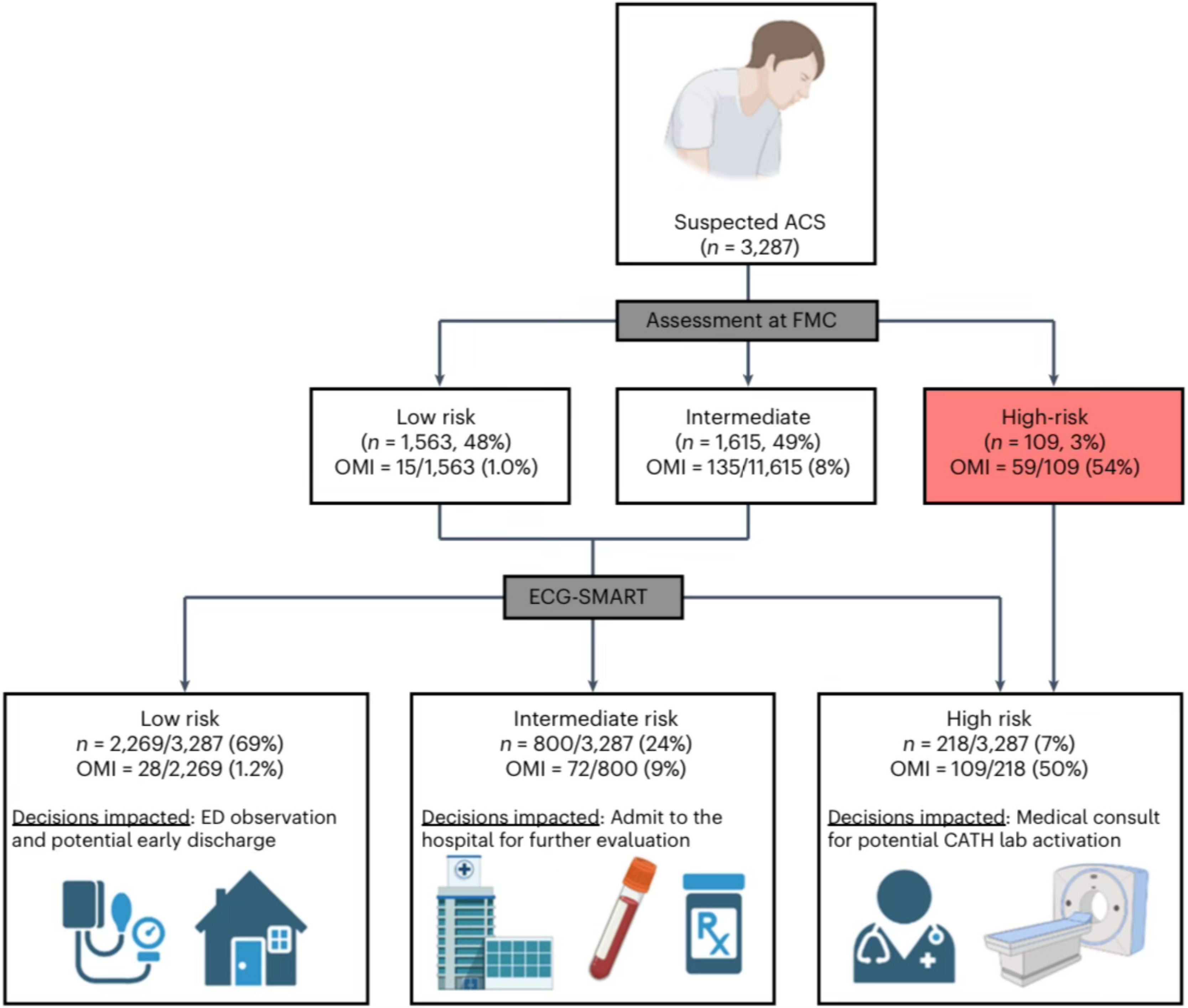
Accepted: 11 May 2023

Published online: 29 June 2023

Check for updates

Salah S. Al-Zaiti[1,2,3,4], Christian Martin-Gill[2,5], Jessica K. Zègre-Hemsey[6], Zeineb Bouzid[3], Ziad Faramand[7], Mohammad O. Alrawashdeh[8,9], Richard E. Gregg[10], Stephanie Helman[1], Nathan T. Riek[3], Karina Kraevsky-Phillips[1], Gilles Clermont[11], Murat Akcakaya[3], Susan M. Sereika[1], Peter Van Dam[12], Stephen W. Smith[13,14], Yochai Birnbaum[15], Samir Saba[4,5], Ervin Sejdic[16,17] & Clifton W. Callaway[2,5]

Patients with occlusion myocardial infarction (OMI) and no ST-elevation


Suspected ACS
(n = 3,287)
Assessment at FMC
Low risk
(n = 1,563, 48%)
OMI = 15/1,563 (1.0%)
Intermediate
(n = 1,615, 49%)
OMI = 135/11,615 (8%)
High-risk
(n = 109, 3%)
OMI = 59/109 (54%)
ECG-SMART
Low risk
n = 2,269/3,287 (69%)
OMI = 28/2,269 (1.2%)
Decisions impacted: ED observation and potential early discharge
Intermediate risk
n = 800/3,287 (24%)
OMI = 72/800 (9%)
Decisions impacted: Admit to the hospital for further evaluation
High risk
n = 218/3,287 (7%)
OMI = 109/218 (50%)
Decisions impacted: Medical consult for potential CATH lab activation

