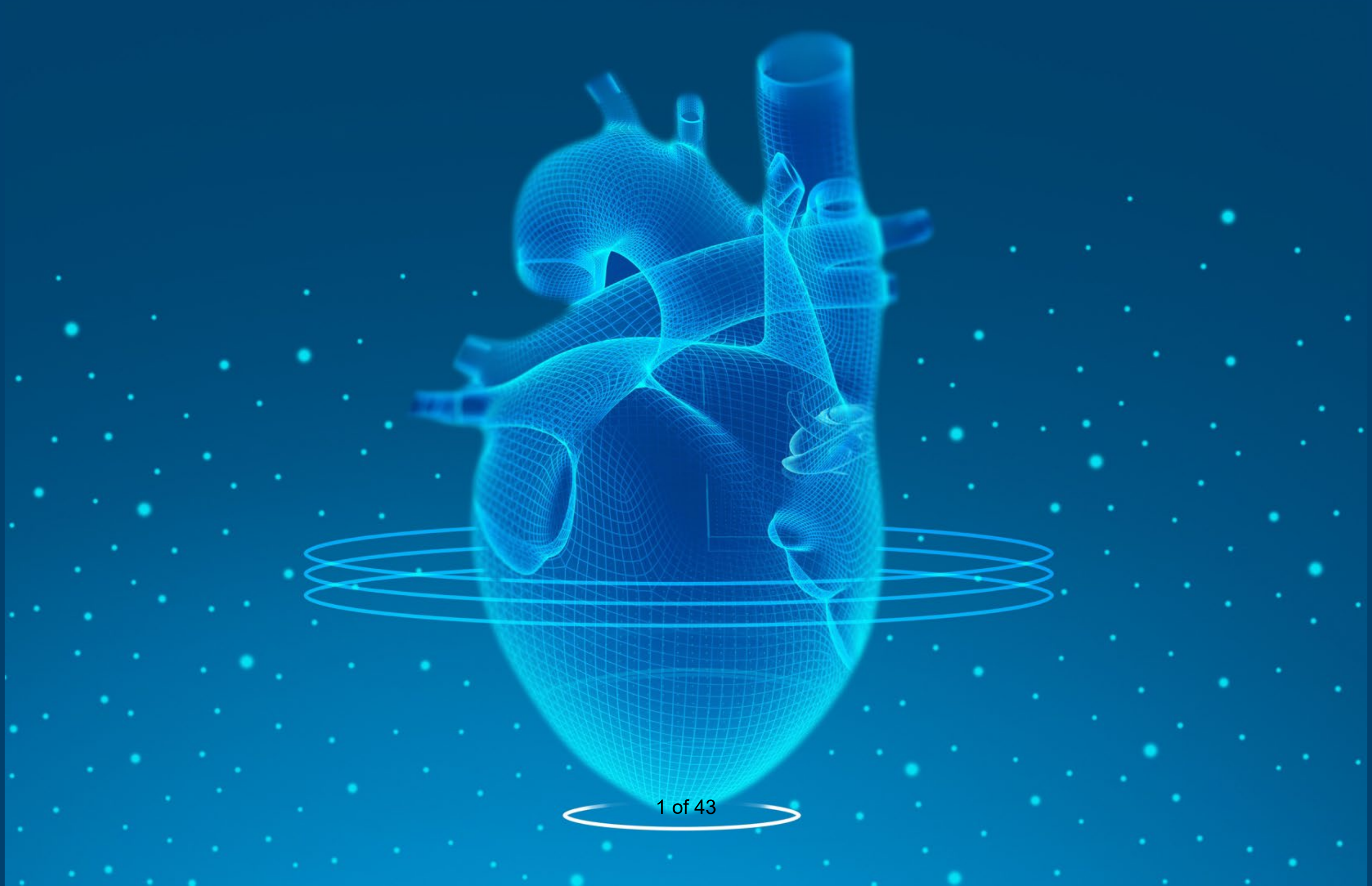
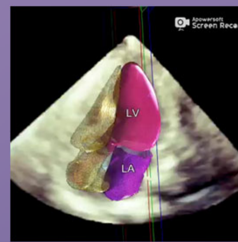
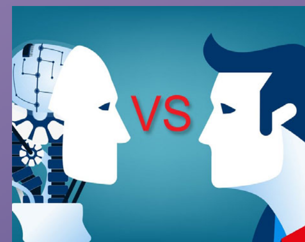
Minneapolis Heart Institute Foundation®

GRAND ROUNDS







The Emerging Role of Artificial Intelligence in Echocardiography

Akhil Narang, MD FACC FASE FSCMR
Director, Echocardiography Laboratory
Assistant Professor of Medicine
Northwestern University, Feinberg School of Medicine
Bluhm Cardiovascular Institute

October 10, 2022, Minneapolis Heart Institute

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AkhilNarangMD

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No Relevant Disclosures

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Outline

I. Definition of artificial intelligence (AI)
II. Applications of AI in echocardiography
III. Challenges with AI in echocardiography
IV. Summary

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The Beginning of Modern AI…

A PROPOSAL FOR THE
DARTMOUTH SUMMER RESEARCH PROJECT
ON ARTIFICIAL INTELLIGENCE

J. McCarthy, Dartmouth College
M. L. Minsky, Harvard University
N. Rochester, I.B.M. Corporation
C.E. Shannon, Bell Telephone Laboratories

August 31, 1955

1956

2006

We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.

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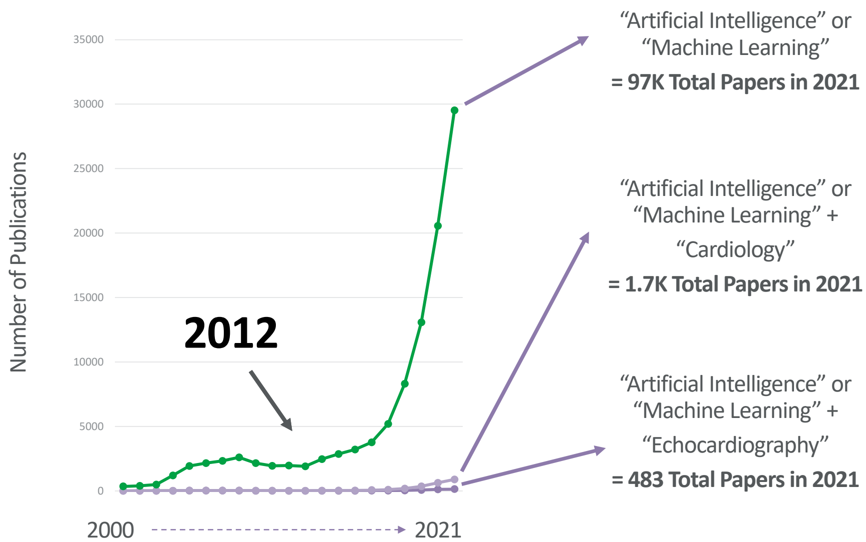
PubMed Publications – December 2021



