Computer-Aided Cardiology

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No Disclosures

What is Artificial Intelligence???

Cool Stuff Computers Do!

Intelligence-Based Medicine: Subspecialty Series

Intelligence-Based Cardiology and Cardiac Surgery

Artificial Intelligence and Human Cognition in Cardiovascular Medicine

Edited by Anthony C. Chang and Alfonso Limon

Section Editors: Robert Brisk, Francisco Lopez-Jimenez, and Louise Y. Sun

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THE PRESENT AND FUTURE

JACC REVIEW TOPIC OF THE WEEK

Artificial Intelligence for Cardiovascular Care—Part 1: Advances

JACC Review Topic of the Week

Pierre Elias, MD,[a,b,*] Sneha S. Jain, MD, MBA,[c,*] Timothy Poterucha, MD,[a] Michael Randazzo, MD,[d] Francisco Lopez Jimenez, MD, MBA,[e] Rohan Khera, MD, MS,[f] Marco Perez, MD,[c] David Ouyang, MD,[g] James Pirruccello, MD,[h] Michael Salerno, MD, PhD,[c] Andrew J. Einstein, MD, PhD,[a] Robert Avram, MD,[i] Geoffrey H. Tison, MD, MPH,[h] Girish Nadkarni, MD, MPH,[j] Vivek Natarajan, MS,[k] Emma Pierson, PhD,[l] Ashley Beecy, MD,[m,n] Deepa Kumaraiah, MD, MBA,[a,m] Chris Haggerty, PhD,[b,m] Jennifer N. Avari Silva, MD,[o,†] Thomas M. Maddox, MD, SM[o,†]

ABSTRACT

Recent artificial intelligence (AI) advancements in cardiovascular care offer potential enhancements in diagnosis, treatment, and outcomes. Innovations to date focus on automating measurements, enhancing image quality, and detecting diseases using novel methods. Applications span wearables, electrocardiograms, echocardiography, angiography, genetics, and more. AI models detect diseases from electrocardiograms at accuracy not previously achieved by technology or human experts, including reduced ejection fraction, valvular heart disease, and other cardiomyopathies. However, AI's unique characteristics necessitate rigorous validation by addressing training methods, real-world efficacy, equity concerns, and long-term reliability. Despite an exponentially growing number of studies in cardiovascular AI, trials showing improvement in outcomes remain lacking. A number are currently underway. Embracing this rapidly evolving technology while setting a high evaluation benchmark will be crucial for cardiology to leverage AI to enhance patient care and the provider experience. (J Am Coll Cardiol 2024;83:2472–2486) © 2024 by the American College of Cardiology Foundation.

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Ambarish Pandey, MD, served as Guest Associate Editor for this paper. Javed Butler, MD, MPH, MBA, served as Guest Editor-in-Chief for this paper.

The authors attest they are in compliance with human studies committees and animal welfare regulations of the authors' institutions and Food and Drug Administration guidelines, including patient consent where appropriate. For more information, visit the Author Center.

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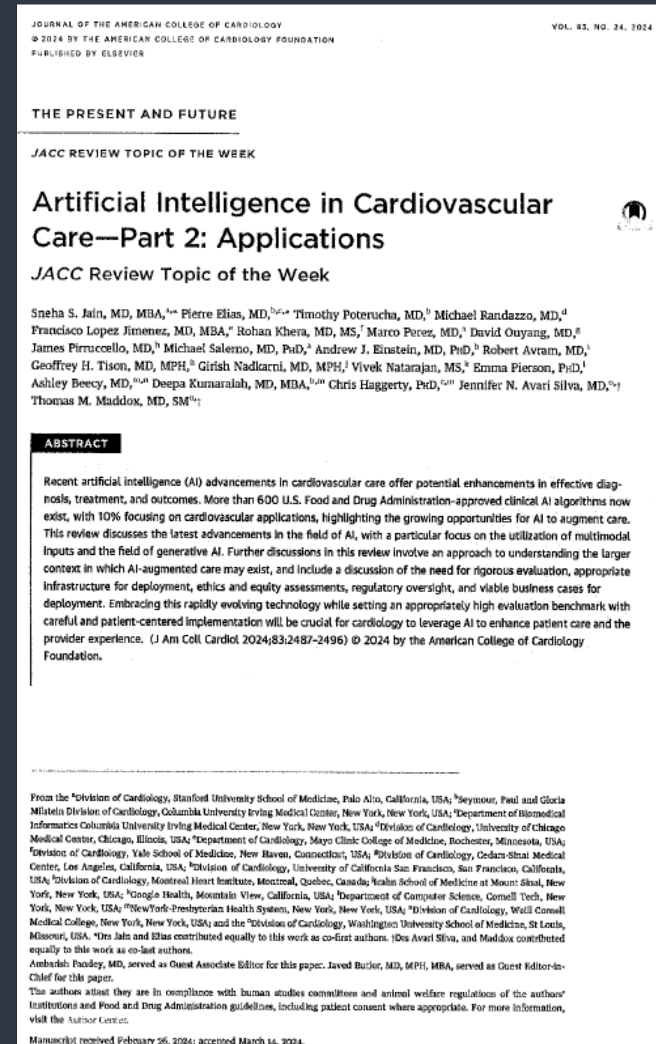

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THE PRESENT AND FUTURE

JACC REVIEW TOPIC OF THE WEEK

Artificial Intelligence in Cardiovascular Care—Part 2: Applications

JACC Review Topic of the Week

Sneha S. Jain, MD, MBA,[a,*] Pierre Elias, MD,[b,c,*] Timothy Poterucha, MD,[b] Michael Randazzo, MD,[d] Francisco Lopez Jimenez, MD, MBA,[e] Rohan Khera, MD, MS,[f] Marco Perez, MD,[a] David Ouyang, MD,[g] James Pirruccello, MD,[h] Michael Salerno, MD, PhD,[a] Andrew J. Einstein, MD, PhD,[b] Robert Avram, MD,[i] Geoffrey H. Tison, MD, MPH,[h] Girish Nadkarni, MD, MPH,[j] Vivek Natarajan, MS,[k] Emma Pierson, PhD,[l] Ashley Beecy, MD,[m,n] Deepa Kumaraiah, MD, MBA,[b,m] Chris Haggerty, PhD,[c,m] Jennifer N. Avari Silva, MD,[o,†] Thomas M. Maddox, MD, SM[o,†]

ABSTRACT

Recent artificial intelligence (AI) advancements in cardiovascular care offer potential enhancements in effective diagnosis, treatment, and outcomes. More than 600 U.S. Food and Drug Administration-approved clinical AI algorithms now exist, with 10% focusing on cardiovascular applications, highlighting the growing opportunities for AI to augment care. This review discusses the latest advancements in the field of AI, with a particular focus on the utilization of multimodal inputs and the field of generative AI. Further discussions in this review involve an approach to understanding the larger context in which AI-augmented care may exist, and include a discussion of the need for rigorous evaluation, appropriate infrastructure for deployment, ethics and equity assessments, regulatory oversight, and viable business cases for deployment. Embracing this rapidly evolving technology while setting an appropriately high evaluation benchmark with careful and patient-centered implementation will be crucial for cardiology to leverage AI to enhance patient care and the provider experience. (J Am Coll Cardiol 2024;83:2487–2496) © 2024 by the American College of Cardiology Foundation.

From the [a]Division of Cardiology, Stanford University School of Medicine, Palo Alto, California, USA; [b]Seymour, Paul and Gloria Milstein Division of Cardiology, Columbia University Irving Medical Center, New York, New York, USA; [c]Department of Biomedical Informatics Columbia University Irving Medical Center, New York, New York, USA; [d]Division of Cardiology, University of Chicago Medical Center, Chicago, Illinois, USA; [e]Department of Cardiology, Mayo Clinic College of Medicine, Rochester, Minnesota, USA; [f]Division of Cardiology, Yale School of Medicine, New Haven, Connecticut, USA; [g]Division of Cardiology, Cedars-Sinai Medical Center, Los Angeles, California, USA; [h]Division of Cardiology, University of California San Francisco, San Francisco, California, USA; [i]Division of Cardiology, Montreal Heart Institute, Montreal, Quebec, Canada; [j]Icahn School of Medicine at Mount Sinai, New York, New York, USA; [k]Google Health, Mountain View, California, USA; [l]Department of Computer Science, Cornell Tech, New York, New York, USA; [m]NewYork-Presbyterian Health System, New York, New York, USA; [n]Division of Cardiology, Weill Cornell Medical College, New York, New York, USA; and the [o]Division of Cardiology, Washington University School of Medicine, St Louis, Missouri, USA. *Drs Jain and Elias contributed equally to this work as co-first authors. †Drs Avari Silva, and Maddox contributed equally to this work as co-last authors.

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LONG History

General Timeline

1600 – Convolution

1600 – Fourier

1763 – Bayesian

1917 – Radon Transform

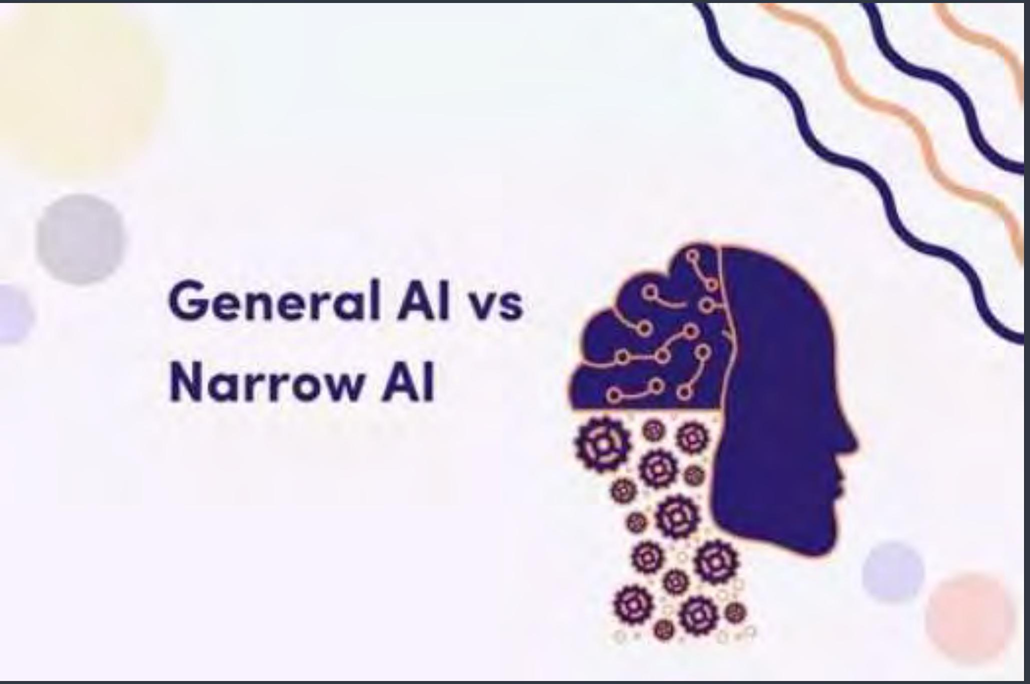
1950 – Turing Test

1956 – Dartmouth Summer Research Project

2018 – Chat GPT-3

Definition

- General AI
- Narrow AI



The Three A's

- Autonomous
- Augmented
- Assisted

Glossary of Terms for AI

Algorithm - A set of mathematical procedures used to learn patterns from data.

Area under receiver operating characteristic curve - metric to evaluate the performance of a binary classification model, representing the trade-off between true positive rate and false-positive rate over different decision thresholds.

Artificial intelligence - The capability of a machine to imitate intelligent human behavior to perform tasks that typically require human intelligence.

Artificial neural networks - generic architecture for a mathematical model to teach computers to learn, inspired by the human brain's neural structure, that is comprised of layers of neurons, which calculate weights that ultimately inform a model if Its current prediction is more or less accurate than prior iterations.

Classification - A type of machine learning task to predict a categorical label of an input.

Convolutional neural networks - A type of deep learning algorithm optimized for processing grid-like data such as images by learning unique features that distinguish them Into different categories.

Deep learning - A subset of machine learning that uses artificial neural networks.

Features - Individual measurable properties of observed data that serve as input variables used by algorithms to learn patterns or make predictions.

Foundation models - Machine learning models trained on amounts of unlabeled data that can be used for different tasks with very little fine tuning.

Joint embedding - A technique where different types of data are transformed and mapped into a shared "embedding" or feature space, with the goal of Identifying relationships between different data types.

Labels – The ground truth output for a given input data, often used to train supervised learning models.

Large language models - A type of machine learning model that has been trained on large amounts of text to recognize, summarize, translate, predict, and/or generate content.

Machine learning – A subset of artificial intelligence in which computers learn from experience without explicit programming.

Preprocessing - Preparing, cleaning, and organizing raw data to make it suitable as Inputs for training AI models.

Reinforcement learning – A type of machine learning where agents learn to make decisions by taking actions in the environment to maximize cumulative reward.

Segmentation - Process of partitioning an Image Into multiple segments.

Semi-supervised learning – A machine learning paradigm that uses both labeled and unlabeled data for training.

Structured data - Data that Is organized Into a predefined format.

Supervised learning – A machine learning paradigm where models are trained using labeled data, so that each example includes a paired input and output.

Unstructured data - A machine learning paradigm where a model Is trained on data with provided labels, often with the goal of discovering hidden patterns or structure to the data.

Unsupervised learning – A machine learning paradigm that uses data without provided labels (unstructured data) to discover underlying structures or patterns.

Wearables – Electronic devices to collect data, track activities, and provided specific functionalities such as health monitoring.

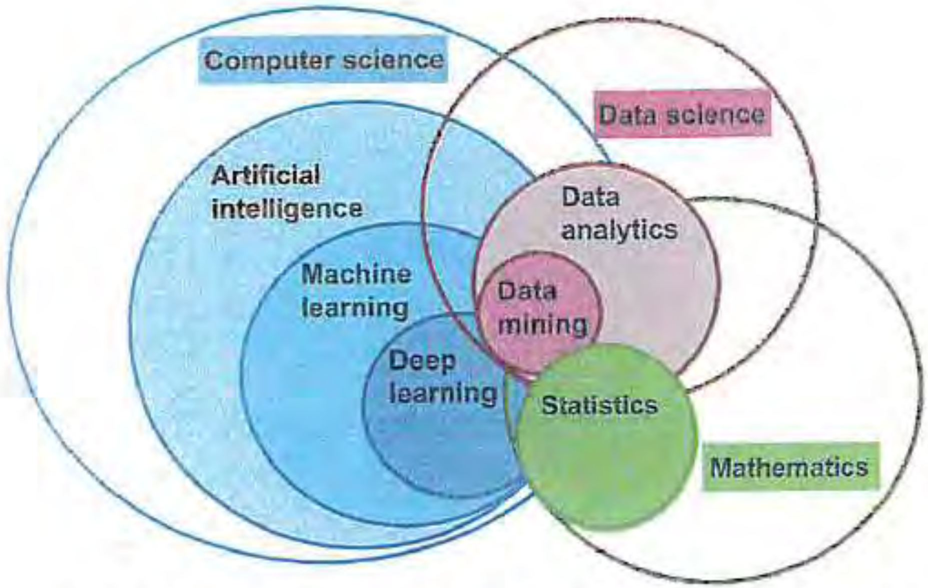


FIGURE 1.2 Artificial intelligence, data science, and mathematics. The circles show the spheres of computer science and AI, data science, and mathematics. Data science is at the intersection of computer science and mathematics. Deep learning and machine learning are within the domain of AI whereas data analytics and data mining are inside the data science realm. There is increasing overlap and convergence of all of these areas. *AI*, artificial intelligence.