 https://doi.org/10.1038/s41591-023-

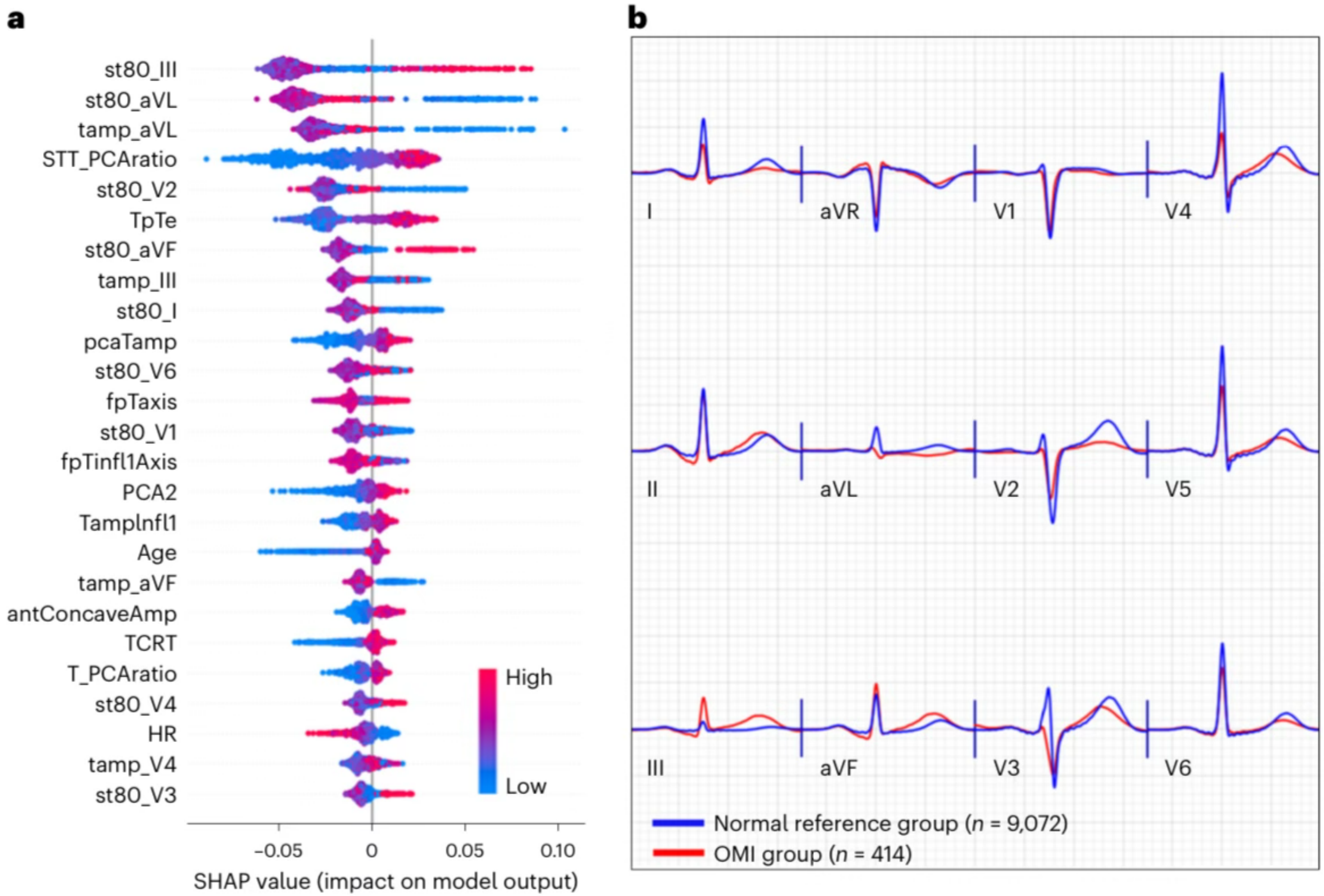