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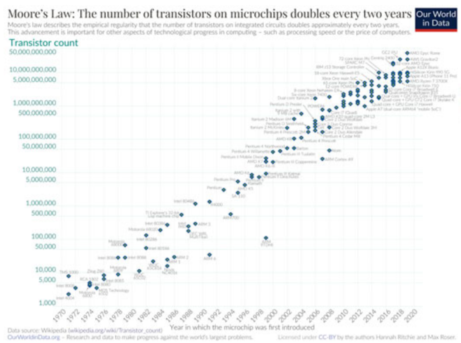
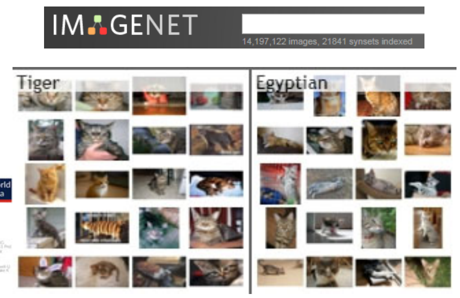
Why Did AI Take Off ~2012?

Three Big Factors

- **The Rise of GPUs**
- **ImageNet**
- **Alex Krizhevsky**





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Artificial Intelligence

Type of artificial intelligence (AI) that provides computers with the ability to mimic human intelligence using logic, if-then rules, machine learning, deep learning

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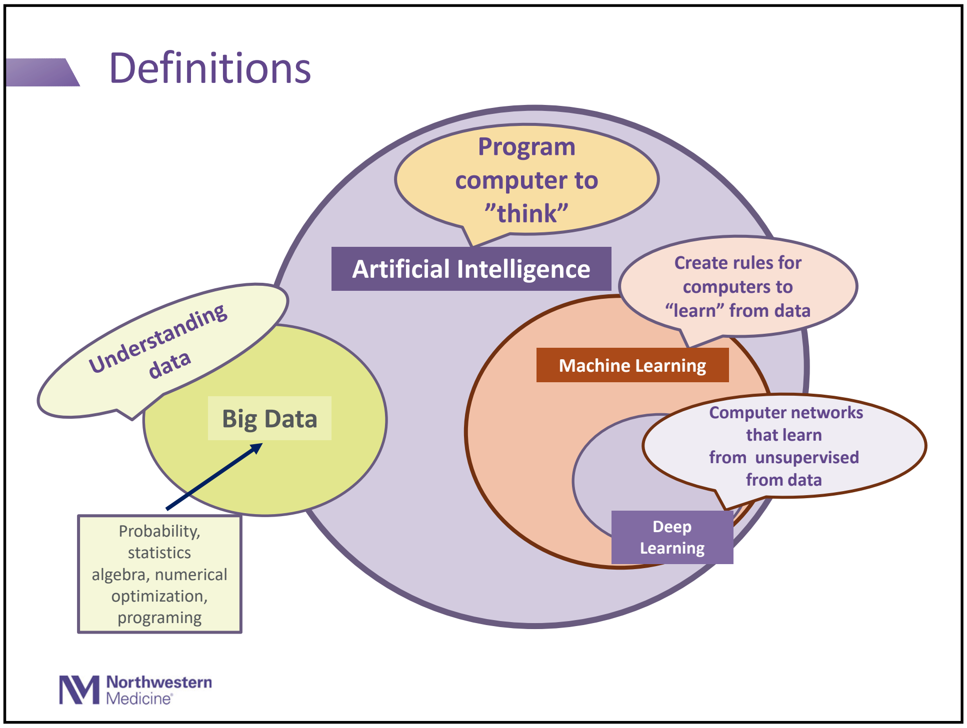
Definitions
Program computer to "think"
Artificial Intelligence
Create rules for computers to "learn" from data
Understanding data
Big Data
Machine Learning
Computer networks that learn from unsupervised from data
Deep Learning
Probability, statistics algebra, numerical optimization, programing
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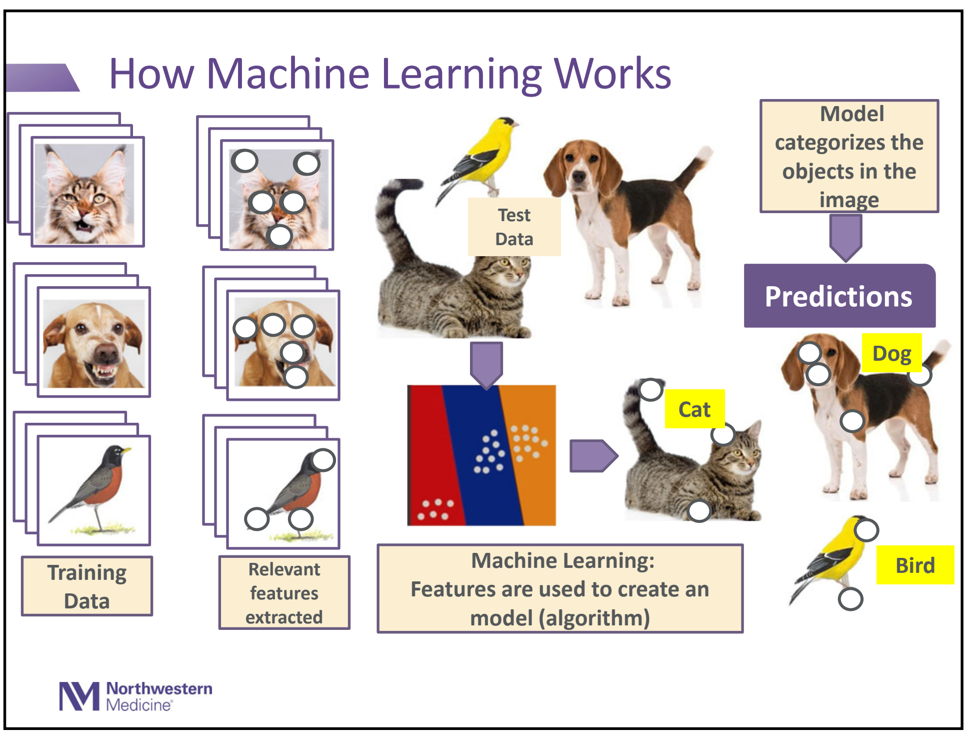
How Machine Learning Works
Model categorizes the objects in the image
Test Data
Predictions
Dog
Cat
Bird
Training Data
Relevant features extracted
Machine Learning: Features are used to create an model (algorithm)
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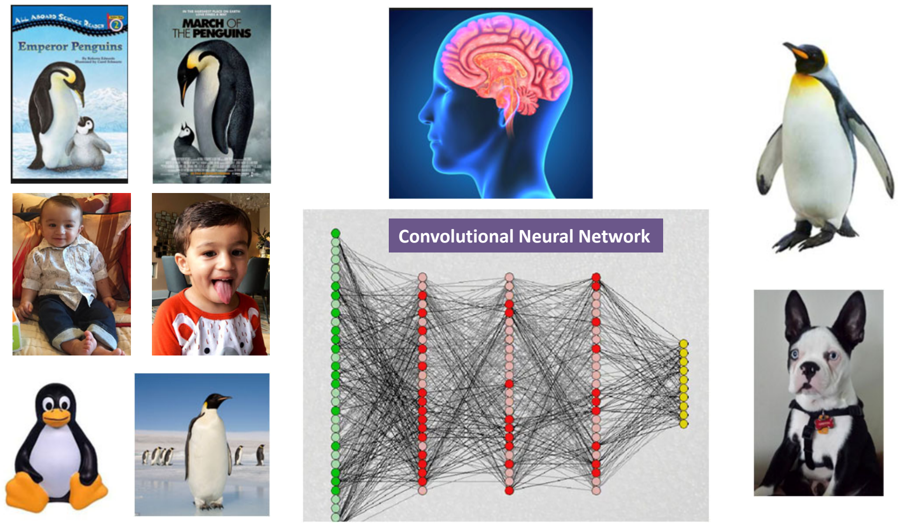
How Deep Learning Works