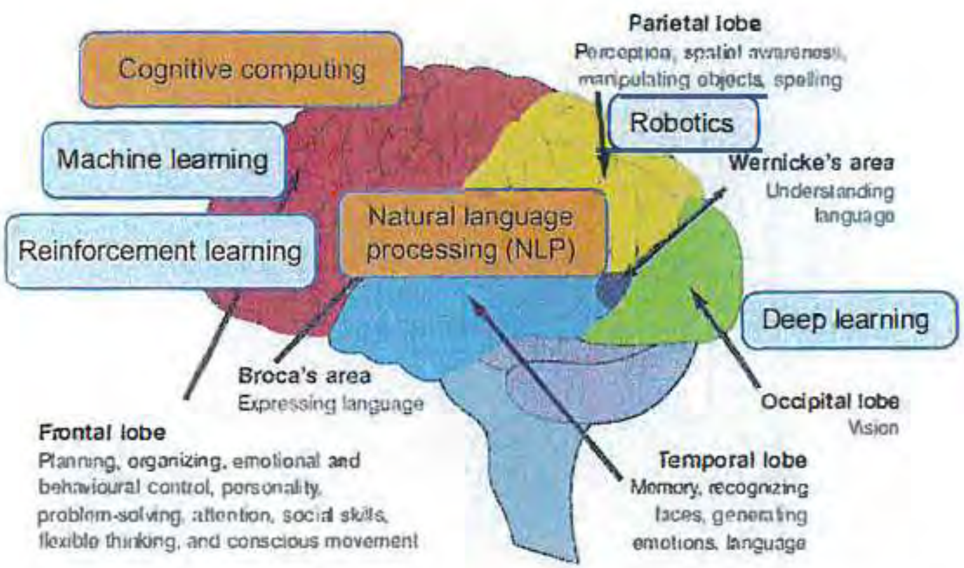
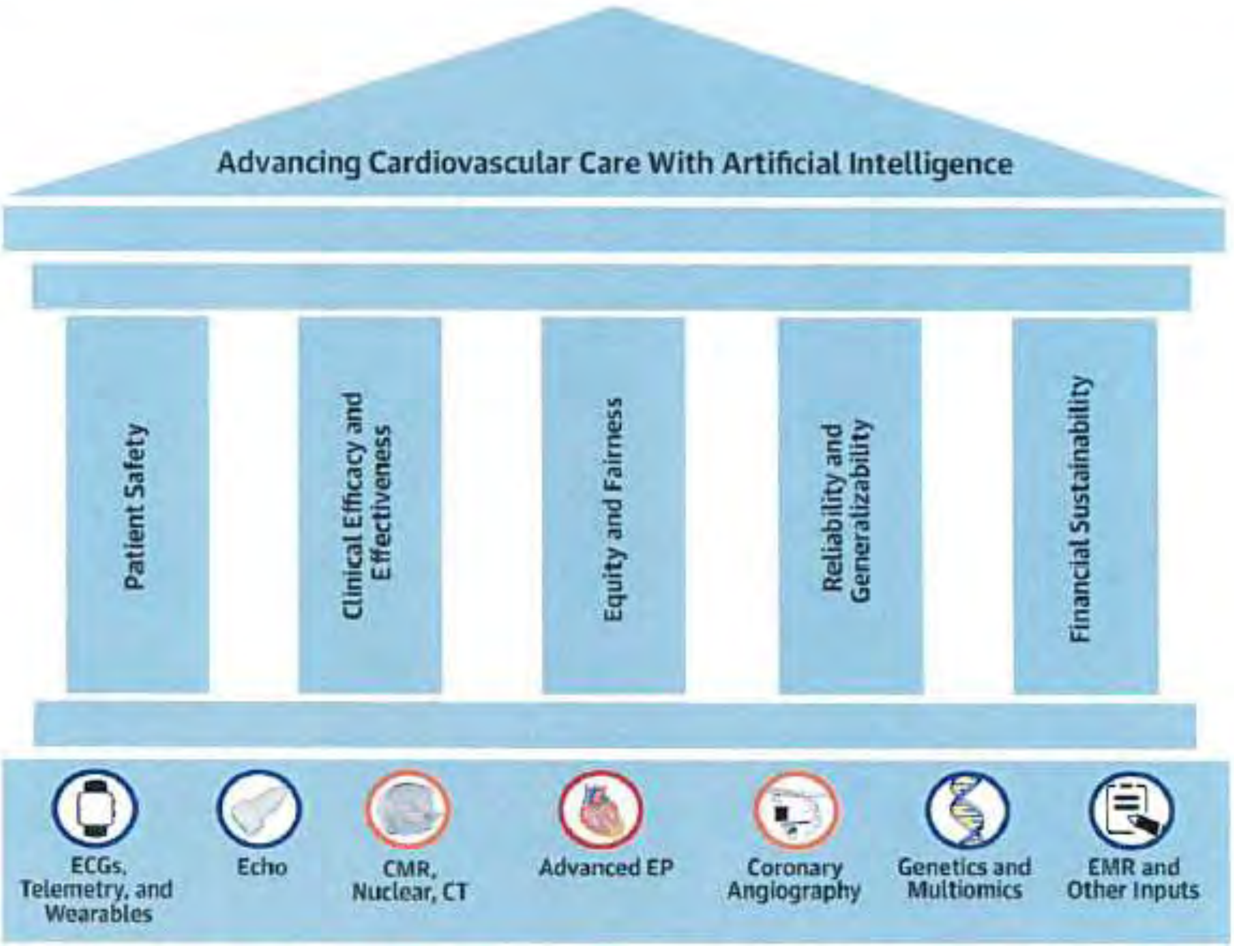


FIGURE 1.4 The doctor's brain. The various parts of the brain are mimicked by different types of machine intelligence. For instance, vision and medical image interpretation can be done by deep learning (and convolutional neural networks; see text for more details).

CENTRAL ILLUSTRATION: Advancing Cardiovascular Care With Artificial Intelligence



Jain SS, et al. J Am Coll Cardiol. 2024;83(24):2487-2496.

Tools

- Machine Learning

- Algorithms

- Neural Networks

- Generative AI and Large Language Models (LLMs)

What is Machine Learning?

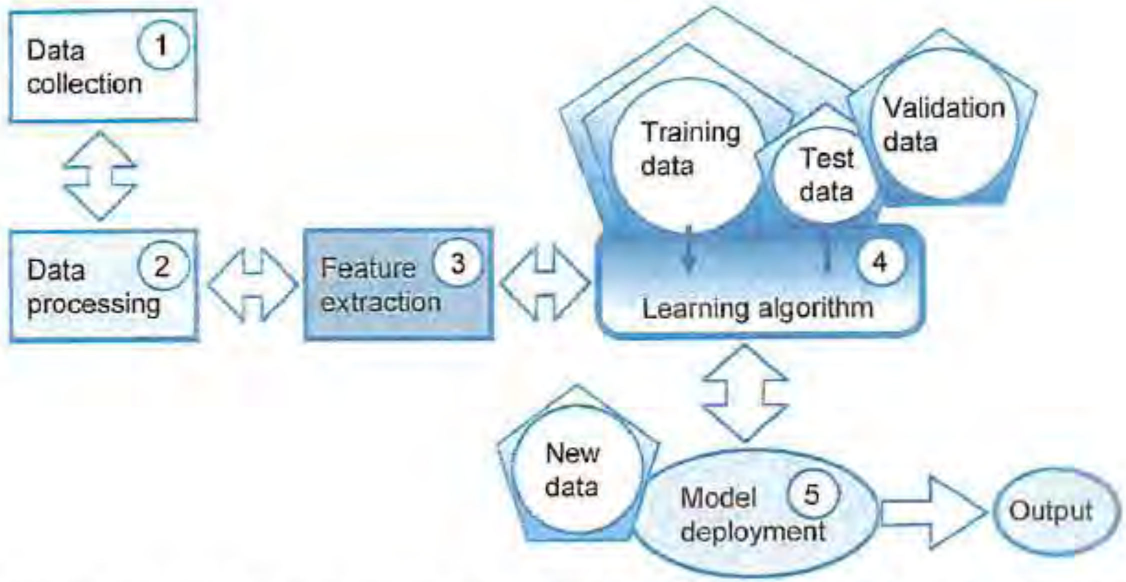


FIGURE 1.13 Machine learning workflow. The entire machine learning workflow is illustrated, from data collection all the way to deployment of the model using real-world data at the very end. Most of the workflow has feedback to the prior step(s) and the model is evaluated and reassessed even during the initial deployment phase so that needed adjustments can be made. The double arrows in the diagram signify fluidity of these steps so that one can return to previous steps to add/refine/change the data, features, or even model. This is not possible for deep learning (to be explained later) as the intermediate steps are "compressed" so that once labeled samples go in, the feature extraction and classification steps are combined in deep learning. In other words, in deep learning, machines are performing feature extraction instead of humans. Therefore, steps 3 and 4 are combined in deep learning. For unsupervised learning, the algorithm yields grouping of objects instead of predictions that a predictive model would yield.

What is Machine Learning?...*continued*

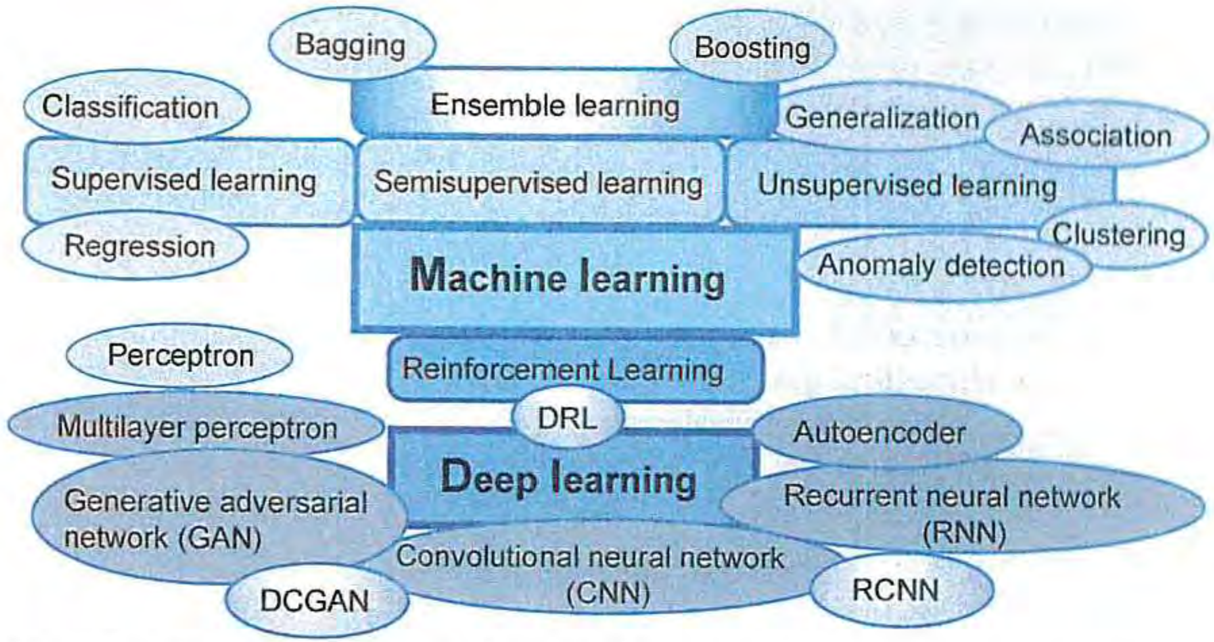
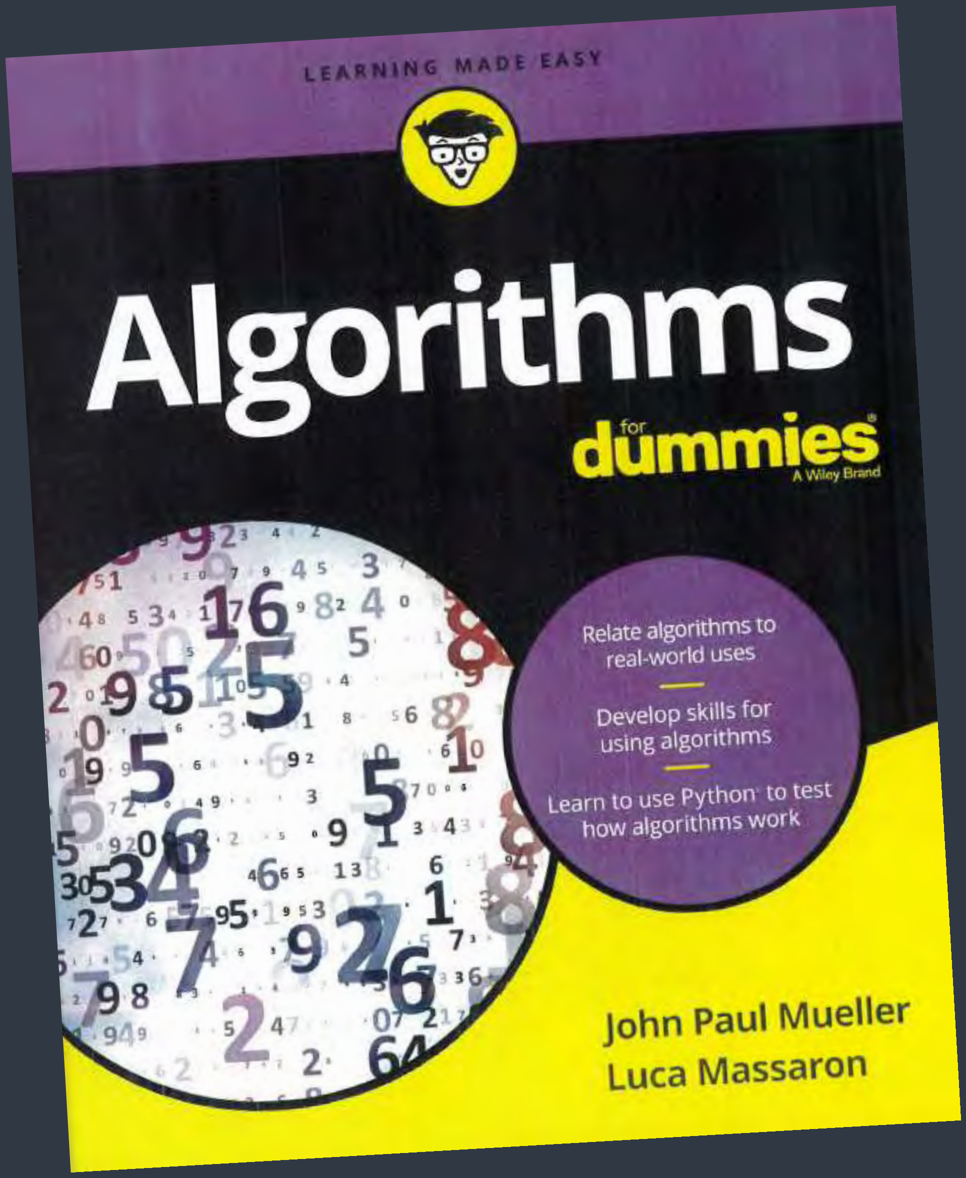
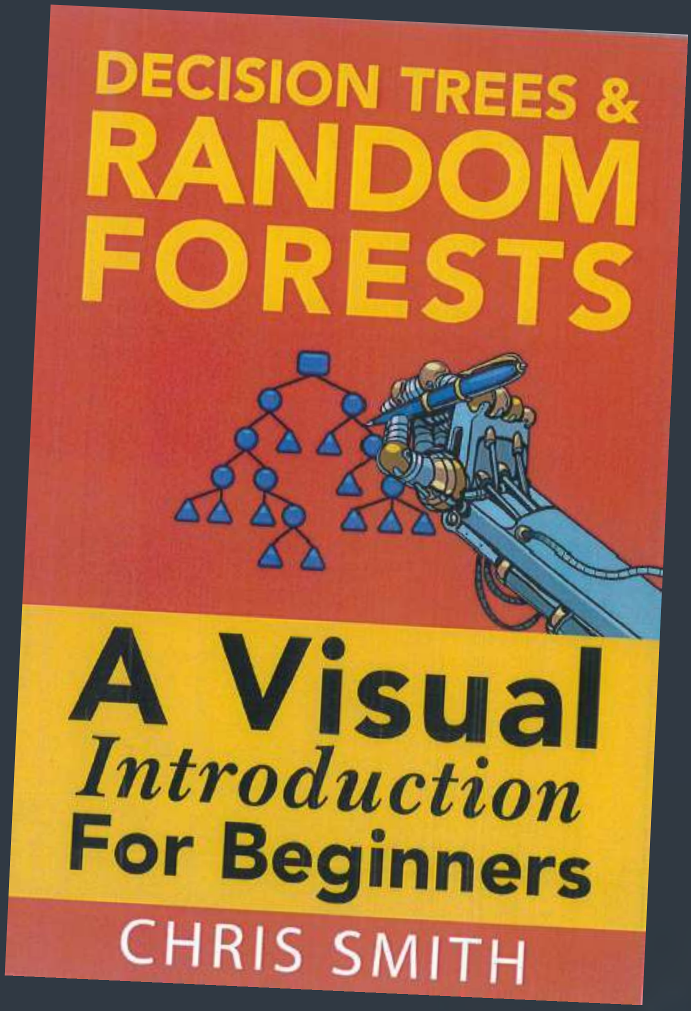


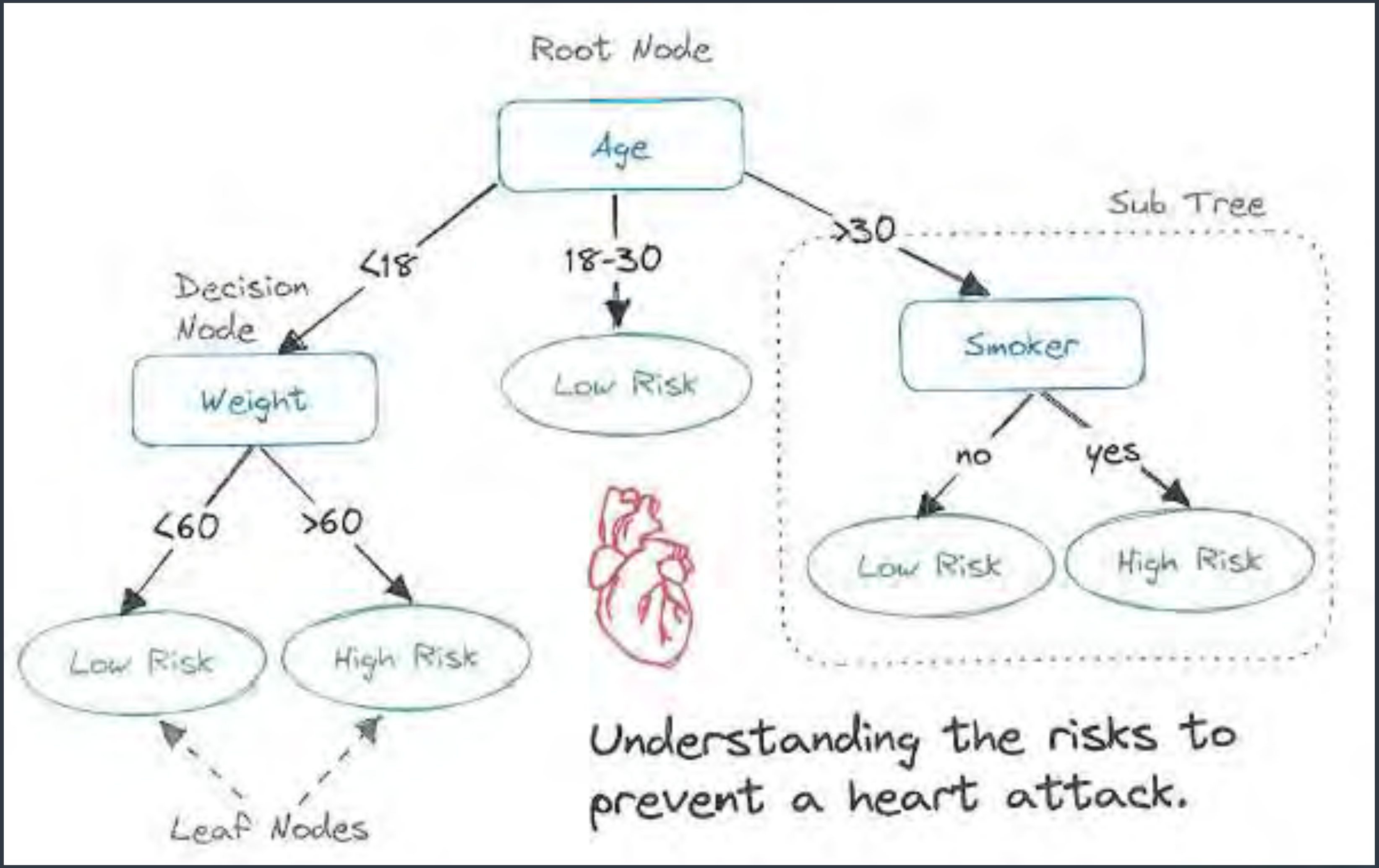
FIGURE 1.14 Machine (classical) and deep learning. Classical machine learning is divided into supervised and unsupervised learning. Ensemble learning as well as semisupervised and self-learning are also variations of machine learning. Deep learning is divided into the various types of deep learning (such as convolutional and recurrent neural networks, or CNN and RNN respectively), and reinforcement learning is considered a different type of learning (although deep reinforcement learning, or DRL, combines aspects of both). *CNN*, convolutional neural network; *DCGAN*, deep convolutional generative adversarial network; *GAN*, generative adversarial network; *RCNN*, recurrent convolutional neural network; *RNN*, recurrent neural network.