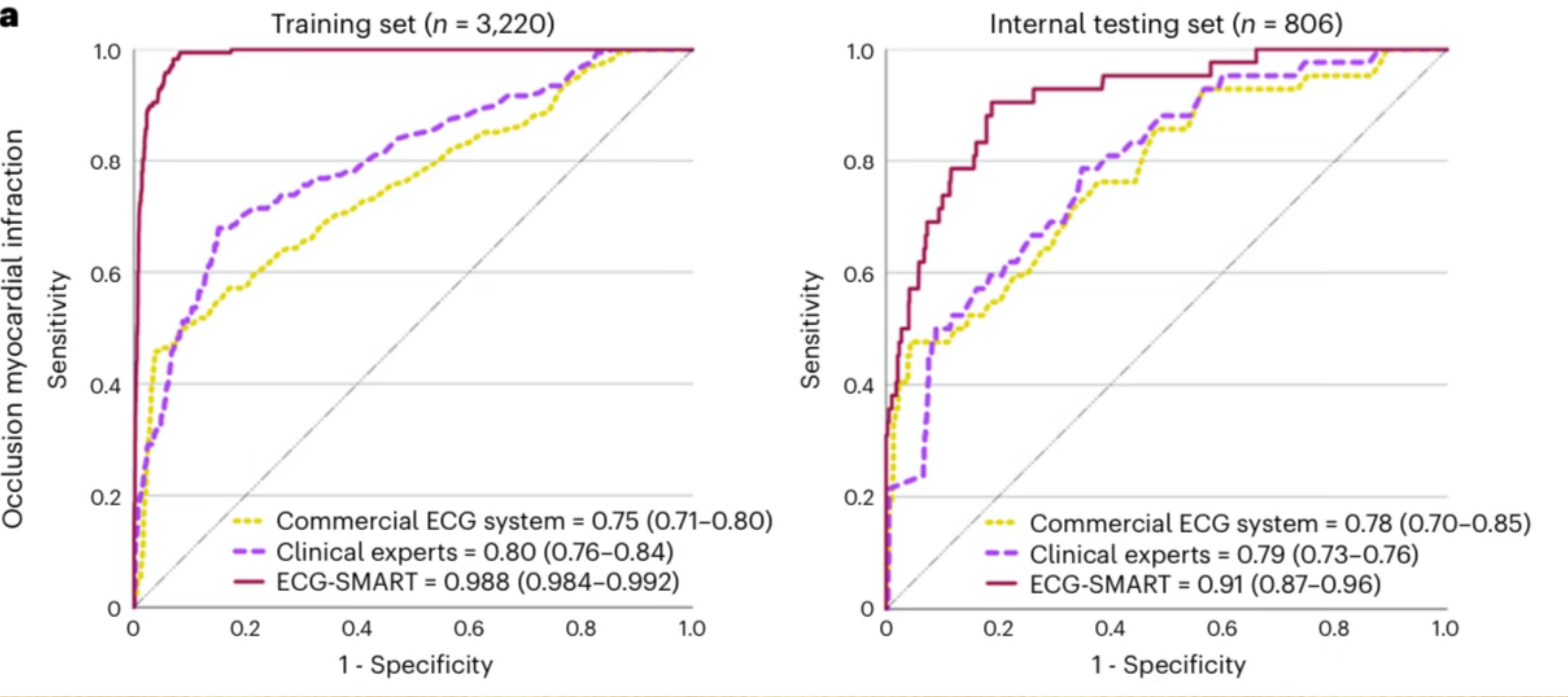