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Deep Learning for Object Detection

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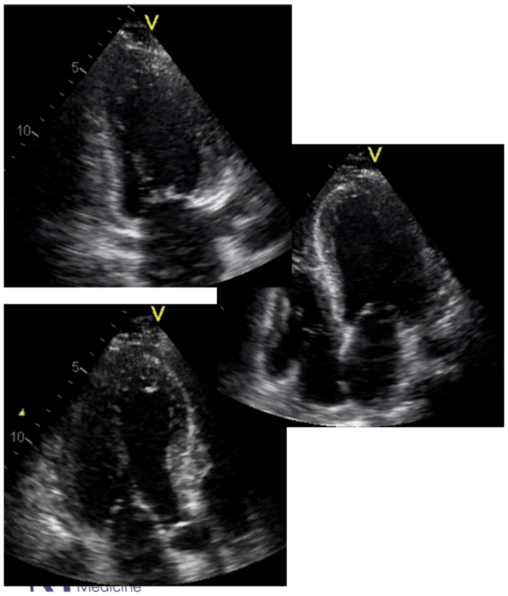
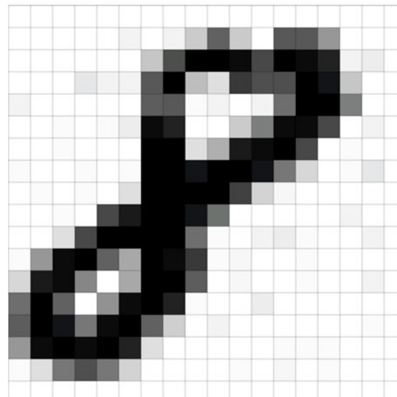
Translating Echocardiography Images Into Data





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Why Do We Need AI in Echocardiography?

- Variability in accuracy and quality of interpretations
  - Depends on expertise of operator
- Quantitative analysis (2D and 3D)
- Disease detection/identification
- Improve efficiency; accommodate growing volume of studies

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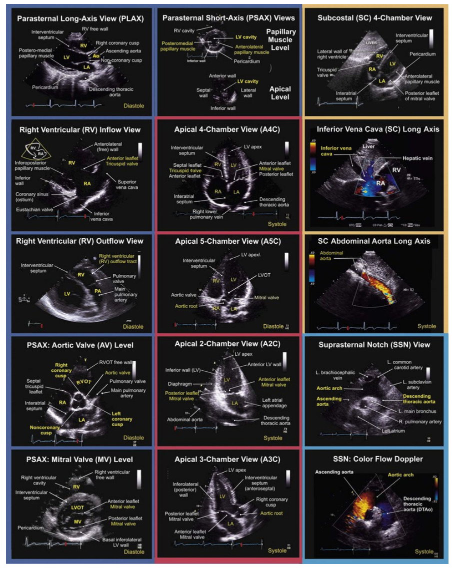
Can AI Help Identify Echocardiographic Views?



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Recognition of Echocardiographic Views

npj | Digital Medicine www.nature.com/npjdigitalmed

ARTICLE OPEN

Fast and accurate view classification of echocardiograms using deep learning

Ali Madani[1], Ramy Arnaout[2], Mohammad Mofrad[1] and Rima Arnaout[3]

Echocardiography is essential to cardiology. However, the need for human interpretation has limited echocardiography's full potential for precision medicine. Deep learning is an emerging tool for analyzing images but has not yet been widely applied to echocardiograms, partly due to their complex multi-view format. The essential first step toward comprehensive computer-assisted echocardiographic interpretation is determining whether computers can learn to recognize these views. We trained a convolutional neural network to simultaneously classify 15 standard views (12 video, 3 still), based on labeled still images and videos from 267 transthoracic echocardiograms that captured a range of real-world clinical variation. Our model classified among 12 video views with 97.8% overall test accuracy without overfitting. Even on single low-resolution images, accuracy among 15 views was 91.7% vs. 70.2–84.0% for board-certified echocardiographers. Data visualization experiments showed that the model recognizes similarities among related views and classifies using clinically relevant image features. Our results provide a foundation for artificial intelligence-assisted echocardiographic interpretation.

npj Digital Medicine (2018)1:6 ; doi:10.1038/s41746-017-0013-1

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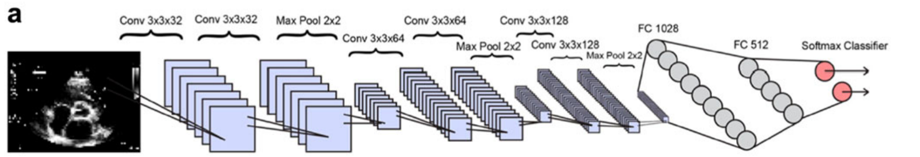
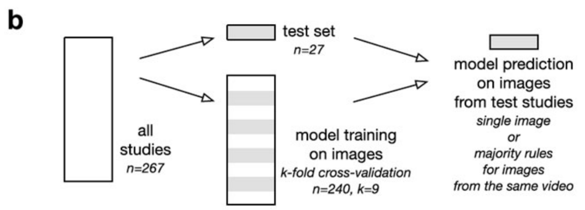
Image Classification





- Deep learning algorithm to detect 15 standard echo views
- Training/validation in 200,000 images (270 studies) and testing in 20,000 images (27 studies)
- Variety of normal/abnormal studies