Algorithms


LEARNING MADE EASY
Algorithms
for dummies
A Wiley Brand
Relate algorithms to real-world uses
Develop skills for using algorithms
Learn to use Python to test how algorithms work
John Paul Mueller
Luca Massaron


DECISION TREES &
RANDOM FORESTS
A Visual
Introduction
For Beginners
CHRIS SMITH

Algorithm Diagram



Neural Networks

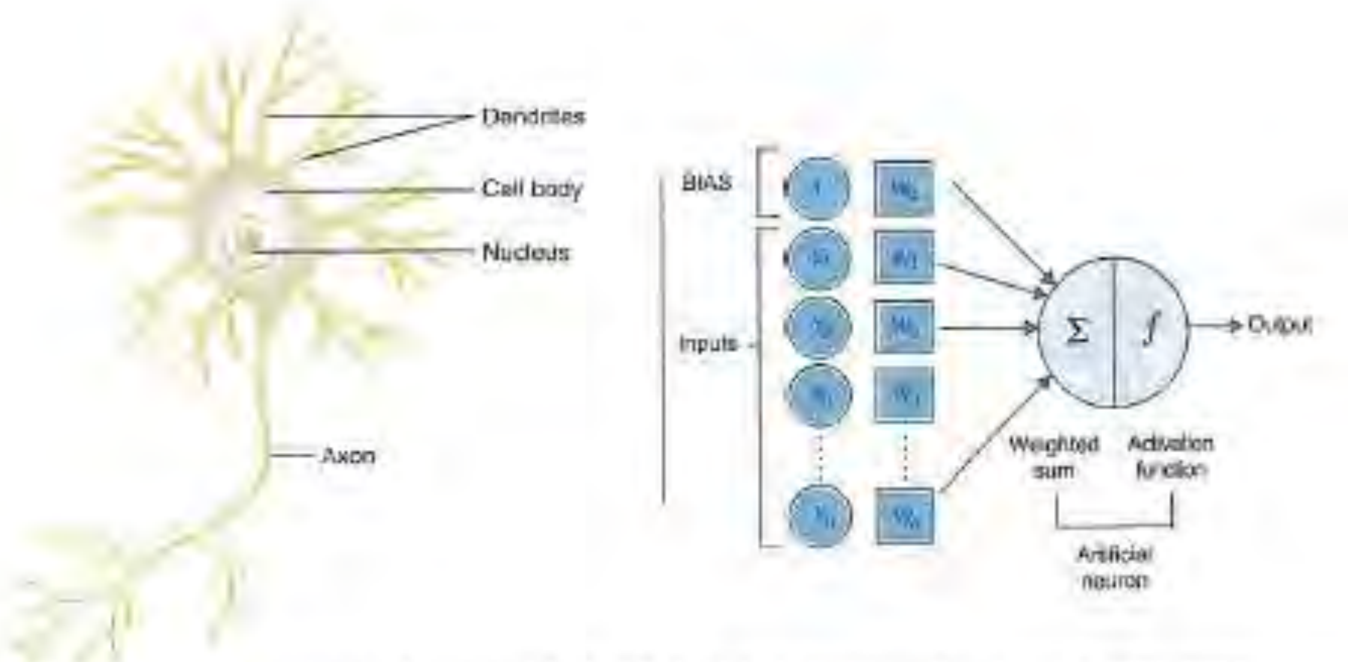
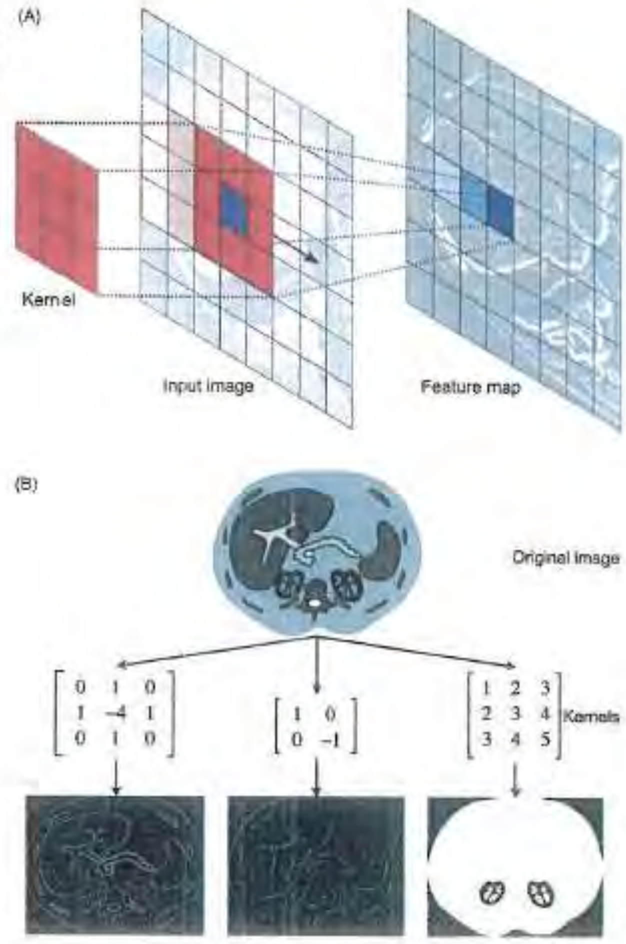


FIGURE 1.5 Biological neuron and computational perceptron. On the left, the biological neuron and its anatomy illustrates dendrites carrying impulses toward the cell body and nucleus, and these impulses are processed and move from the cell body via an axon and its connections and terminals. On the right is a schematic diagram of a perceptron. The inputs x are multiplied by their weights w and the resultant weighted sum then is all the multiplied values added together (note that w_0 is an extra weight that helps to neutralize bias in the classifier). These inputs are equivalent to the dendrites carrying impulses toward the neuronal body. The activation function (or step function) is placed in the node and is linear or nonlinear depending on the data. The activation functions can be sigmoid, tanh (similar to a sigmoid), or ReLU (rectified linear unit) which has a slope of 1. After this function processes the sum, the output is delivered. These concepts will be explained later in the book under machine learning. *Source: Shiland BJ. Chapter 8-Introduction to anatomy and physiology. In: Zenith, editor. Medical assistant: introduction to medical assisting—MAIntro. 2nd ed. Elsevier; 2016. p. 204.*

Neural Networks…continued

FIGURE 1.30 Convolution. (A). A convolution kernel (or filter matrix) in red is placed over the source input image and this convolving process leads to a new destination pixel with a new value on the feature map. (B). The feature maps extracted with different kernels are seen.



Neural Networks…continued

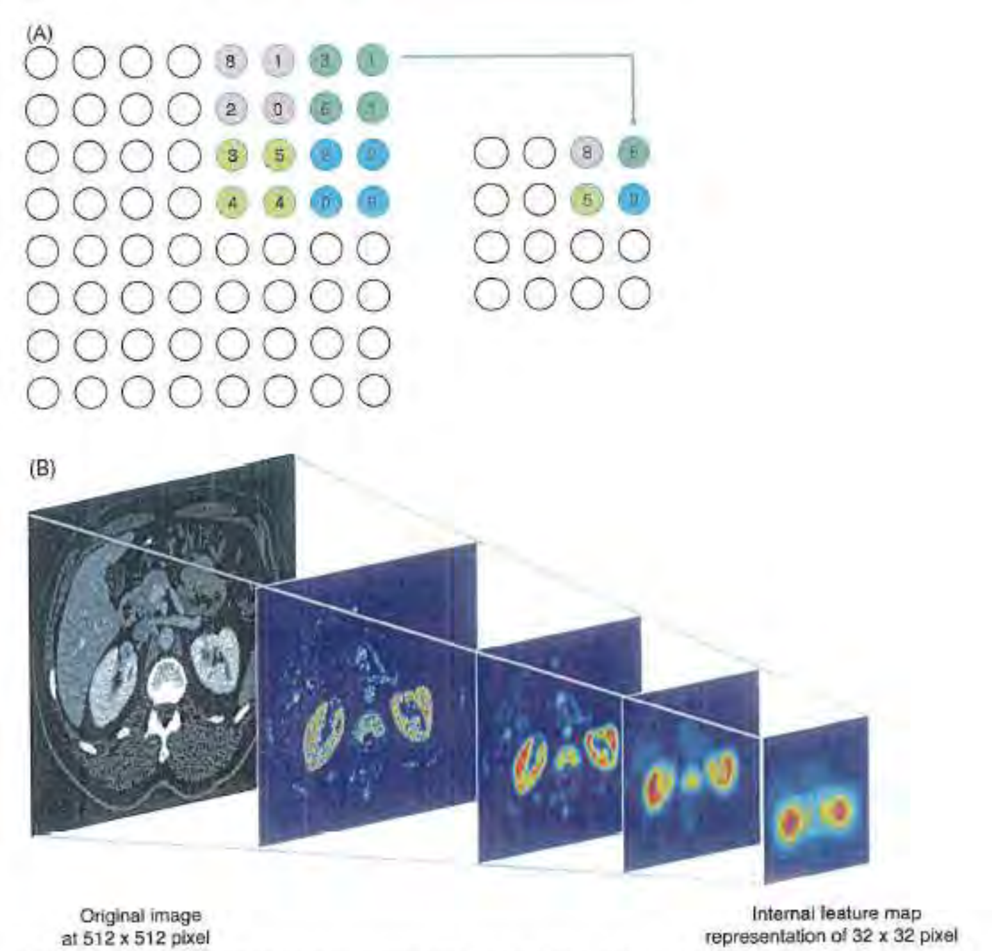
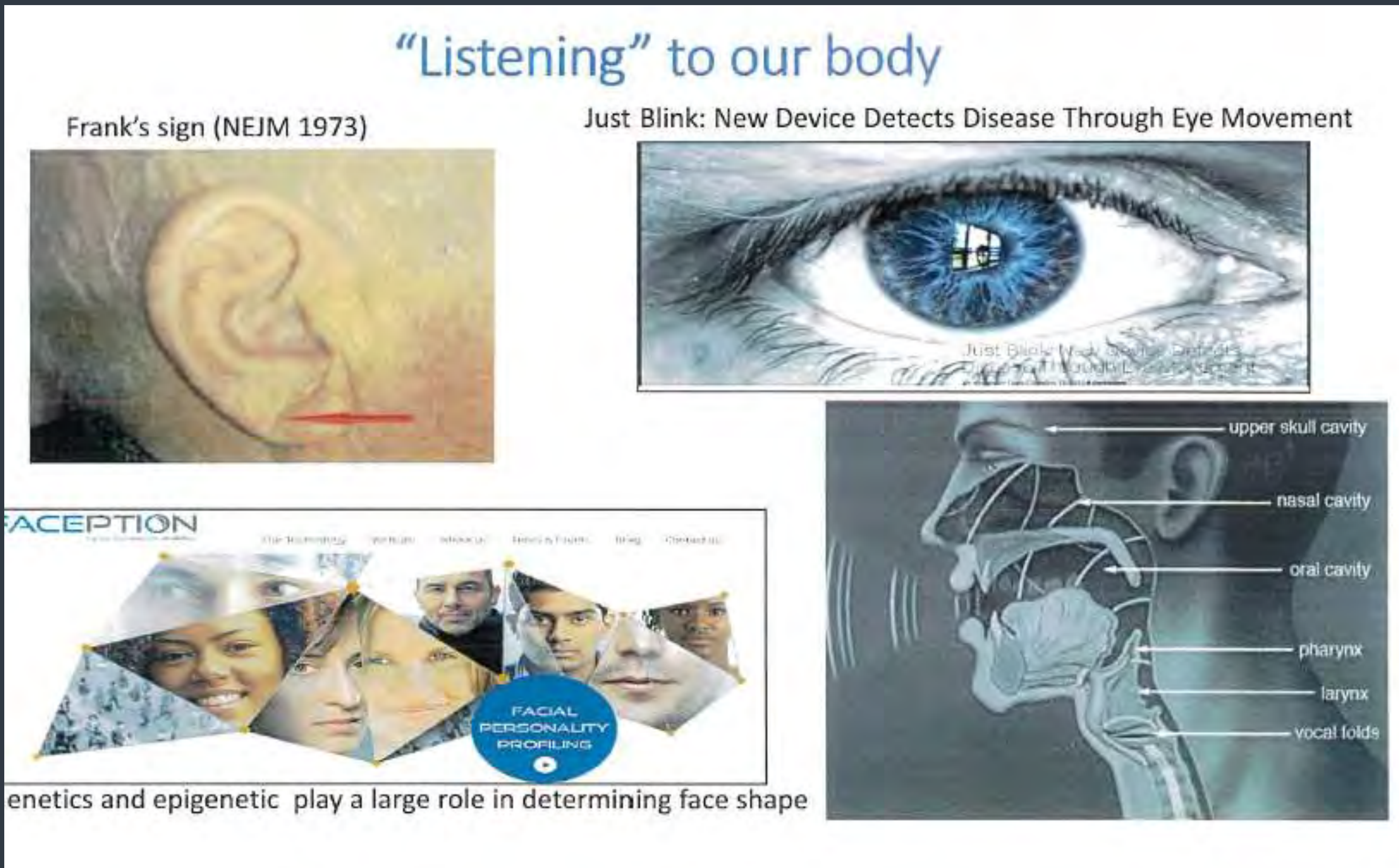
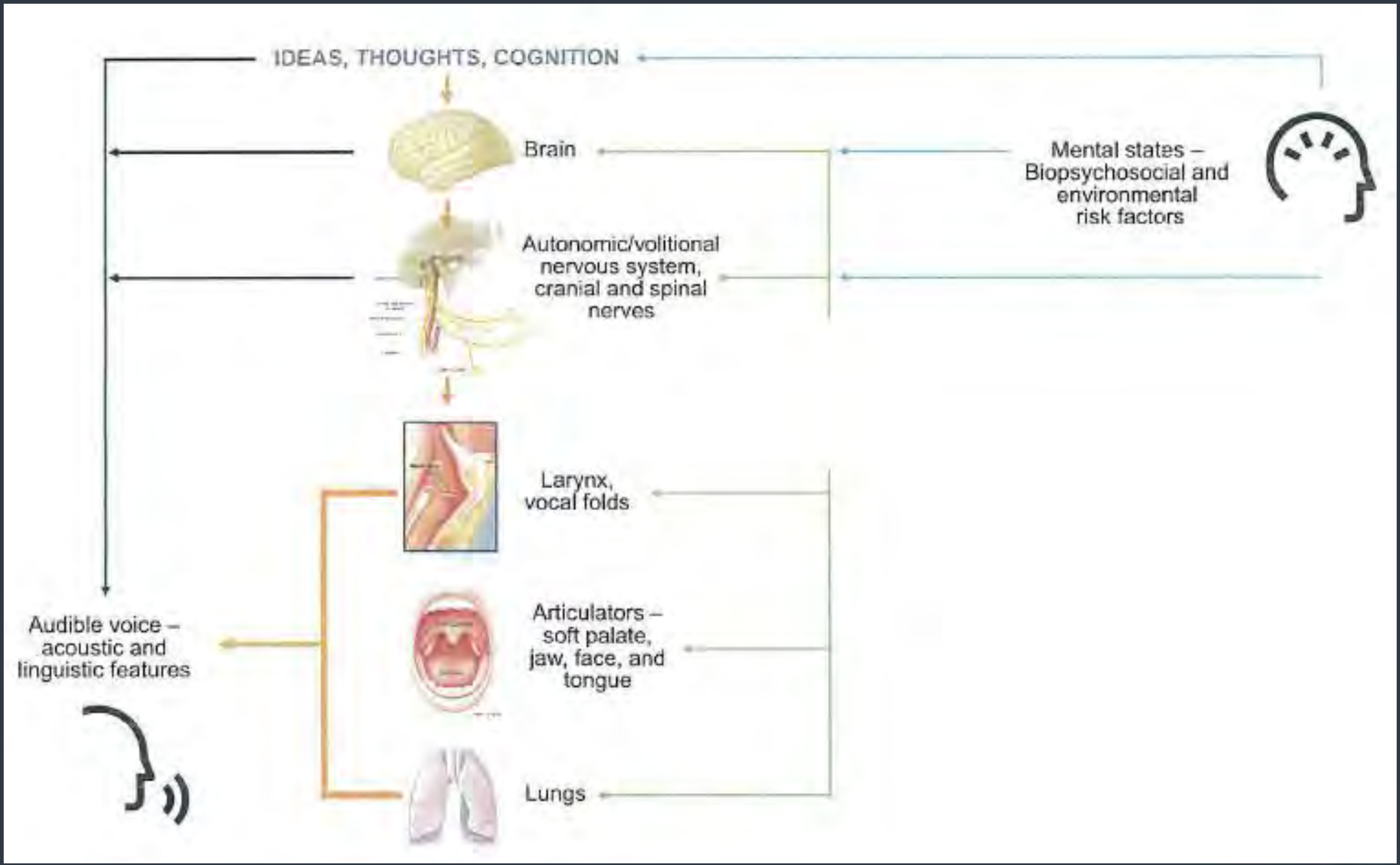


FIGURE 1.31 Pooling. In (A), the max pooling process is illustrated with only the maximum activation propagating to the next layer. For example, the green numbers of 1,1,3, and 6 are downsampled to a single number 6. In (B), the downsampled representation of the original 512 × 512 kidney CT image to the internal feature map of 32 × 32 pixels is shown. This process reduces the memory requirements while retaining the most important information. *CNN*, convolutional neural network.