Fig. 3 | Model explainability for OMI detection. This figure shows SHAP values for the 25 most important features driving the predictions of the machine learning classifier in the derivation cohort (**a**) and the aggregate median beats of ECGs with OMI class (red) and the aggregate median beats of ECGs with normal sinus rhythm and no OMI (blue) (**b**). antConcaveAmp, the sum of concave amplitudes in the anterior leads; fpTaxis, T axis in the frontal plane; HR, rate; Infl1, the first inflection point before T peak; ST80, ST amplitude at J point + 80 ms; tamp, T amplitude; TCRT, total cosine R-to-T; TpTe, T_{peak} interval.


a
Training set (n = 3,220)
Occlusion myocardial infraction
Sensitivity
1 - Specificity
Commercial ECG system = 0.75 (0.71–0.80)
Clinical experts = 0.80 (0.76–0.84)
ECG-SMART = 0.988 (0.984–0.992)
Internal testing set (n = 806)
Sensitivity
1 - Specificity
Commercial ECG system = 0.78 (0.70–0.85)
Clinical experts = 0.79 (0.73–0.76)
ECG-SMART = 0.91 (0.87–0.96)

nature medicine

Article | Published: 29 April 2024

AI-enabled electrocardiography alert intervention and all-cause mortality: a pragmatic randomized clinical trial

Chin-Sheng Lin, Wei-Ting Liu, Dung-Jang Tsai, Yu-Sheng Lou, Chiao-Hsiang Chang, Chiao-Chin Lee, Wen-Hui Fang, Chih-Chia Wang, Yen-Yuan Chen, Wei-Shiang Lin, Cheng-Chung Cheng, Chia-Cheng Lee, Chih-Hung Wang, Chien-Sung Tsai, Shih-Hua Lin & Chin Lin

Nature Medicine **30**, 1461–1470 (2024)

- **A 90 días. Mortalidad global 3,6% frente a 4,3% en el grupo control**
- **n=15.000**
- **Mortalidad cv 0,2% frente a 2,4% en el control**