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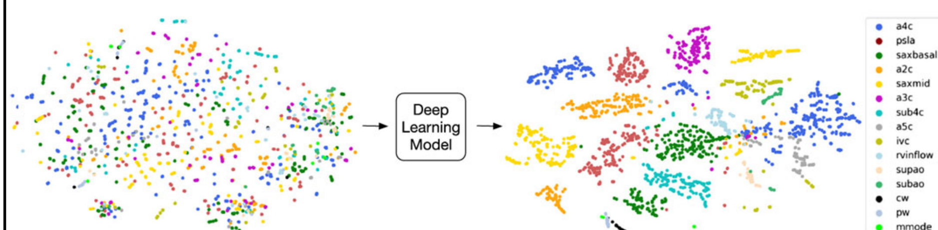
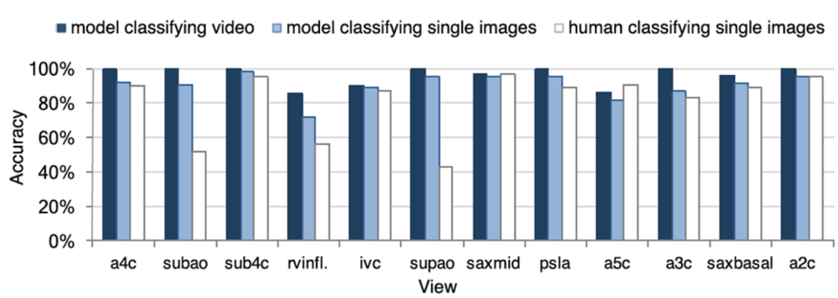
Image Classification





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Circulation

ORIGINAL RESEARCH ARTICLE

Fully Automated Echocardiogram Interpretation in Clinical Practice

Feasibility and Diagnostic Accuracy

Jeffrey Zhang, BA
Sravani Gajjala, MBBS
Pulkit Agrawal, PhD
Geoffrey H. Tison, MD, MPH
Laura A. Hallock, BS
Lauren Beussink-Nelson, RDCS
Mats H. Lassen, BM
Eugene Fan, MD
Mandar A. Aras, MD, PhD
ChaRandle Jordan, MD, PhD
Kirsten E. Fleischmann, MD, MPH
Michelle Melisko, MD
Atif Qasim, MD, MSCE
Sanjiv J. Shah, MD
Ruzena Bajcsy, PhD
Rahul C. Deo, MD, PhD

- >14,000 TTEs were analyzed using a deep leaning algorithm and compared to >8000 manually analyzed TTEs
- Algorithm: automated identification of 23 viewpoints and segmentations, LV mass, LVEF, LV GLS (speckle tracking)

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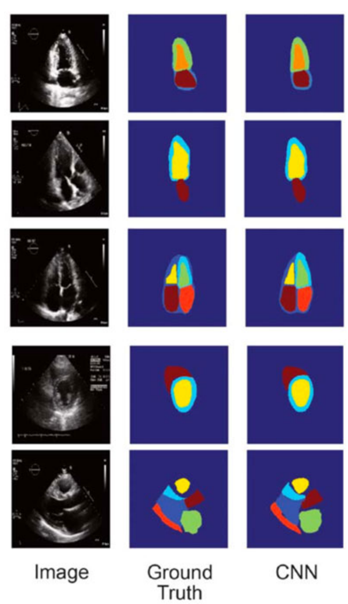
Accurate Segmentation

View	Number of Images Used for Training	Segmented Area	IoU Accuracy
A2c	214	Left atrium blood pool	88.2
		Left ventricle blood pool	89.1
		Left ventricle myocardium	72.2
A3c	141	Left atrium blood pool	88.3
		Left ventricle blood pool	88.3
		Left ventricle myocardium	72.7
A4c	182	Left atrium blood pool	89.8
		Left ventricle blood pool	88.9
		Left ventricle myocardium	73.7
		Right atrium blood pool	88.1
		Right ventricle blood pool	83.3
PLAX	130	Left atrium blood pool	86.1
		Left ventricle blood pool	87.9
		Right ventricle blood pool	85.2
		Aortic root	86.4
		Anterior septum	76.8
		Posterior wall	74.9
PSAX	124	Left ventricle blood pool	79.6
		Left ventricle myocardium	74.0
		Right ventricle blood pool	64.6



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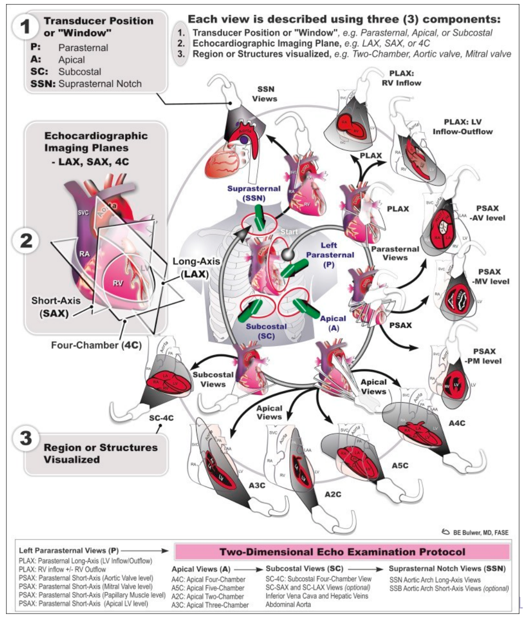
What is This Important?

- Paradigm shift in the workflow of echocardiogram interpretation
- Focus on pathology rather than order of image acquisition



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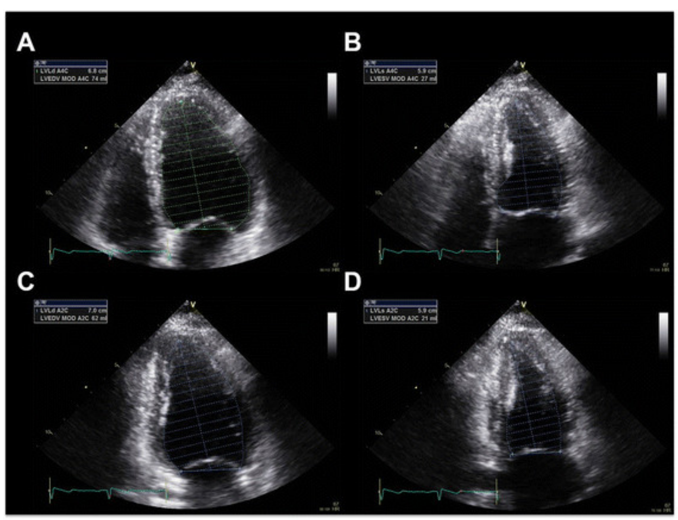
Quantitative Analysis – 2D



Up to 14% variability reported in Biplane Simpson's Method of Discs Quantification of LVEF

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Can AI Improve 2D Quantification?