Voice Recognition



Voice Recognition…continued



Voice Recognition…continued

Guess What We Can Hear—Novel Voice Biomarkers for the Remote Detection of Disease

Classification of Voice Biomarkers

VERBAL SOUNDS (SPEECH)

Words and sentences

i) Automatic speech

- Counting
- Days of the week
- Months of the year

ii) Repeated speech

iii) Read aloud speech

- Sentences (e.g. CAPE-V[73])
- Paragraph (e.g. Rainbow Passage[74])

iv) Semi-structured story telling

- Picture description (e.g. Cookie Theft[75])
- Short narration

v) Structured or semi-structured interview

vi) Running spontaneous speech (e.g. describing an event, conversation)

VOCAL SOUNDS

Sustainable sounds with linguistic meaning

i) Individual sounds

- Sustained vowels
- Sustained consonants (voiced and voiceless fricatives, glides, nasals)

ii) Single syllables

- Consonant vowel constructs (clinically used to assess diadochokinesis e.g., voiceless plosives followed by vowel e.g. /pa/ /ta/ /ka/ /hi/; category includes any consonant vowel form)
- Consonant-vowel-consonant constructs (i.e. single syllable words; can be used to assess vowels e.g., beet, bit, bait, bet, bat, but, bought, boot)

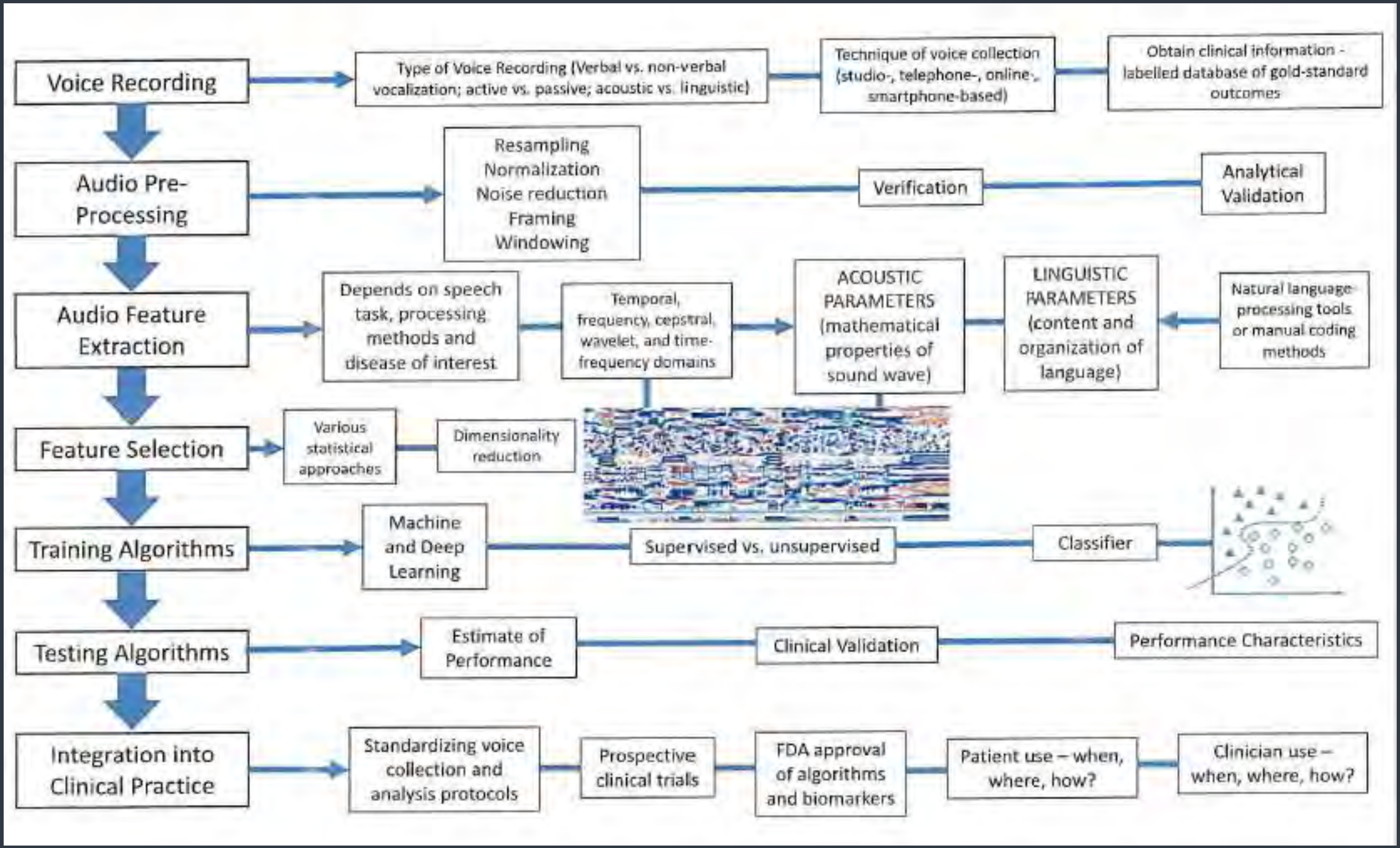
NON-VERBAL SOUNDS

Non-speech sounds with no linguistic meaning

i) Sounds generated from the larynx and upper and lower airway tracts

- Snore
- Grunt
- Cough
- Trill
- Breathing (larynx has passive movement during quiet breathing)
- Wheeze
- Stridor (inspiratory laryngeal noise associated with paradoxical vocal fold motion)

Voice Recognition…continued



Voice Recognition…continued

Journal of the American Heart Association

ORIGINAL RESEARCH

Vocal Biomarker Is Associated With Hospitalization and Mortality Among Heart Failure Patients

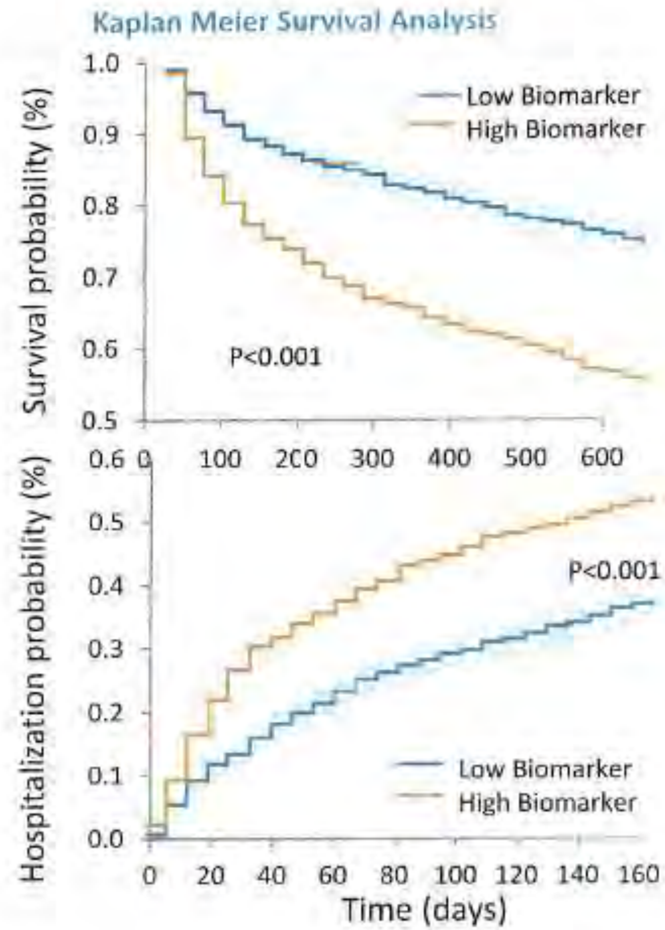
Elad Maor, MD, PhD; Daniella Perry, PhD; Dana Mevorach, MA; Nimrod Taiblum, PhD; Yotam Luz, PhD; Israel Mazin, MD; Amir Lerman, MD; Gideon Koren, MD; Varda Shalev, MD, MPH

The study cohort included 10 583 patients who were registered to a call center of patients who had chronic conditions including CHF in Israel between 2013 and 2018.

A total of 223 acoustic features were extracted from 20 s of speech for each patient. 3 languages

A biomarker was developed based on a training cohort of non-CHF patients (N=8316).

The biomarker was tested on a mutually exclusive CHF study cohort (N=2267) and was evaluated as a continuous and ordinal (4 quartiles) variable.



Voice Recognition…continued

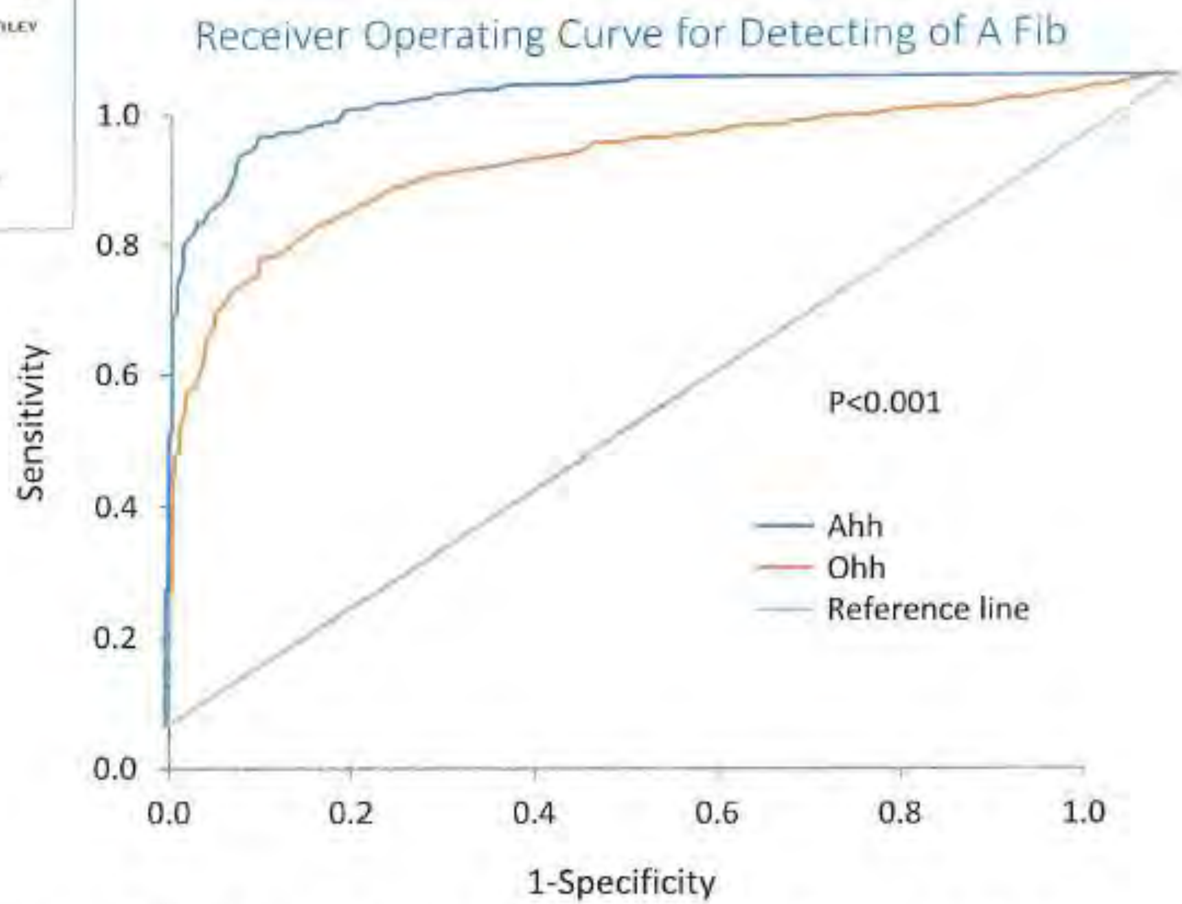
ORIGINAL ARTICLE

WILEY

Automated detection of atrial fibrillation based on vocal features analysis

Gregory Golovchiner MD[1] | Michael Glikson MD[2] | Moshe Swissa MD[2] |
Yaron Sela PhD[4] | Aryeh Abelow MD[1] | Olga Morelli MD[1] | Amir Beker PhD[5]

- *Duration 4 seconds each individual recorded both vowels*



The AUC (area under the curve) is above 0.98 for the verb "Ahh" and above 0.89 for the verb 'Ohh" with a P<0.001

Voice Recognition…continued

Hey Goglexiri, Do I Have Coronary Artery Disease?

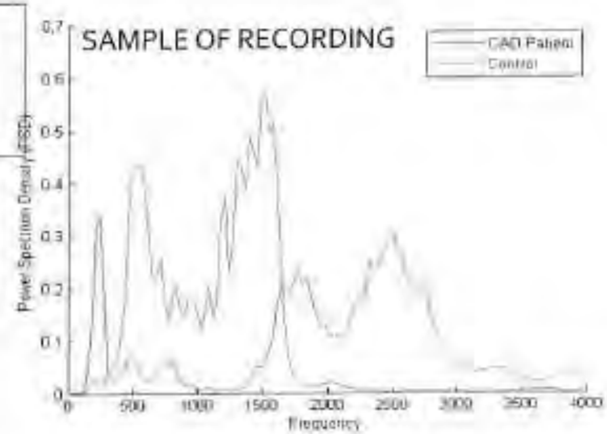
Voice Signal Characteristics Are Independently Associated With Coronary Artery Disease

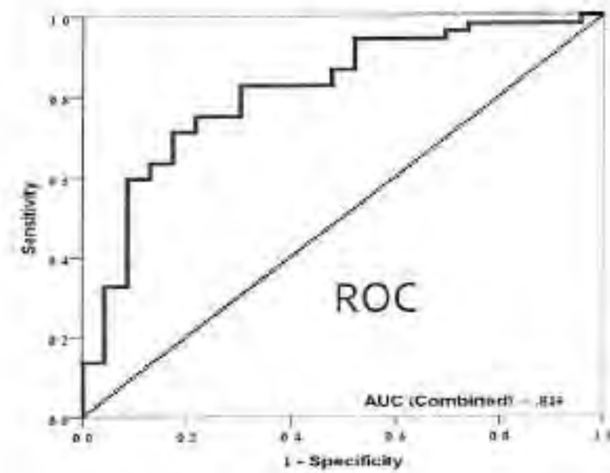
Elad Maor, MD, PhD; Jaskanwal D. Sara, MBChB; Diana M. Orbelo, PhD;

A multivariate binary logistic regression, with adjustment for age, gender, and cardiovascular traditional risk factors, showed that this features was independently associated with a significant 2.6-fold increased likelihood of CAD (95% CI 1.16-5.80, p=0.020).

Areas under the ROC curves for Framingham score, and for a combined new score are shown. The AUROC of the Framingham score was 0.807. When a simple new score was used (Framingham + Feature 15), the AUROC increased to 0.814.

No difference between the three texts





Voice Recognition…continued

Cardiovocal syndrome or Ortner's syndrome: **Ortner's syndrome**

Ortner N. Recurrent nerve paralysis in mitral stenosis. *Wien Klin Wochenschr.* **1897**
refers to **hoarseness due to recurrent laryngeal nerve palsy secondary to a cardiovascular abnormality** described as the compression of the recurrent laryngeal nerve of pathologically enlarged cardiac structures

- left atrium in mitral stenosis,
- aortic aneurysm,
- Pericardial effusion

VOCAL-CORD PARALYSIS IN HEART DISEASE

MILTON PLOTZ, M.D.
AND
MORRIS J. BROOKS, M.D.
BROOKLYN

THE ASSOCIATION of hoarseness and heart disease is a well-defined, although uncommon, clinical syndrome. Nevertheless, this combination has not received the attention it merits in the laryngological literature, either text or periodical. Two illustrative cases will, therefore, be included in this article, together with a brief résumé of the literature and a discussion of the pathogenesis.