npj | digital medicine

Article

Published in partnership with Seoul National University Bundang Hospital

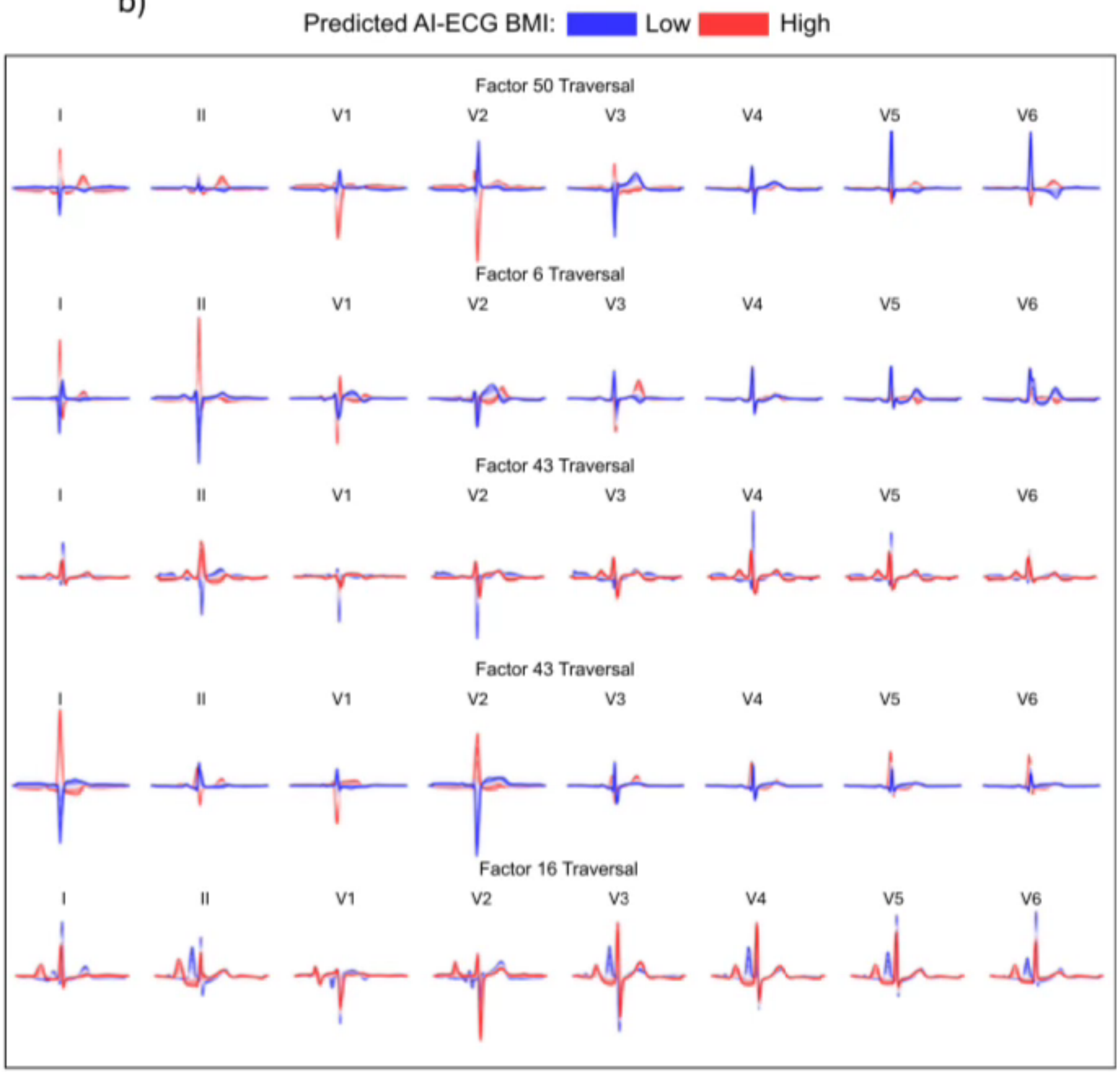
https://doi.org/10.1038/s41746-024-01170-0

Artificial intelligence-enhanced electrocardiography derived body mass index as a predictor of future cardiometabolic disease

Libor Pastika[1,11], Arunashis Sau[1,2,11], Konstantinos Patlatzoglou[1], Ewa Sieliwonczyk[1,3], Antônio H. Ribeiro[4], Kathryn A. McGurk[1,3], Sadia Khan[1,5], Danilo Mandic[6], William R. Scott[3,7], James S. Ware[1,3], Nicholas S. Peters[1,2], Antonio Luiz P. Ribeiro[8], Daniel B. Kramer[1,9], Jonathan W. Waks[10] & Fu Siong Ng[1,2,5]

- delta BMI=predicho por AI-BMI medido

b)


Predicted AI-ECG BMI: Low High
Factor 50 Traversal
I II V1 V2 V3 V4 V5 V6
Factor 6 Traversal
I II V1 V2 V3 V4 V5 V6
Factor 43 Traversal
I II V1 V2 V3 V4 V5 V6
Factor 43 Traversal
I II V1 V2 V3 V4 V5 V6
Factor 16 Traversal
I II V1 V2 V3 V4 V5 V6

¿Y qué hacemos con todo ésto?