Fully Automated Versus Standard Tracking of Left Ventricular Ejection Fraction and Longitudinal Strain

The FAST-EFs Multicenter Study

Christian Knackstedt, MD,* Sebastiaan C.A.M. Bekkers, MD, PhD,* Georg Schummers,† Marcus Schreckenberg,† Denisa Muraru, MD, PhD,‡ Luigi P. Badano, MD, PhD,‡ Andreas Franke, MD,§ Chirag Bavishi, MD, MPH,|| Alaa Mabrouk Salem Omar, MD, PhD,|| Partho P. Sengupta, MD, DM||

Fully automated machine learning software tested in 255 patients to measure LV volumes and LVEF

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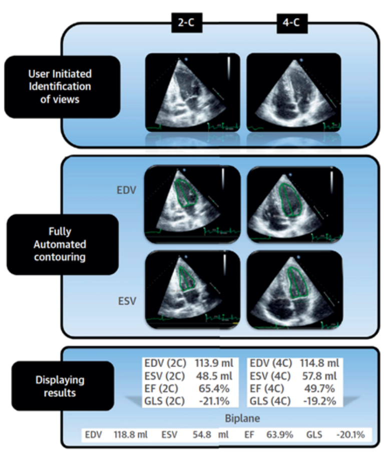
Can AI Improve 2D Quantification?



- **Agreement**
  - AutoEF feasible in 98% of studies
  - Average analysis 8.1 sec/patient
  - ICC: AutoEF vs. manual tracing 0.83
  - Bland-Altman bias: AutoEF vs. manual tracing -2.2%
- **Variability (Intra/inter-observer)**
  - High for visual LVEF, manual LVEF
  - Zero for AutoLVEF

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Can AI Improve 2D Quantification?

Video-based AI for beat-to-beat assessment of cardiac function

David Ouyang, Bryan He, Amirata Ghorbani, Neal Yuan, Joseph Ebinger, Curtis P. Langlotz, Paul A. Heidenreich, Robert A. Harrington, David H. Liang, Euan A. Ashley & James Y. Zou

Nature **580**, 252–256(2020) | Cite this article

ARTICLE OPEN

Deep learning interpretation of echocardiograms

Amirata Ghorbani[1,6], David Ouyang[2,6*], Abubakar Abid[1], Bryan He[3], Jonathan H. Chen[2], Robert A. Harrington[2], David H. Liang[2], Euan A. Ashley[2] and James Y. Zou[1,3,4,5*]

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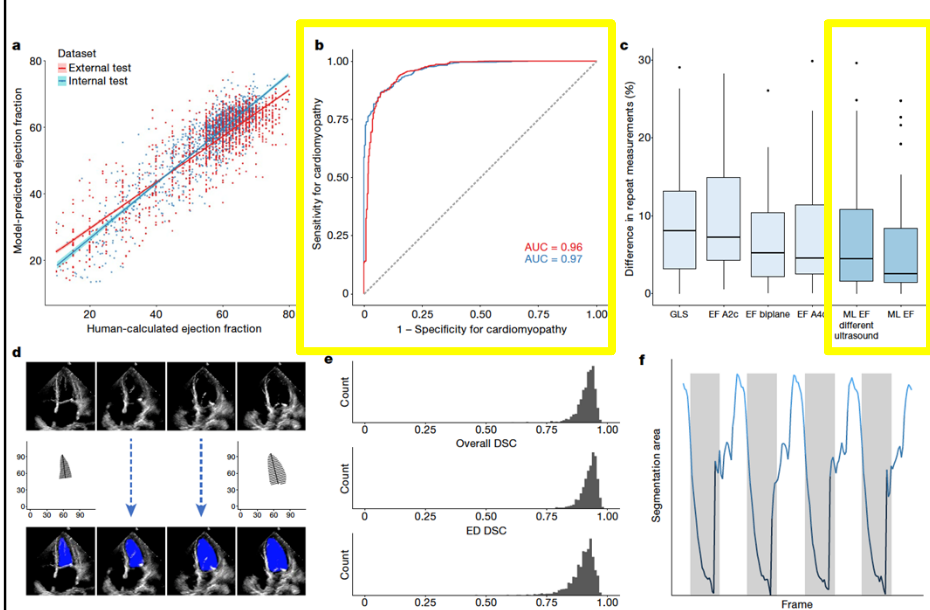

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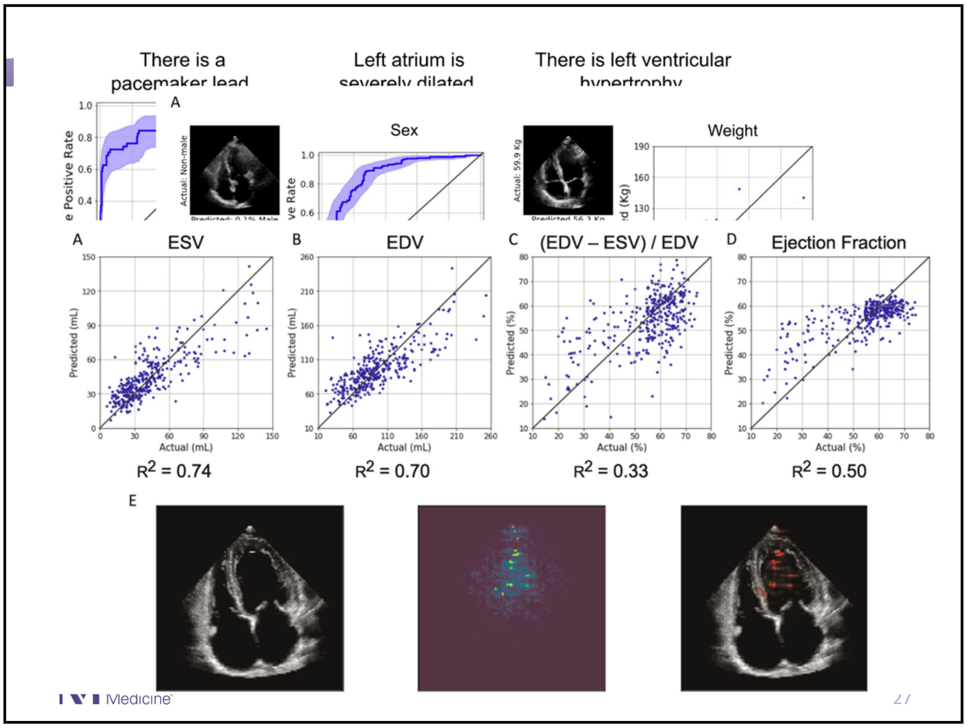
There is a pacemaker lead
Left atrium is severely dilated
There is left ventricular hypertrophy
Sex
Weight
ESV
EDV
(EDV – ESV) / EDV
Ejection Fraction
Predicted (mL)
Actual (mL)
Predicted (%)
Actual (%)
R^2 = 0.74
R^2 = 0.70
R^2 = 0.33
R^2 = 0.50