AMA Arch Otolaryngol. 1951;54(3):273-278

Voice Recognition…continued

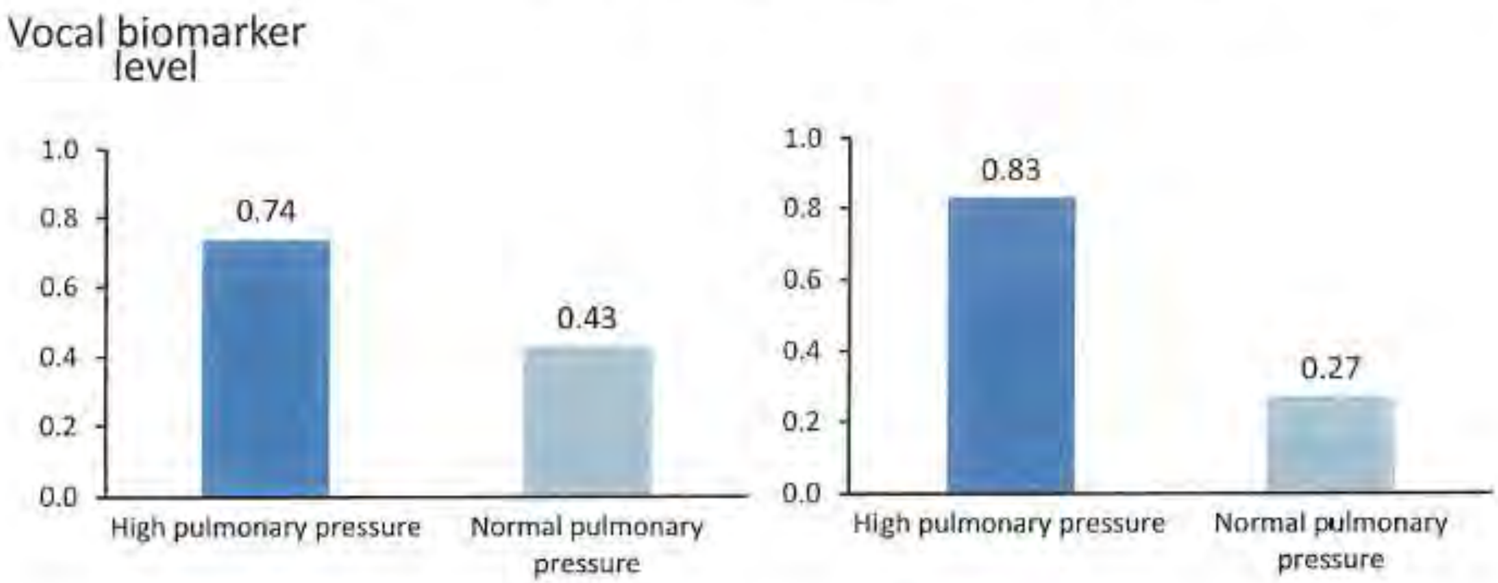
RESEARCH ARTICLE

PLOS ONE

Non-invasive vocal biomarker is associated with pulmonary hypertension

Jaskanwal Deep Singh Sara[1], Elad Maor[2,3], Barry Borlaug[1], Bradley R. Lewis[4], Diana Orbelo[5], Lliach O. Lerman[6], Amir Lerman[1]*

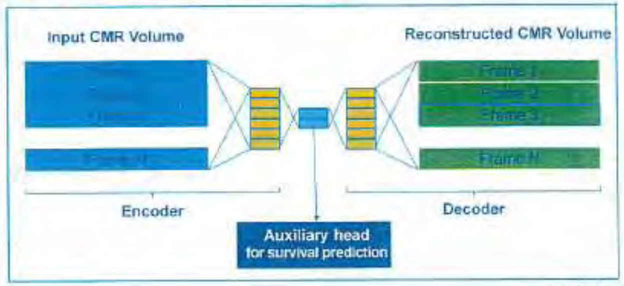
- ***Each standard deviation increase in the vocal biomarker was significantly associated with a 49% increased likelihood of a high PA pressure (95% CI 1.07-2.08, P=0.019)***



MRI and CT

SURVIVAL PREDICTION

- E.g. **4Dsurvival,** is a hybrid network comprising of a denoising **autoencoder** paired with a Cox proportional hazards model.
- The autoencoder learns a latent representation of the data, which is then linked to a linear predictor of survival, ensuring that the latent code is optimized not just for reconstructing inputs but also for predicting survival outcomes effectively.



Bello, Nat Mach Intell 2019

CHALLENGES OF AI

Explainablity

Referred as 'Black box'

Saliency maps can show **which** pixels help decide but don't tell **why**

Fosters trust in model—at least it is looking at the right pixels

Not flawless

Generalizability

Ability to perform well on unseen data different from training data

Non-matching data curation for 1 inference will produce errors

Unmatched population distribution poses a challenge

Imbalanced datasets can skew model's learning
e.g. Fewer cases of a condition makes it less accurate in identifying that condition

Uncertainty

Ability to express confidence of lack of it in predictions

Epistemic = lack of training data or incorrect assumptions (Reduced with more data or model refinement)

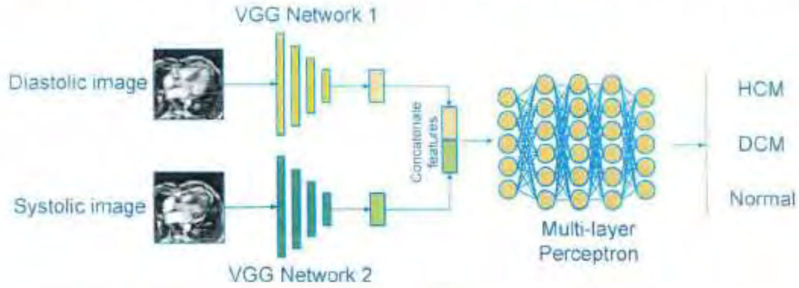
Aleatoric = inherent noise or variability in data (Cannot be reduced but can be modeled and estimated)

Quantifying Uncertainty in Deep Learning of Radiologic Images

Radiology, 2023

MRI and CT…continued

CARDIOMYOPATHY CLASSIFICATION



A fine-tuned VGG network classified cine-MR images of different cardiomyopathies, using diastolic and systolic frames from 1200 subjects. The model achieved an accuracy of 0.982 ± 0.009, matching experienced human experts.

Germain et al., Diagnostics

PROGNOSIS

Deep learning predicts survival in many diseases

Prediction of survival time from cine CMR

PULMONARY HYPERTENSION

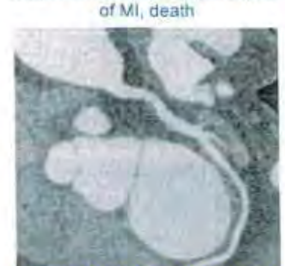
Bello, Nat Mach Intell 2019

Prediction of survival time from cine CMR

TETRALOGY OF FALLOT

Diller, Heart, 2020

ML-based plaque severity and composition from coronary CTA outperforms traditional predictors of MI, death



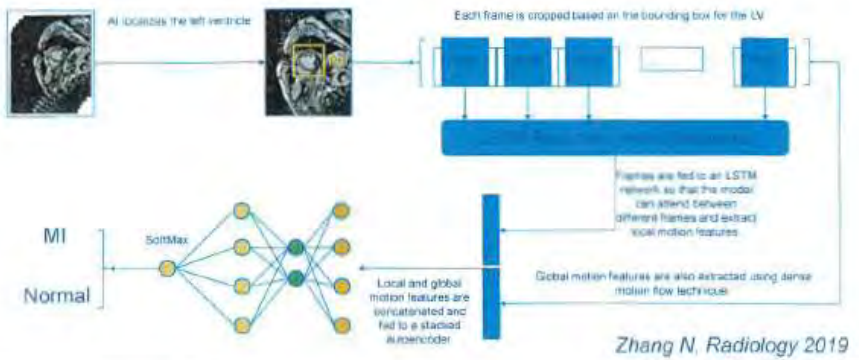
CORONARY ARTERY DISEASE

van Rosendeal, J Cardiovasc Comput Tomogr. 2020

MRI and CT…continued

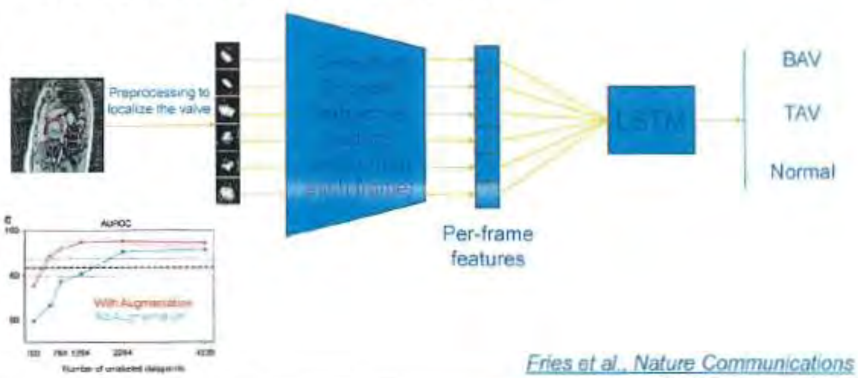
MYOCARDIAL INFARCTION DIAGNOSIS

A deep learning model was trained on 212 patients with MI and 87 normal control cases to predict MI based on local and global LV motion abnormalities.



Zhang N, Radiology 2019

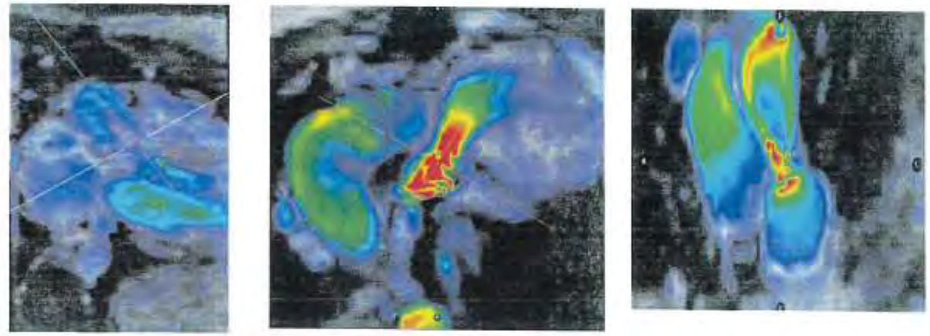
AORTIC VALVE DIESEASE CLASSIFICATION



Fries et al., Nature Communications

MRI and CT…continued

AUTOMATED FLOW PROCESSING



Automated post-processing of 4D flow data

CLASSIFICATION OF DISEASE

Myocardial infarction

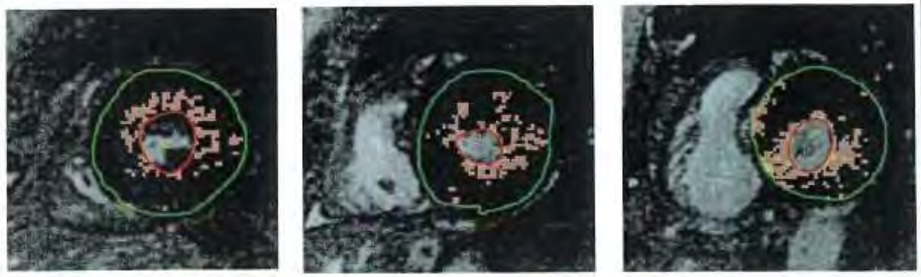
Valvular diseases

Cardio-myopathies

MRI and CT…continued

AUTOMATED SCAR QUANTIFICATION

Quantification of scar in patients with hypertrophic cardiomyopathy



Automated quantification of scar correlates well with manual quantification.

Fahmy, Radiology 2020

AUTOMATED STRAIN QUANTIFICATION

CMR strain can be performed with AI-contouring and post processing

AI- based contouring | Feature tracking | AI- quantification of strain

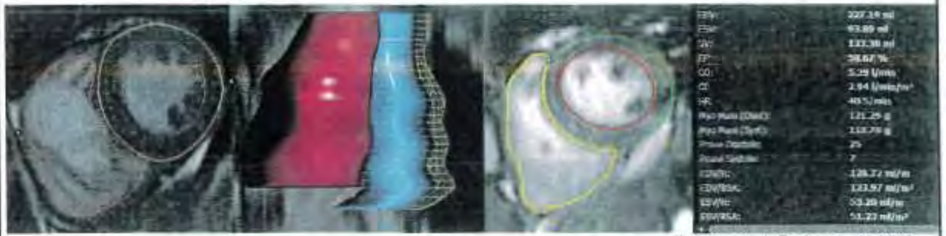
MRI and CT…continued

DEEP LEARNING SEGMENTATION

- U-Net and more advanced variants of that, e.g., nn-U-Net (which stands for "No New U-Net"), can learn to generate a corresponding **"segmentation mask"** for each input image. In segmentation masks, each pixel is assigned a class label, where labels indicate whether a pixel belongs to the background or one or more objects of interest. Segmentation can be performed on 2D images or 3D volumes.
- The processed segmentation maps can also be utilized for quantitative analyses:
  - **Morphological operations** (e.g., erosion and dilation), can be applied to segmentation masks to refine the outlines of segmented objects and reduce noise.
  - **Connected component analysis** can be used to identify and extract individual objects within a segmentation mask.
  - **Filters**, such as Gaussian blur or median filters, can be applied to smooth the segmentation masks, reducing high-frequency noise and improving the overall appearance and accuracy of the segmented regions.
  - **Edge detection and contour tracing** can then be applied to extract the outlines of these objects, which is essential for shape analysis and object recognition.
  - **Radiomics** can help extract relevant features from the segmentation masks, such as texture, shape, and intensity.

VOLUMETRIC EVALUATION

- AI-based volumetric ventricular quantification algorithms are now commercially available
- Correlates with manual expert contours for EDV, ESV, EF, both for RV and LV
- Majority of errors (73 %) occur at the cardiac base
- The differences between manual and automatic were same as between expert readers
- The automated contours can be used for expert segmentation, who will correct base and apex

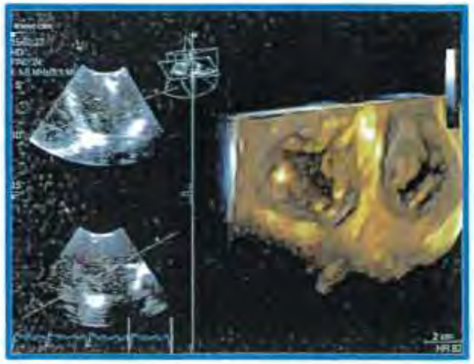


Retson, et al. Radiology AI 2020

AI and Echo

CHALLENGES TO APPLYING AI TO ECHO

- Datasets are massive
- Skill of imager
- Variation in ultrasound systems and settings
- Differing protocols
- Individual variations in anatomy
- Noisy signal



AI: Data Mining for Echo

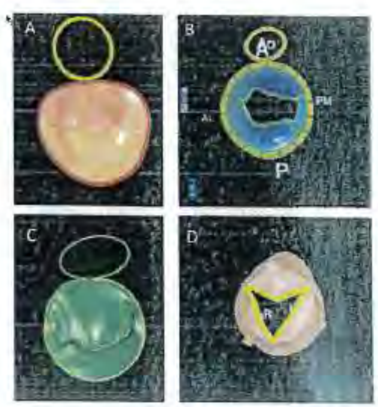
- REQUIREMENTS FOR ACCURACY:
- Large amounts of accurately labeled data
- REQUIREMENTS FOR GENERALIZABILITY:
- Different ultrasound systems
- Different operators, different laboratories
- Broad spectrum of patients
- Broad spectrum of disease
- Independent testing of the model

AI and Echo…continued

CLINICAL DECISIONS ARE BASED ON NUMBERS

- Ejection fraction:
  - Basis for classification of heart failure
  - Guidelines for device implantation
  - Intervention in severe valve disease
  - Enrollment in clinical trials
  - Prognosis
- Chamber volumes, regurgitant volumes, gradients, valve areas
- Diastolic function

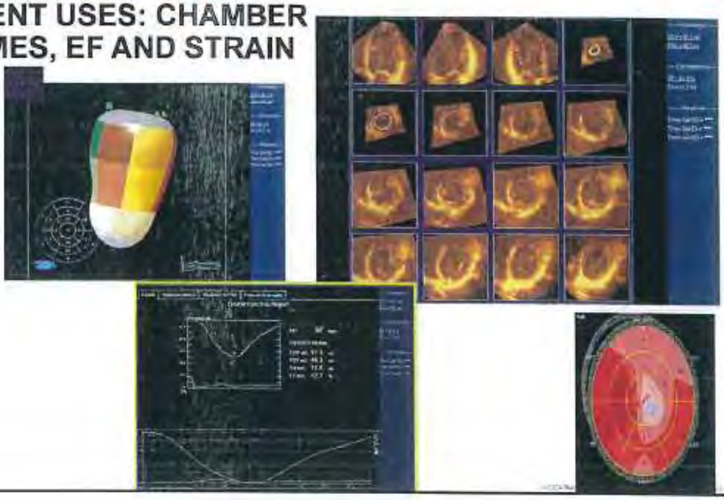
CURRENT USES OF AI IN ECHO LABS VALVE ANALYSIS SOFTWARE



Nedadur R. Heart 2022

AI and Echo…continued

CURRENT USES: CHAMBER VOLUMES, EF AND STRAIN



REDUCED VARIABILITY OF MEASUREMENT WITH AI

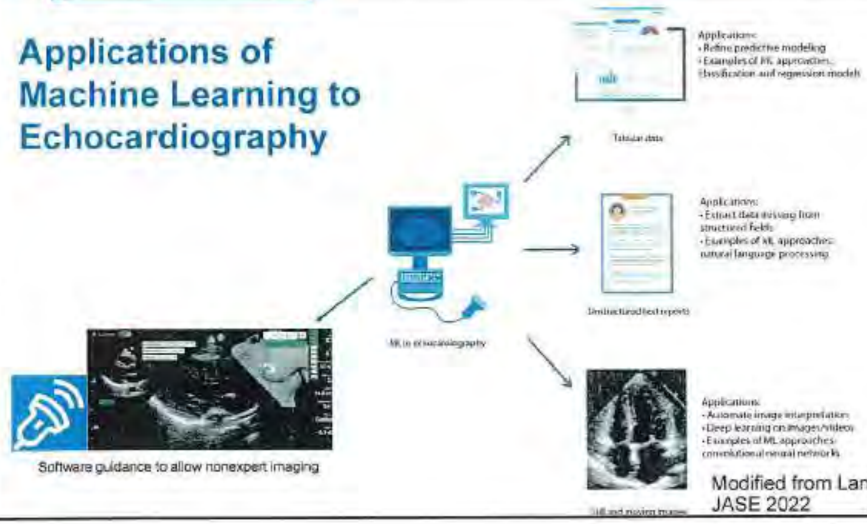
Table 2 Interoperator agreement using manual or AI-based analysis and dependent on frame selection

Method	Measure	Frame selection	*n*	*R* (Pearson correlation) (95% CI)	ICC (95% CI)
AI	LVEF	All	385	0.853 (0.824-0.878)	0.854 (0.824-0.879)
Manual			319	0.670 (0.605-0.727)	0.655 (0.573-0.722)
AI	LVEF	Same	49	0.996 (0.994-0.998)	0.996 (0.993-0.998)
Manual			14	0.683 (0.239-0.891)	0.680 (0.240-0.886)
AI	LVEF	Different	336	0.832 (0.796-0.862)	0.832 (0.796-0.862)
Manual			305	0.671 (0.504-0.728)	0.654 (0.569-0.723)