“In the medical field, AI is expected to significantly impact daily practice. Patients with AF present an ideal opportunity to evaluate AI's potential in enhancing cardiac management through predictive tools for risk and comorbidity evolution.”

Prof. Gregory Lip

Co-principal Investigator at ARISTOTELES, Chair of Cardiovascular Medicine at the University of Liverpool (UK) and Medical Advisor for Idoven

ARISTOTELES

Willem platform

IDOVEN

Under clinical validation in 5 state-of-the-art trials with leading institutions

At Idoven, we are actively involved in 5 state-of-the-art clinical trials, validating the effectiveness of Willem and ensuring its reliability in real-world medical settings through collaboration with renowned institutions.

Visit our Collaborative Research page

WILLEM

Spain

To validate the use of AI software to analyse EGM and ECG to identify cardiac patterns at a cardiologist-level. Funded by European Innovation Council with €2.5M

Multiple Cardiac Diseases | 40.000 patients*

FAITHFUL

Spain, France, Sweden

To redefine heart failure detection in Primary Care by integrating Willem AI platform into clinical practice. Funded by EIT Health with €1.7M.

Heart Failure | 2.545 patients

ASSIST

Spain, Netherlands, Portugal, America

To diagnose suspected heart attacks in emergency units using Willem AI platform. Funded by EIT Health with €1.5M

Heart attacks | 10.340 patients*

MAESTRIA

France, UK, Netherlands, Germany, Spain

To develop the world's first ML platform for atrial cardiomyopathy diagnosis. Funded by Horizon 2020 with €14M.

Atrial Fibrillation | 660 patients

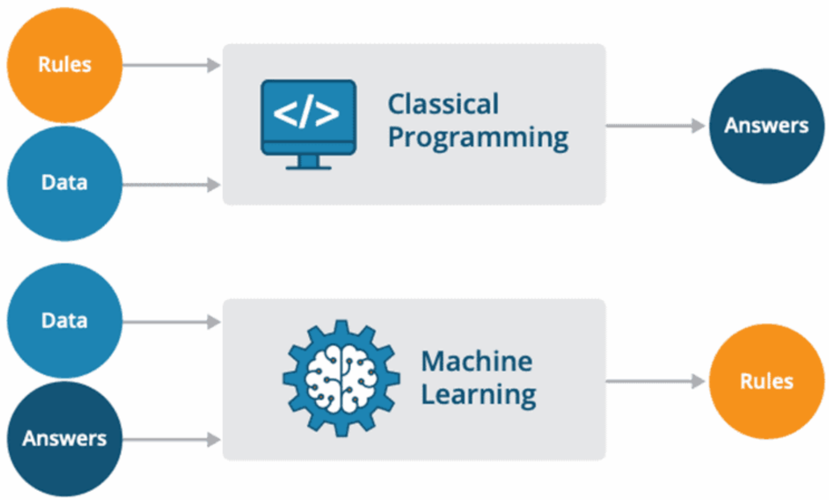
ARISTOTELES

Italy, UK, Spain, Belgium, Norway, Others

To develop AI tools to predict the risk of chronic diseases and their progression. Funded by Horizon Europe 2022 with €6M.

Chronic diseases | 1200 patients

*Number of expected patients



AI ECG Compared to classical algorithms, which require a set of rules to provide answers based on input data, machine learning algorithms, using previous examples, can automatically learn these rules, which can then be applied to new data. Source

This is where AI (and PMcardio) joins the ECG interpretation game – by training AI algorithms on ECGs with patient outcomes; the AI can detect specific patterns and associate them with a certain outcome (diagnoses, measurements, etc.).

By crunching millions of previous ECGs in a matter of hours, the machine can spot and learn even very subtle patterns possibly missed by the human eye.

Can you interpret this ECG?