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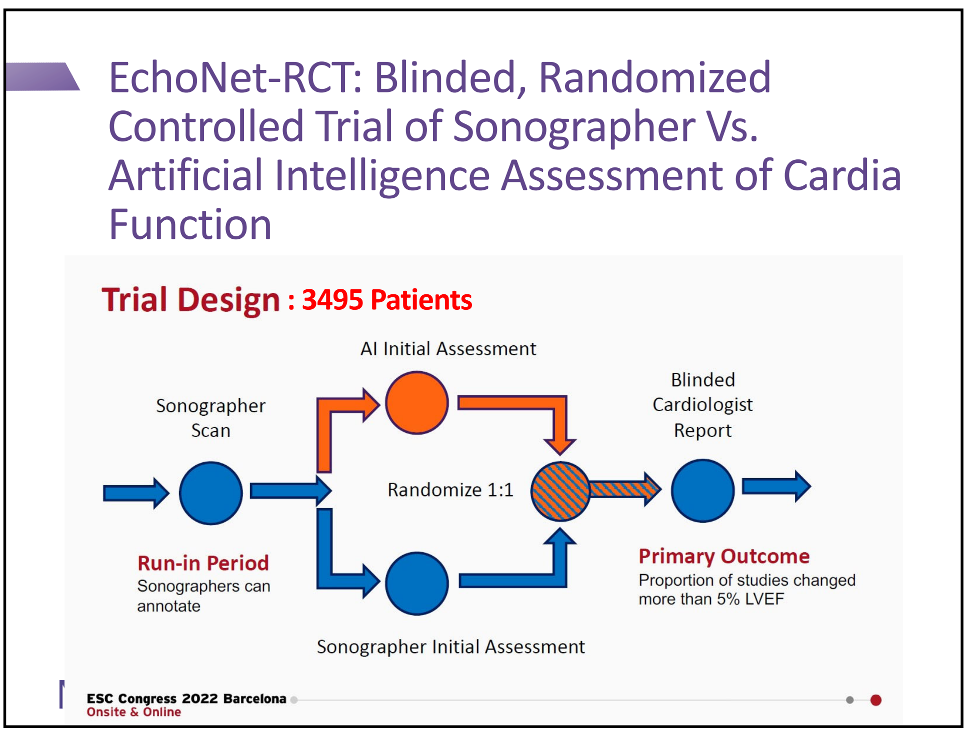
EchoNet-RCT: Blinded, Randomized Controlled Trial of Sonographer Vs. Artificial Intelligence Assessment of Cardia Function
Trial Design : 3495 Patients
AI Initial Assessment
Sonographer Scan
Blinded Cardiologist Report
Randomize 1:1
Run-in Period
Sonographers can annotate
Primary Outcome
Proportion of studies changed more than 5% LVEF
Sonographer Initial Assessment
ESC Congress 2022 Barcelona
Onsite & Online

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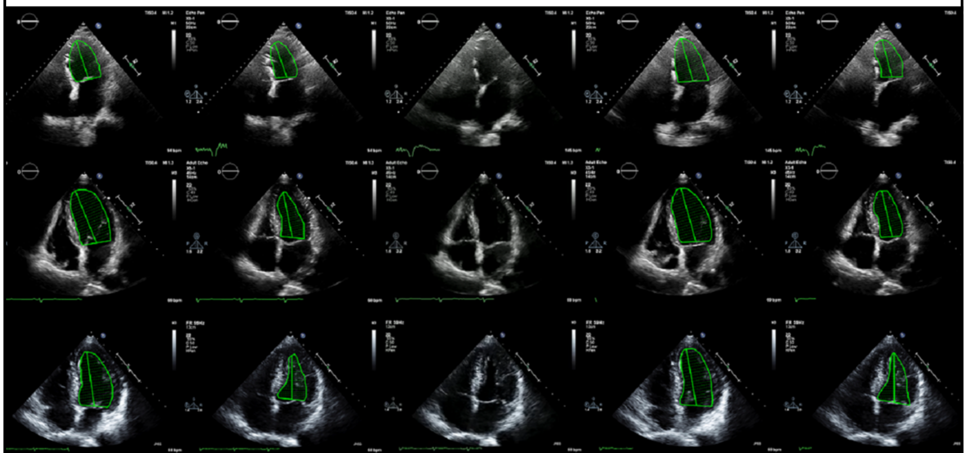
3 Echocardiograms: Artificial Intelligence vs. Sonographer Tracing: *Can You Tell?*



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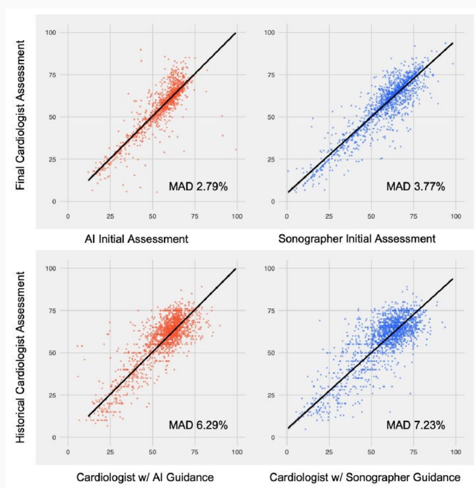
Trial Results

Primary Outcome

degree of change from initial (AI vs. sonographer) assessment to final cardiologist assessment

Key Secondary Outcome

degree of change from final cardiologist assessment to historical cardiologist assessment



ESC Congress 2022 Barcelona
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Conclusion

- For adult patients undergoing echocardiographic quantification of cardiac function, initial assessment of LVEF by AI was noninferior and superior to initial sonographer assessment.
- After blinded review of initial LVEF assessment, cardiologists were less likely to substantially change their final report with initial AI assessment than sonographer assessment.
- AI guided assessment took less time for cardiologists to overread and was more consistent with historical cardiologist assessment (test-retest precision).

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Can AI Improve 2D Quantification: Strain?