Asch FM: Human vs AI in COVID. JASE 2022

AI and Echo…continued

Applications of Machine Learning to Echocardiography



Modified from Lam C: JASE 2022

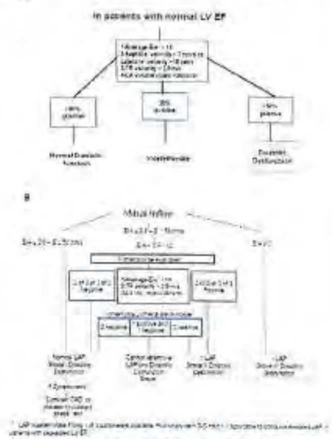
APPLICATION OF AI TO DETECTION OF HFPEF

- HF affects 6.5 million US adults; expected to increase by 46% by 2030
- High morbidity and mortality
- HFpEF is increasing in prevalence, becoming the predominant form of HF worldwide
- Difficulty in performing and interpreting Doppler echocardiography leads to challenges in diagnosis and worse outcome for HFpEF

AI and Echo…continued

OPPORTUNITY: ASSESSMENT OF DIASTOLIC FUNCTION

- Multiple measurements
- Accurate alignment of Doppler beam and correct sample volume positioning
- Correct gain settings
- Exclusions
- Indeterminate in 1/3

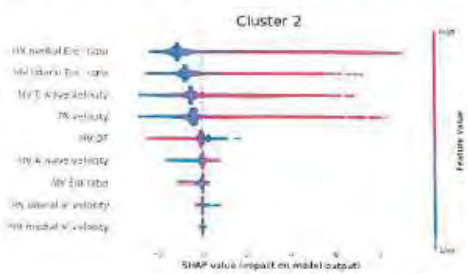


Nagueh S: ASE Guidelines

UNSUPERVISED ML- 3 DIASTOLIC FUNCTION CLUSTERS

- Adult echos in 2015
- Exclusions (MVR, transplant, congenital; n=24,414)
- Standard candidate variables
- Three clusters with features of
  - Normal diastolic function (cluster 0, n= 8,312)
  - Impaired relaxation (cluster 1, n=11,779)
  - Increased filling pressure (cluster 2, n =4,323)

K means algorithm to determine cluster
SHAP analysis for variable importance



- Higher medial and lateral E/e' ratio
- Higher E wave velocity
- Higher TR peak velocity
- Shorter DT

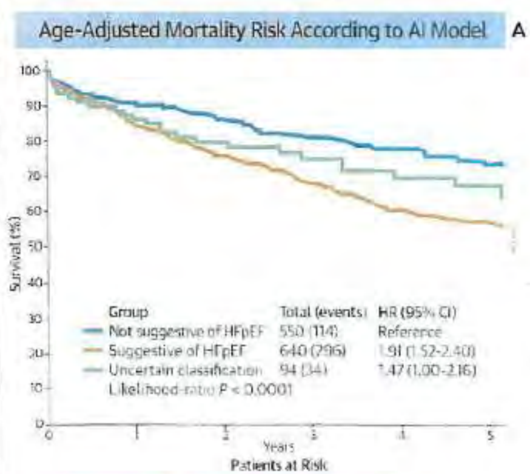
Chao C-J, JASE 2022

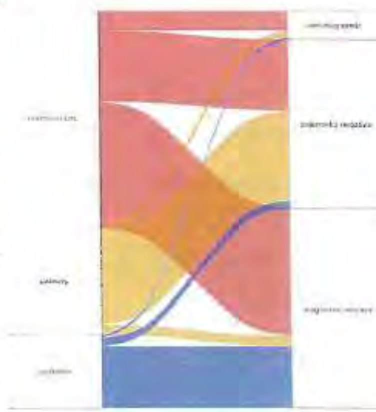
AI and Echo…continued

AI TO DETECT HEART FAILURE PRESERVED EJECTION FRACTION FROM APICAL 4 CH VIDEO

- Pts without heart failure, ejection fraction >50%, normal or grade 1 diastolic function
- Pts with heart failure, ejection fraction >50%, increased filling pressure
- 15% withheld for validation
- Separate group for testing: sens 88%, spec 82%

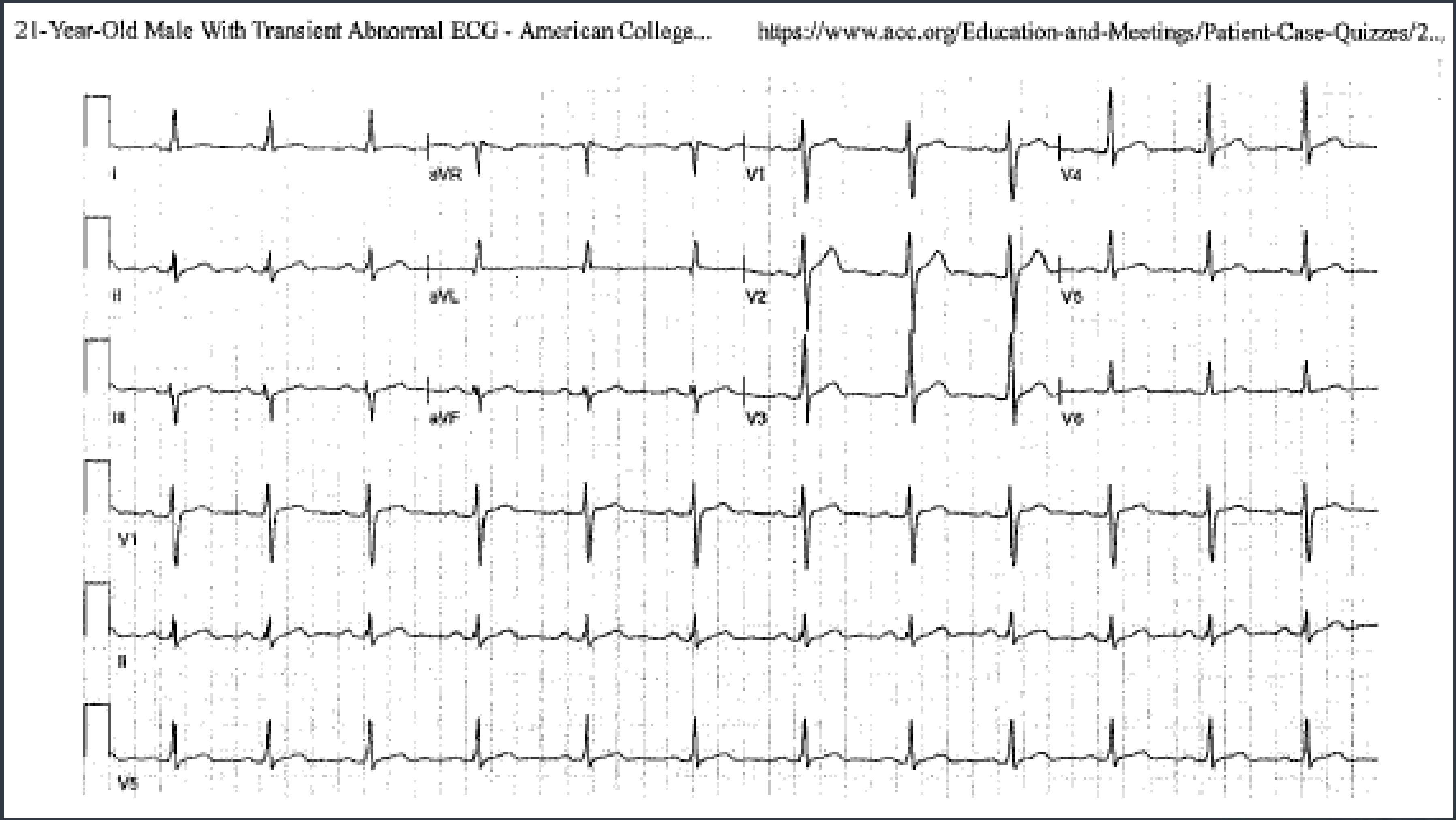
FDA approval November 2022





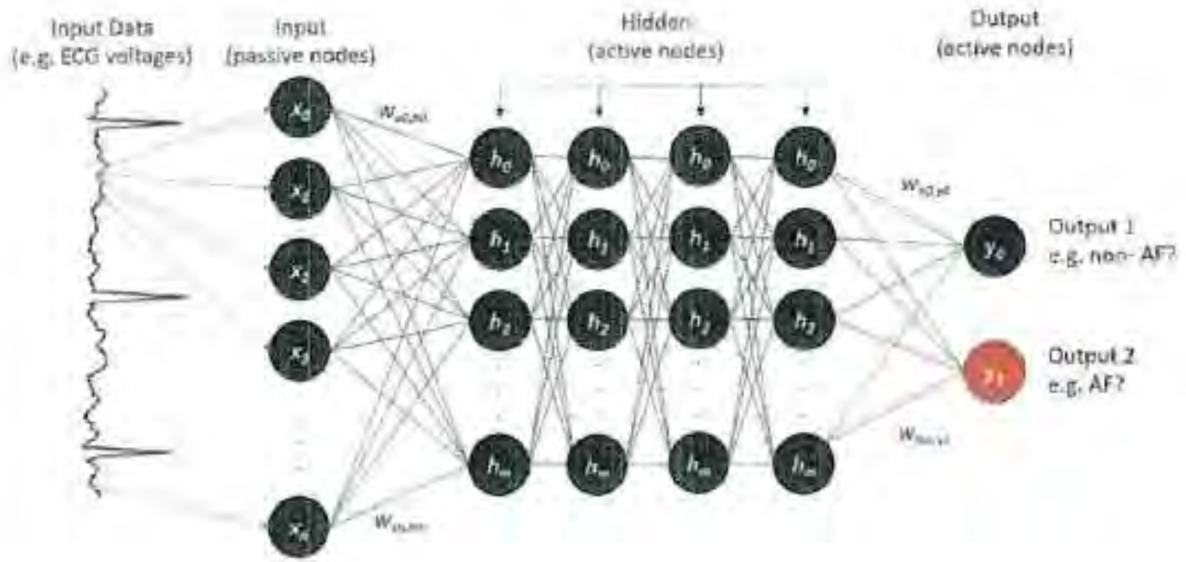
Akerman A. JACC Advances 2023

AI and ECG



21-Year-Old Male With Transient Abnormal ECG - American College...
https://www.acc.org/Education-and-Meetings/Patient-Case-Quizzes/2...
I
aVR
V1
V4
II
aVL
V2
V5
III
aVF
V3
V6
V1
II
V5

AI and ECG…continued

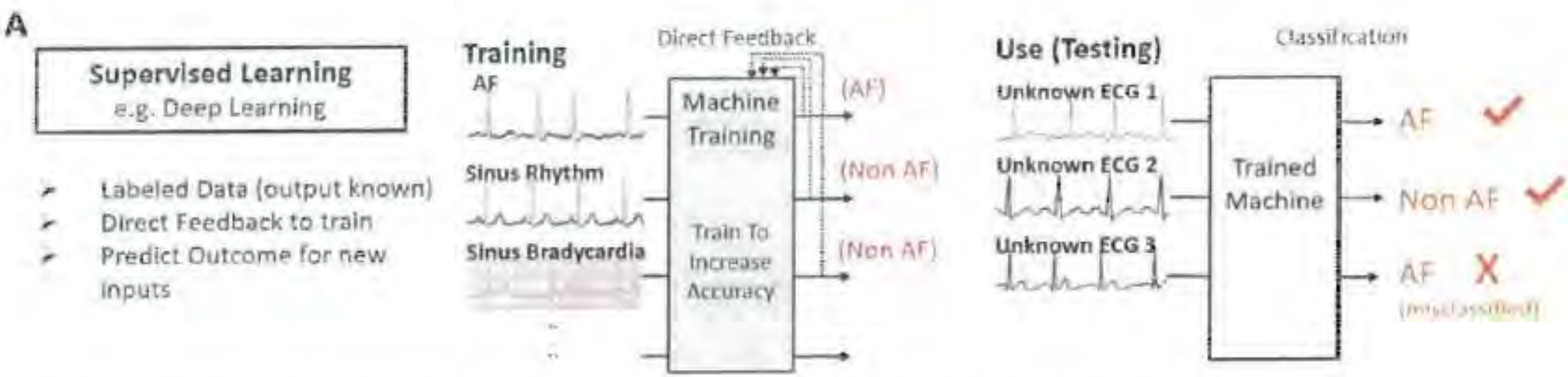


- Input layer: x
- Hidden layers: (H), where processing occurs
- Output layers: result

- Black circles in each layer represent "neurons"
- Each layer is connected to each subsequent layer, using pathways that are assigned a weight "W"

AI and ECG…continued

DNN and ECGs



- In Supervised Learning, the DNN is given both the ECG (input) and diagnosis (output)
- Direct Feedback: after each ECG examined, the machine then adjusts the activation scores and pathway weights accordingly for each neuron based upon the given output/result, ie whether that pathway is deemed correct or not!
- ****As a result, over thousands to millions of ECGs, the machine hones its algorithm (by adjusting activation scores and pathway weights) to increase accuracy and "teaches" itself to recognize patterns in the ECGs!

AI and ECG…continued

Neural Network to Identify Latent AF on Normal Sinus Rhythm ECG

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

Summary

Background Atrial fibrillation is frequently asymptomatic and thus underdetected but is associated with stroke, heart failure, and death. Existing screening methods require prolonged monitoring and are limited by cost and low yield. We aimed to develop a rapid, inexpensive, point-of-care means of identifying patients with atrial fibrillation using machine learning.

Methods We developed an artificial intelligence (AI)-enabled electrocardiograph (ECG) using a convolutional neural

Lancet 2019; 394

Published Online August 1, 2019

See Comment page

AI and ECG…continued

The Next Step: Using AI-ECG to Predict AF

ORIGINAL RESEARCH ARTICLE

Deep Neural Networks Can Predict New-Onset Atrial Fibrillation From the 12-Lead ECG and Help Identify Those at Risk of Atrial Fibrillation–Related Stroke

Editorial, see p 1299

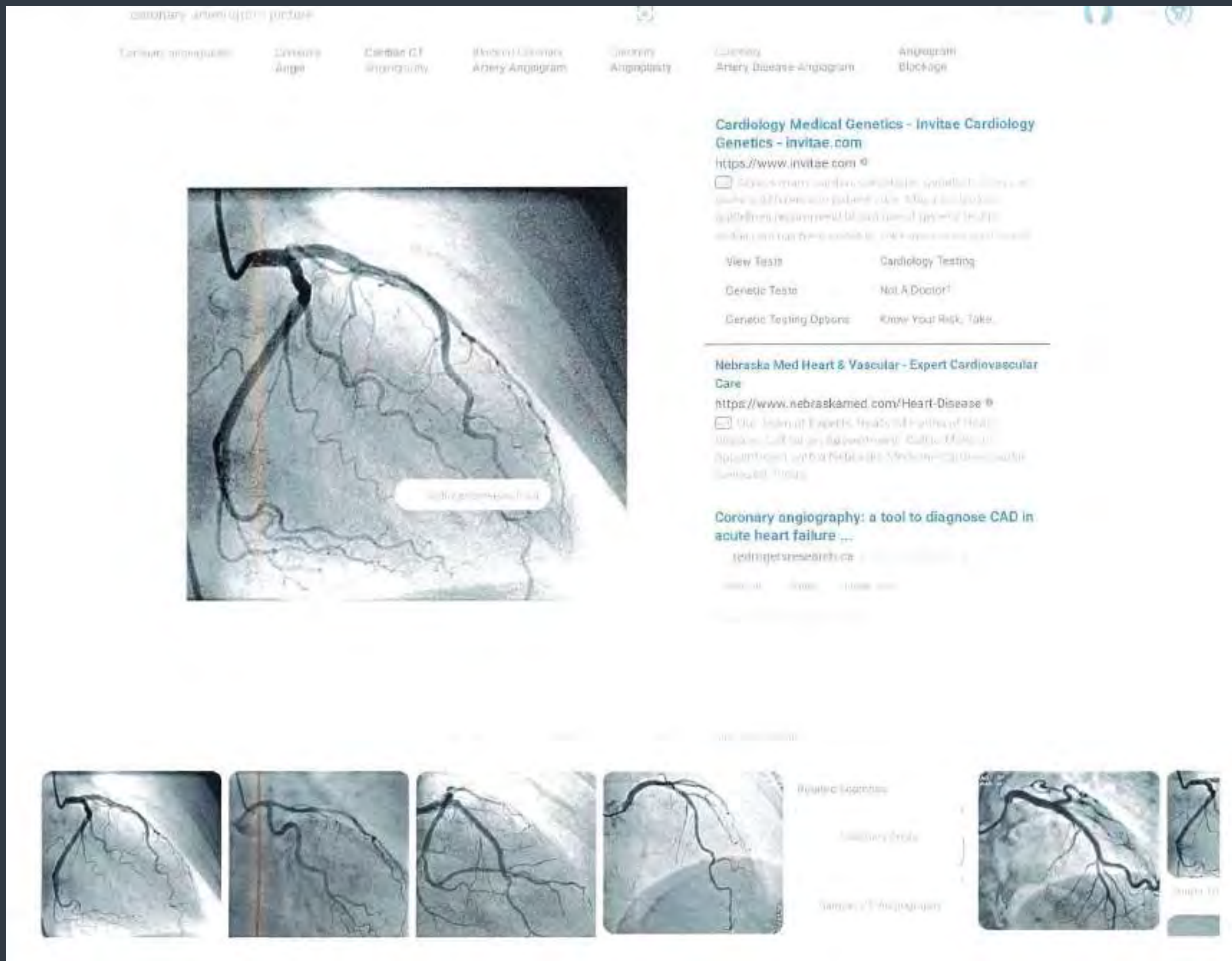
Sushravya Raghunath, PhD*
John M. Pfeifer, MD, MPH*
⋮
Brandon K. Fornwalt, MD, PhD†
Christopher M. Haggerty, PhD†

BACKGROUND: Atrial fibrillation (AF) is associated with substantial morbidity, especially when it goes undetected. If new-onset AF could be predicted, targeted screening could be used to find it early. We hypothesized that a deep neural network could predict new-onset AF from the resting 12-lead ECG and that this prediction may help identify those at risk of AF-related stroke.

ECG Diagnosis

1. Age
2. Gender
3. Ethnicity
4. LV Ejection Fraction
5. Diastolic Function
6. Pulmonary Artery Pressures
7. Latent Atrial Fibrillation

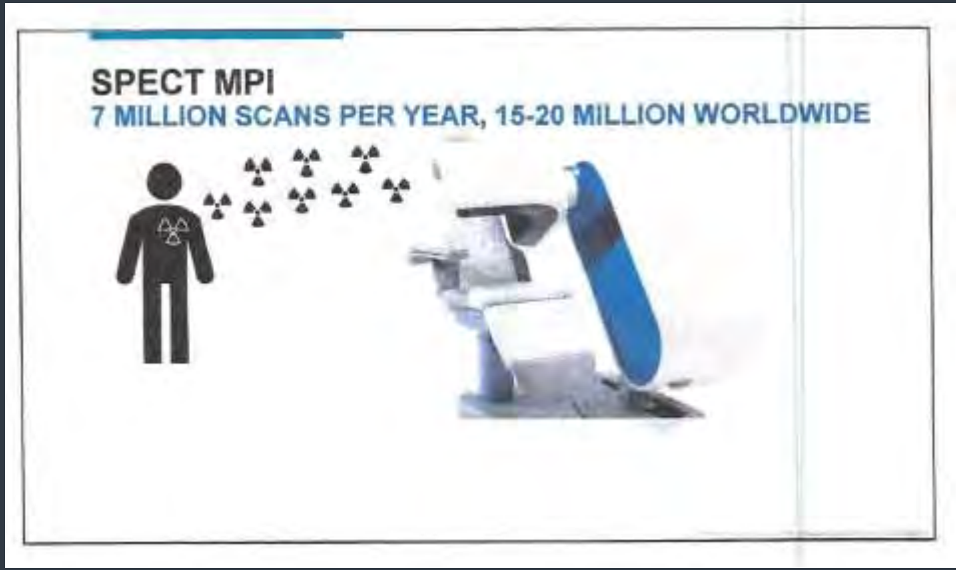
AI and Coronary Arteriograms

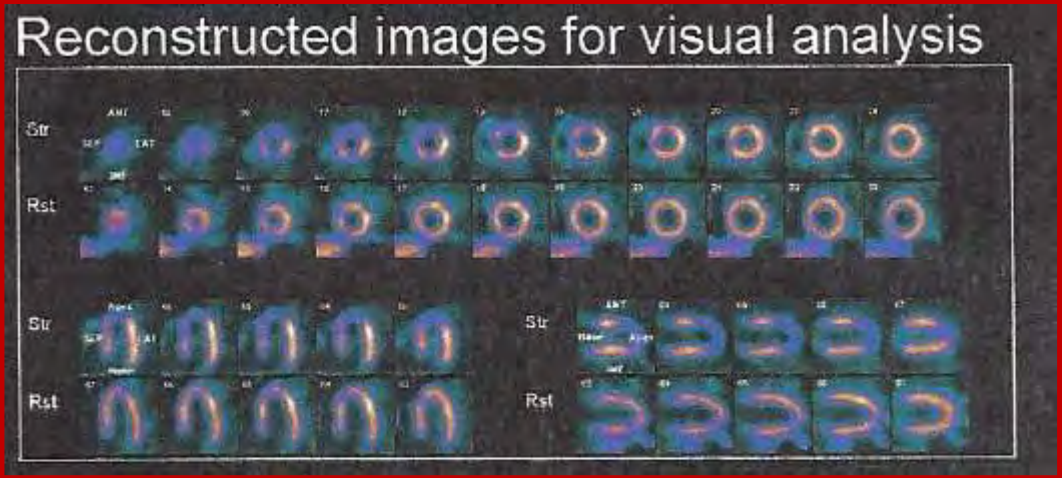


AI and Coronary Arteriograms Diagnosis

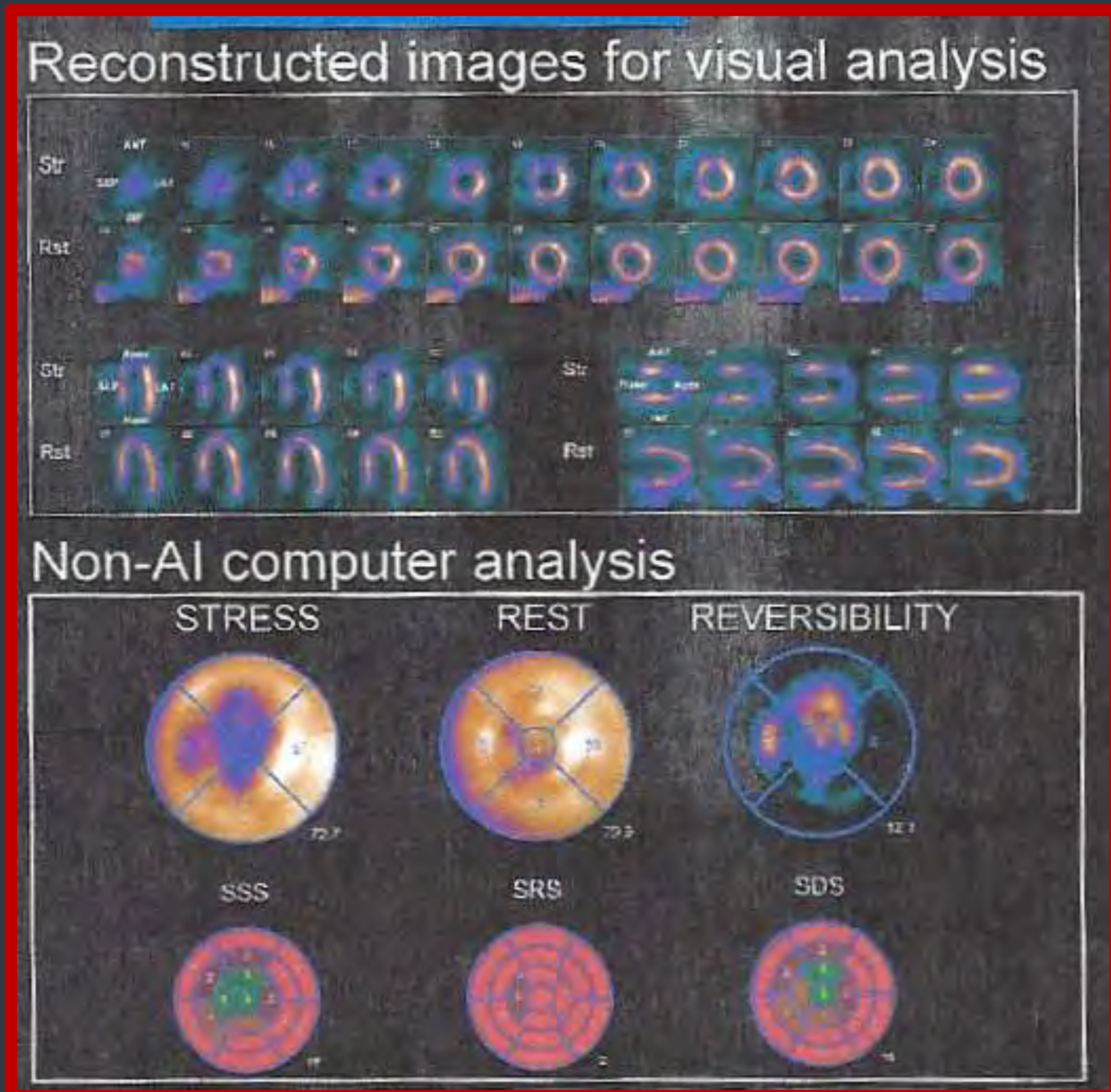
1. Coronary Anatomy
2. LV Ejection Fraction
3. Peri Arterial Inflamation

AI and Nuclear Scans

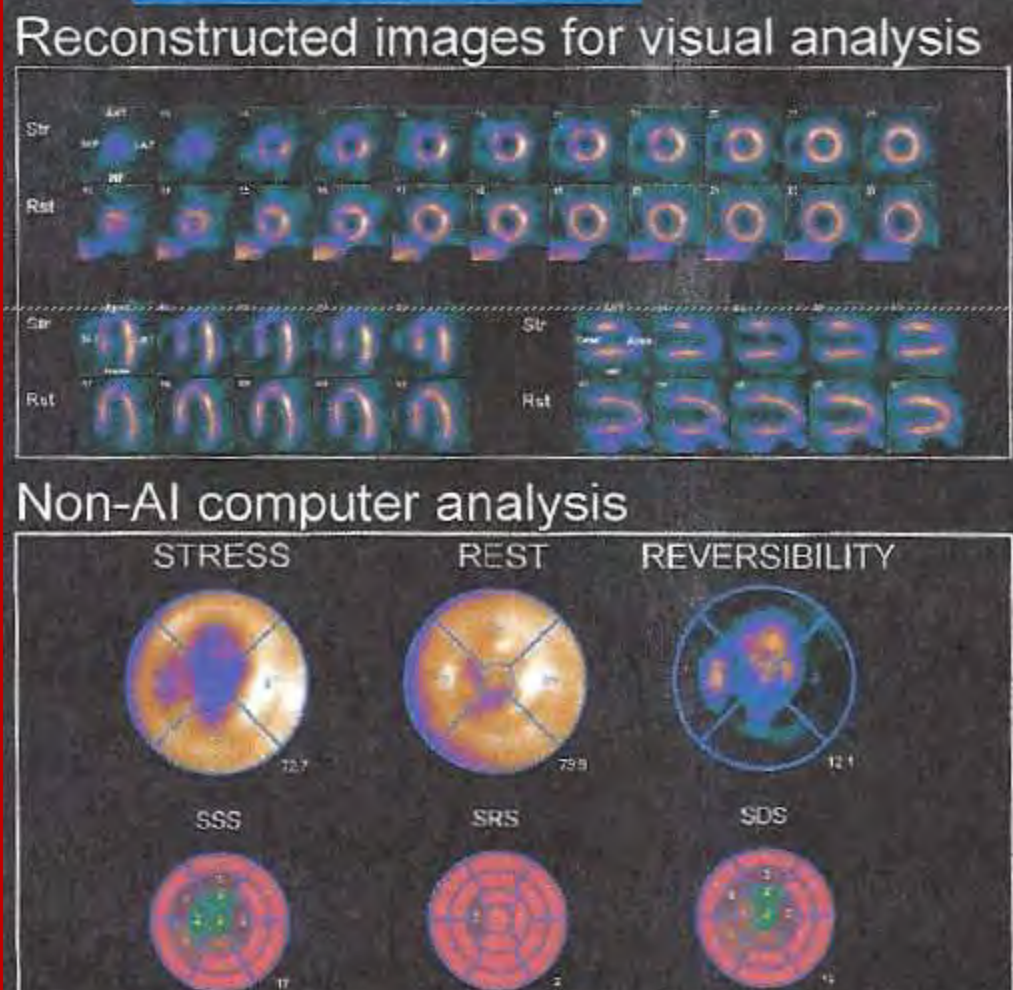




AI and Nuclear Scans…continued

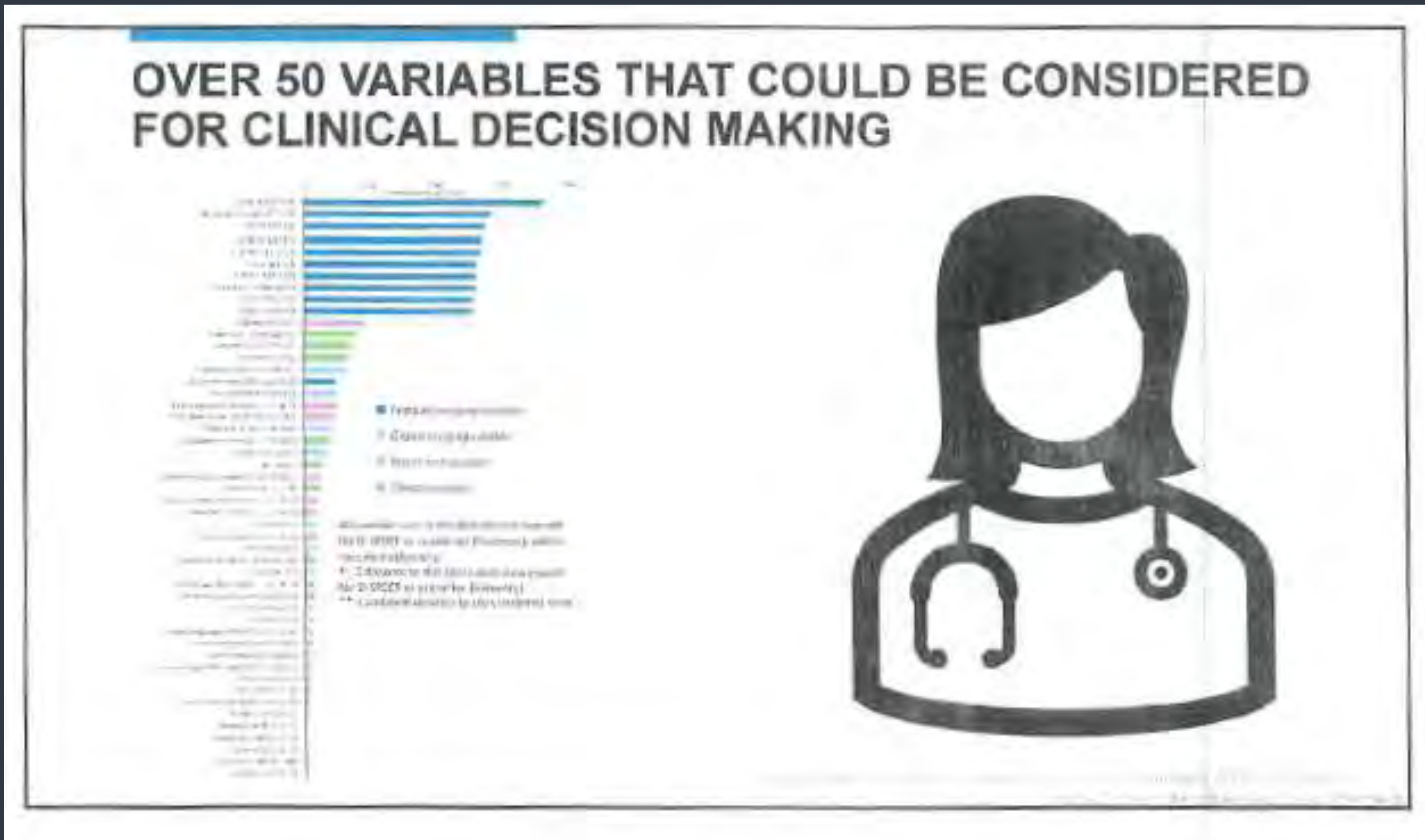


AI and Nuclear Scans…continued

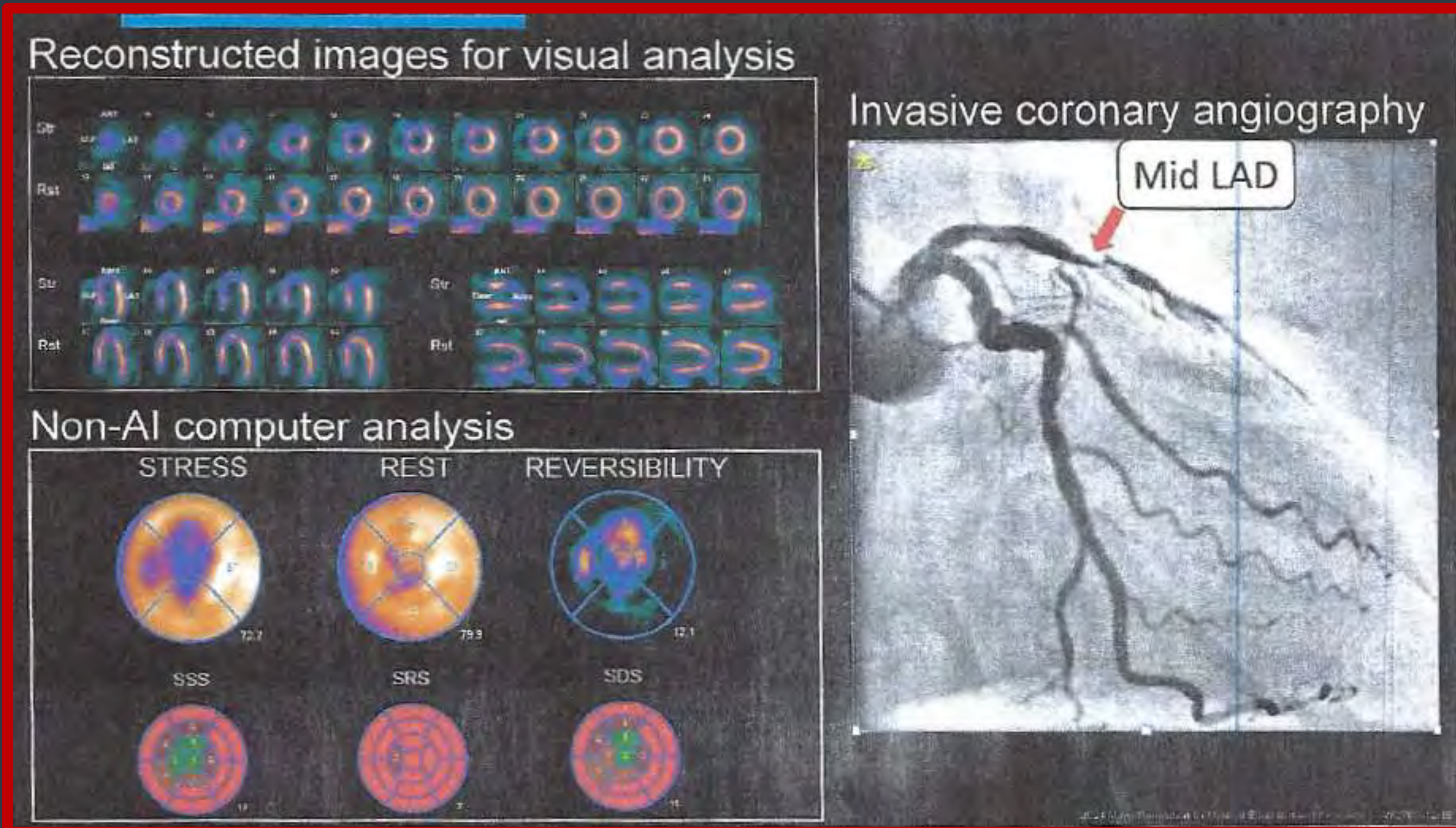


Reversible apical, anterior and septal defect compatible with **ischemia** (insufficient blood supply to the heart muscle) involving the mid left anterior descending (LAD) coronary artery