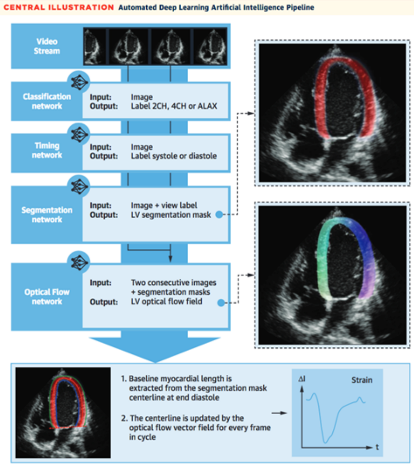
MINI-FOCUS: AI, MACHINE LEARNING, AND ECHOCARDIOGRAPHY

Artificial Intelligence for Automatic Measurement of Left Ventricular Strain in Echocardiography

Ivar M. Salte, MD,[a,b] Andreas Østvik, MSc,[c] Erik Smistad, MSc, PhD,[c] Daniela Melichova, MD,[b,d] Thuy Mi Nguyen, MD,[a,b] Sigve Karlsen, MD,[d] Harald Brunvand, MD, PhD,[d] Kristina H. Haugaa, MD, PhD, Thor Edvardsen, MD, PhD,[b,e] Lasse Lovstakken, MSc, PhD,[c] Bjørnar Grenne, MD, PhD[c,f]

- 200 patients – LV GLS measured by AI and conventional analysis
  - AI algorithm able to identify apical views, perform timing of cardiac events, trace the myocardium, perform motion estimation, and measure GLS
    - Pearson R correlation 0.93

CENTRAL ILLUSTRATION Automated Deep Learning Artificial Intelligence Pipeline



Salte, I.M. et al. J Am Coll Cardiol Img. 2021;14(10):1918-1928.

The artificial intelligence (AI) pipeline for automatic measurement of global longitudinal strain consisting of 4 artificial neural networks. Visual feedback of the key steps involved in calculating the global longitudinal strain (GLS) is illustrated, such as the segmentation used to initiate the region of interest, an optical flow field visualizing the predicted local velocities, the extracted centerline from the segmentation mask, and the points visualizing the motion used to calculate GLS; LV = left ventricle.

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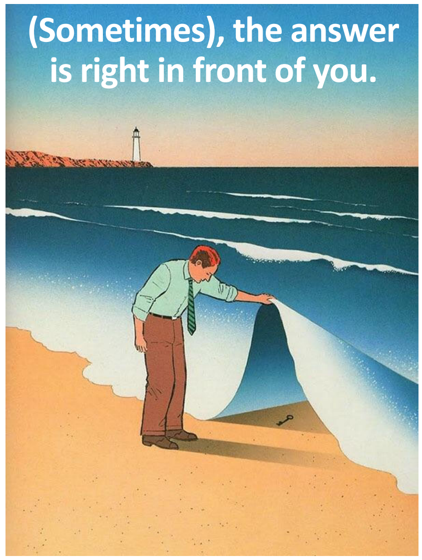
Can AI Aid in Disease Detection?



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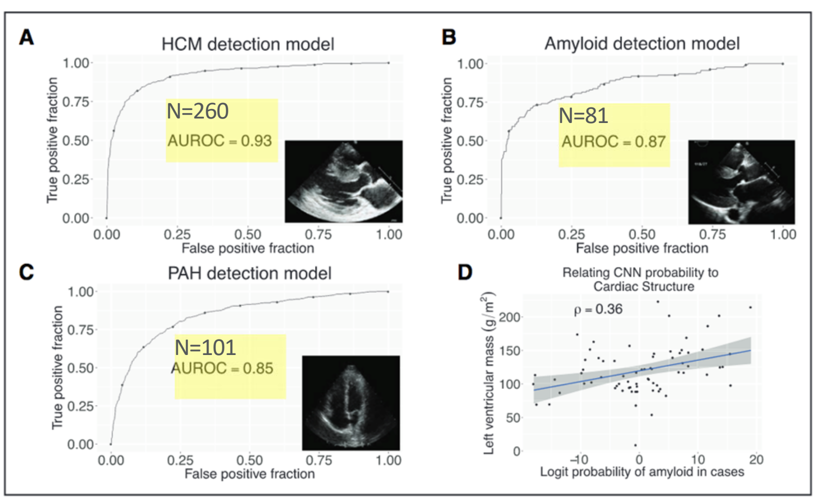
Disease Detection: HCM, Amyloid, pHTN

Algorithm: trained to detect HCM, amyloid, and pHTN



Circulation 2018; 138:1623-1635

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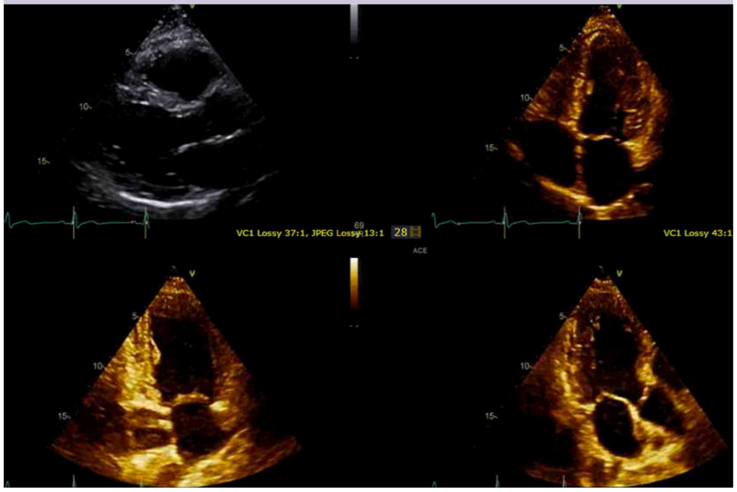
Disease Detection: WMA

37 year old male, no medical history, with atypical chest pain



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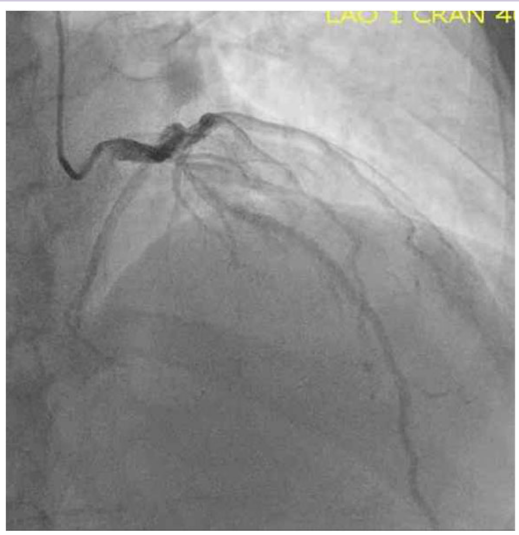
Disease Detection: WMA

37 year old male, no medical history, with atypical chest pain



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Disease Detection: WMA

Algorithm: detection of wall motion abnormalities with deep learning

	Number	Sensitivity	Specificity	Accuracy
Raghavendra (2018)	279 images	96%	96%	96%
Omar (2018)	4392 maps	81%	75%	75%

Biomedical Signal Processing and Control 2018 **40** 324–334.
2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), 2018