AI and Nuclear Scans…continued



AI and Nuclear Scans…continued



AI and Nuclear Scans…continued

STRENGTHS AND LIMITATIONS OF SPECT MPI

- Variable image quality
- Very good diagnostic accuracy
  - Sensitivity = 70-80%
  - Specificity = 60-70%
- Powerful prognostic value
- Guides management
- Variable interpretation with the vast array of variables
- Radiation exposure
- Long protocols

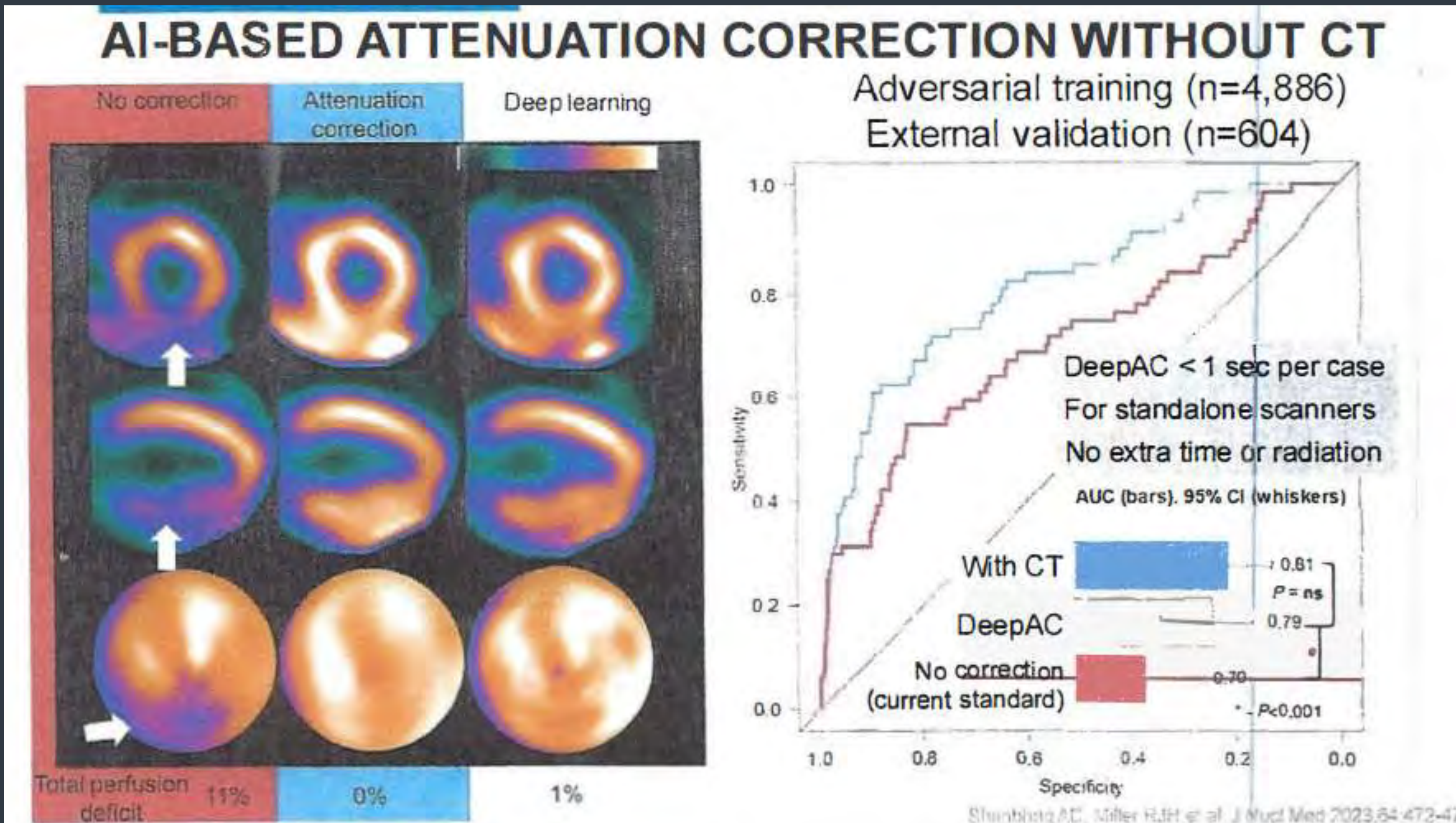
AI and Nuclear Scans…continued

AI APPLICATIONS IN SPECT MPI

IMPROVE/ENHANCE/REFINE

- Image quality
- Diagnosis of obstructive CAD
- Risk prediction
- Treatment
- Integration of large volumes of data
- Radiation exposure
- Duration of testing

AI and Nuclear Scans…continued



AI Improves Risk Prediction – *Two Selected Studies*

Study 1 – Spect Only

JACC

Prognostic Value of Combined Clinical and Myocardial Perfusion Imaging Data Using Machine Learning

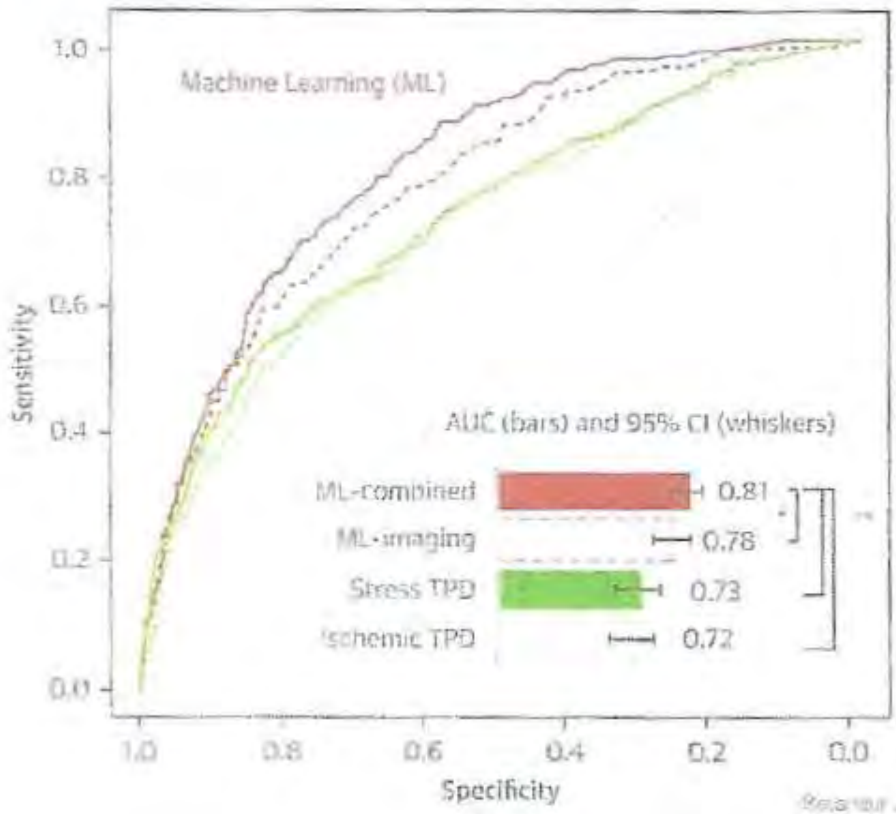
Julian Betancur, PhD, Yuka Otaki, MD, Manish Motwani, MB, ChB, PhD, Mathews B. Fish, MD, Mark Lemley, CNMT, Damini Dey, PhD, Heidi Gransar, MS, Balaji Tamarappoo, MD, PhD, Guido Germano, PhD, Tali Sharir, MD, Daniel S. Berman, MD, Piotr J. Slomka, PhD

- 2,619 patients (52% male, age 62 ± 12y)
- 2010 – 2011
- Endpoint: 3-yr MACE (all-cause mortality, nonfatal MI, unstable angina, or late CABG/PCI)
  - 239 patients (9.1%) had MACE
- Variable selection and LogitBoost algorithm
- Compared software interpretation vs machine learning (ML), without reader interpretation

AI Improves Risk Prediction – *Two Selected Studies*

Study 1 – Spect Only - *continued*

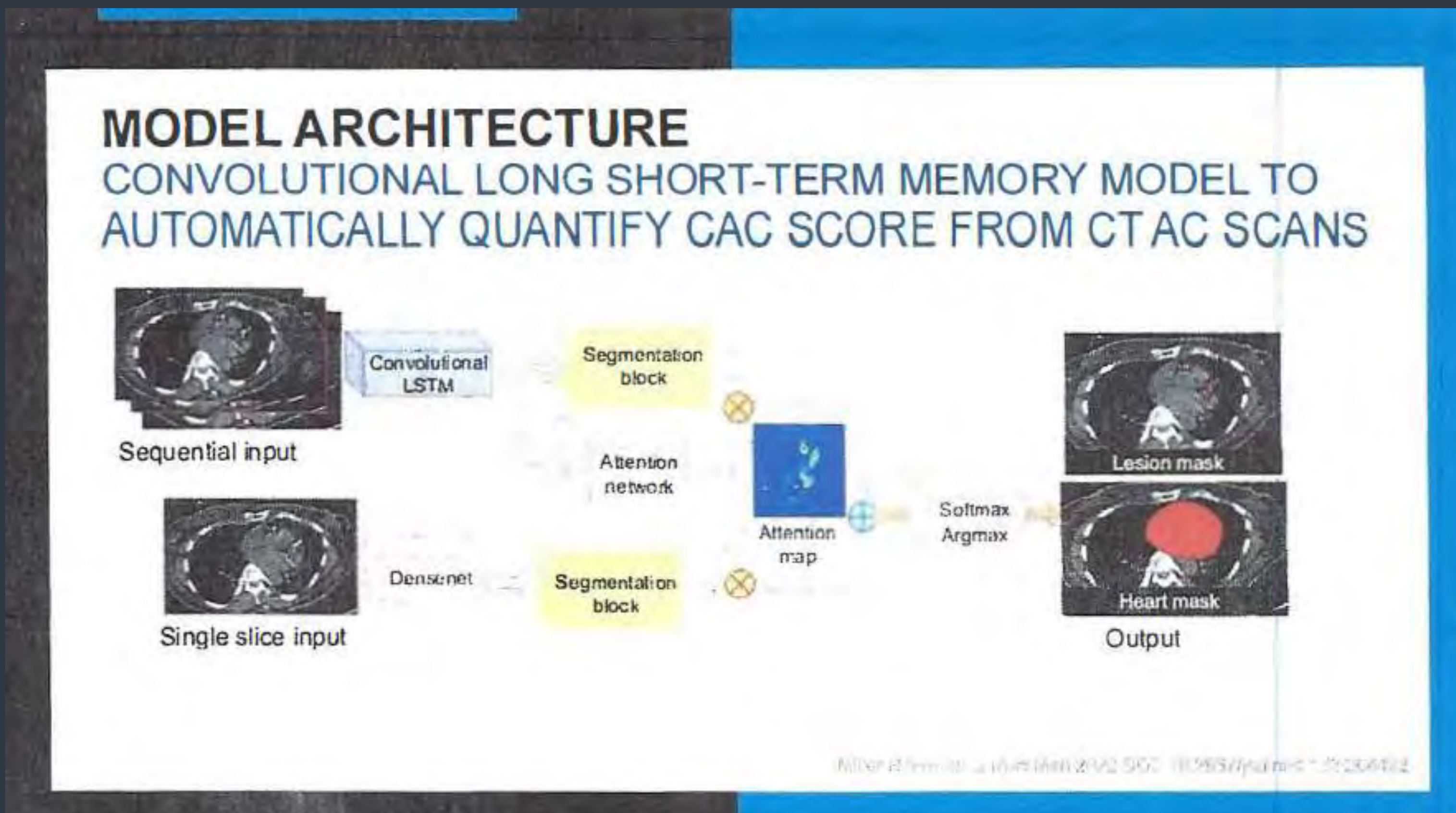
ROC CURVES FOR PREDICTION OF 3-YR MACE



*p < 0.01;
**p < 0.001

AI Improves Risk Prediction – *Two Selected Studies*

Study 2 – HYBRID SPECT/CT WITH ADDITION OF DEEP-LEARNING CORONARY ARTERY CALCIUM SCORE



AI Improves Risk Prediction –
Two Selected Studies

Study 2 – HYBRID SPECT/CT WITH ADDITION OF DEEP-LEARNING CORONARY ARTERY CALCIUM SCORE

REFINE SPECT

Deep Learning Coronary Artery Calcium Scores from SPECT/CT Attenuation Maps Improve Prediction of Major Adverse Cardiac Events.

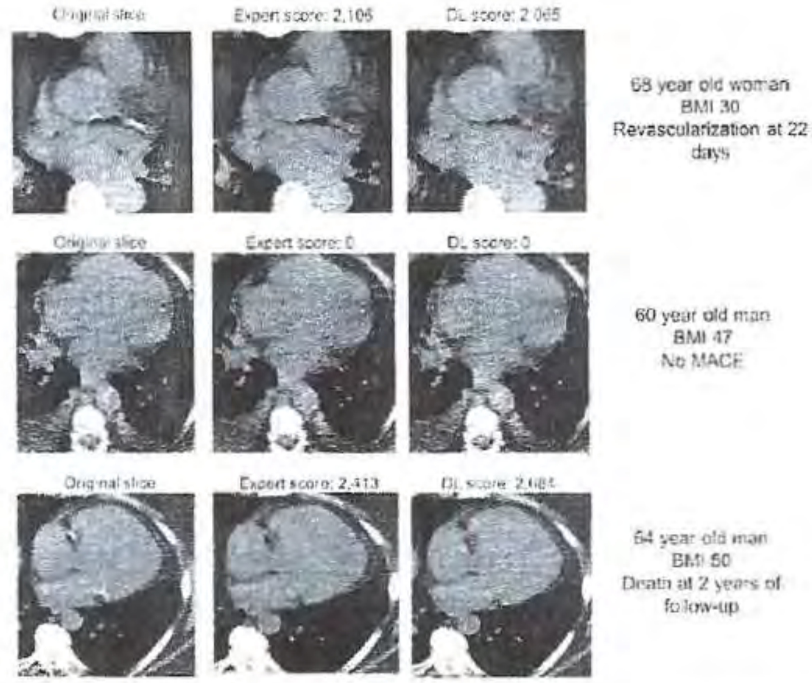
Miller RJH, Pieszko K, Shanbhag A, Feher A, Lemley M, Killekar A, Kavanagh PB, Van Kriekinge SD, Liang JX, Huang C, Miller EJ, Bateman T, Berman DS, Dey D, Slomka PJ.

- 2-site training dataset (n = 6,608)
- 1-site external testing dataset (n = 2,271)
- Assessed agreement between DL and expert annotated CAC scores, and associations between MACE and CAC categories

AI Improves Risk Prediction –
Two Selected Studies

Study 2 – HYBRID SPECT/CT WITH ADDITION OF DEEP-LEARNING CORONARY ARTERY CALCIUM SCORE

EXAMPLES OF EXPERT COMPARED TO DL CAC SCORES

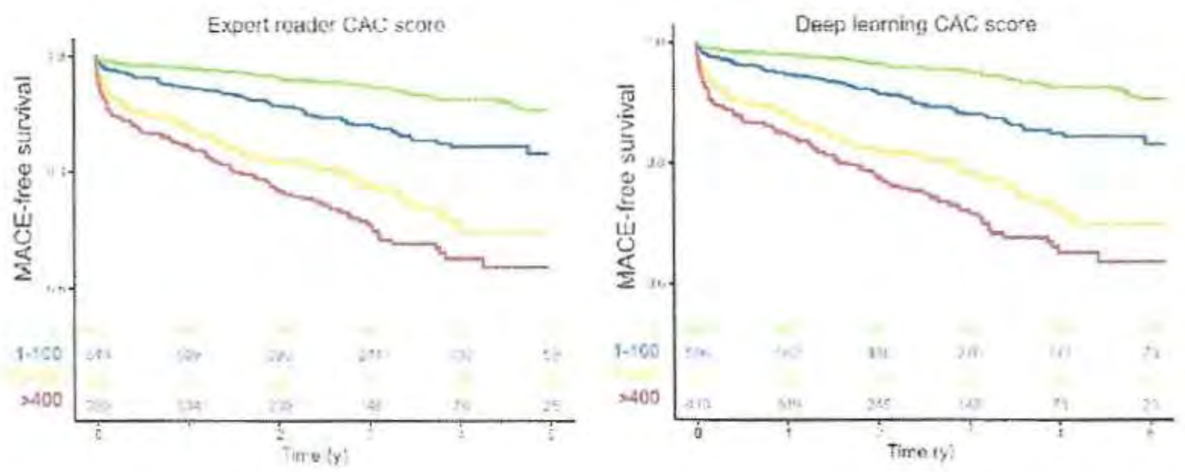


Miller RJH et al. J Nucl Med 2022;64:652-658

AI Improves Risk Prediction –
Two Selected Studies

Study 2 – HYBRID SPECT/CT WITH ADDITION OF DEEP-LEARNING CORONARY ARTERY CALCIUM SCORE

KAPLAN-MEIR SURVIVAL CURVES FOR MACE FOR EXPERT READER VS DL CAC SCORES



Final Thoughts

University of Nebraska Medical Center