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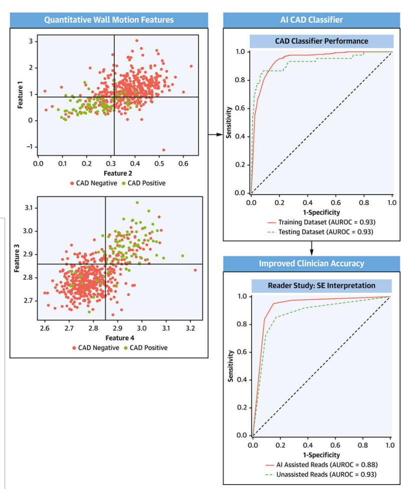
Automated Detection of CAD

Automated Echocardiographic Detection of Severe Coronary Artery Disease Using Artificial Intelligence

Ross Upton, PhD,[a,b] Angela Mumith, PhD,[a,*] Arian Beqiri, PhD,[a,*] Andrew Parker, PhD,[a,*] William Hawkes, PhD,[a,*] Shan Gao, PhD,[a] Mihaela Porumb, PhD,[a] Rizwan Sarwar, MD,[b] Patricia Marques, BSc,[a] Deborah Markham, PhD,[a] Jake Kenworthy, BSc,[a] Jamie M. O'Driscoll, PhD,[a,c] Neelam Hassanali, PhD,[a] Kate Groves, PhD,[a] Cameron Dockerill, BSc,[b] William Woodward, BSc,[b] Maryam Alsharqi, MSc,[b] Annabelle McCourt, MSc,[b] Edmund H. Wilkes, PhD,[a] Stephen B. Heitner, MD,[d] Mrinal Yadava, MD,[d] David Stojanovski, MEng,[e] Pablo Lamata, PhD,[e] Gary Woodward, PhD,[a] Paul Leeson, MB, BChir, PhD[a,b]

- Stress echocardiograms + invasive angiogram within 6 months
- Training data 578 patients, testing data 154 patients
- Feature extraction LVEF, GLS, wall motion, geometric (shape), and kinematic (mechanical, rate) changes of LV
- 31 geometric and kinematic features
- AUC for detecting severe CAD similar for CAD classifier and human read



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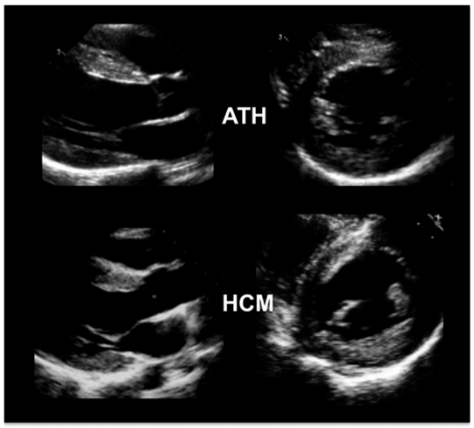
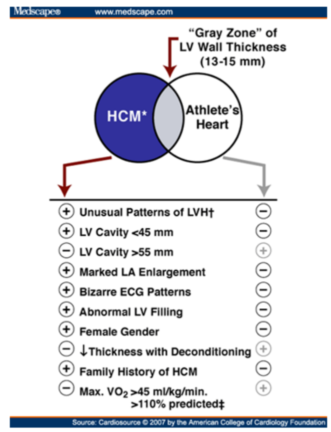
Disease Detection: HCM vs. Athlete's Heart

Algorithm: discrimination between hypertrophic cardiomyopathy and athlete's heart





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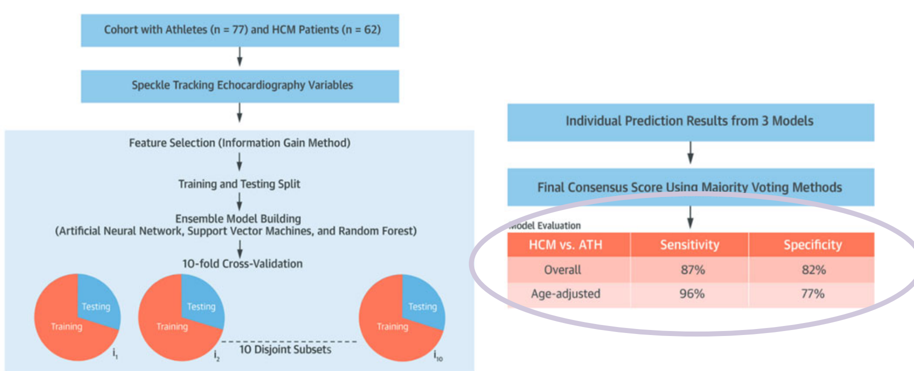
Disease Detection: HCM vs. Athlete's Heart

Algorithm: discrimination between hypertrophic cardiomyopathy and athlete's heart



J Am Coll Cardiol. 2016 Nov 29;68(21):2287-2295.

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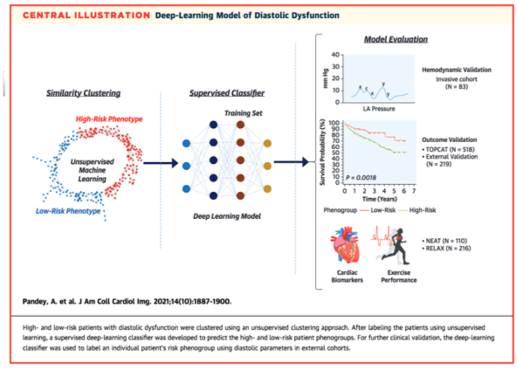
Disease Detection: Diastolic Dysfunction

MINI-FOCUS: AI, MACHINE LEARNING, AND ECHOCARDIOGRAPHY

Deep-Learning Models for the Echocardiographic Assessment of Diastolic Dysfunction

Ambarish Pandey, MD, MSCS,[a,*] Nobuyuki Kagiyama, MD, PhD,[b,c,d,*] Naveena Yanamala, MS, PhD,[b,*] Matthew W. Segar, MD, MS,[a] Jung S. Cho, MD, PhD,[b,e] Márton Tokodi, MD,[b,f] Partho P. Sengupta, MD, DM[b]

- Deep Neural Network model that integrates echocardiographic data to identify distinct subgroups of HFpEF
- Derivation cohort 1242 patients; validation cohort 84 and 219 patients
- DNN AUC for identifying elevated LV filling pressures higher than 2016 ASE guidelines (0.88 vs 0.67)



Pandey, A. et al. J Am Coll Cardiol Img. 2021;14(10):1887-1900.

High- and low-risk patients with diastolic dysfunction were clustered using an unsupervised clustering approach. After labeling the patients using unsupervised learning, a supervised deep-learning classifier was developed to predict the high- and low-risk patient phenogroups. For further clinical validation, the deep-learning classifier was used to label an individual patient's risk phenogroup using diastolic parameters in external cohorts.

- High-risk (vs. low-risk) phenogroup higher rates of HF hospitalization and/or death

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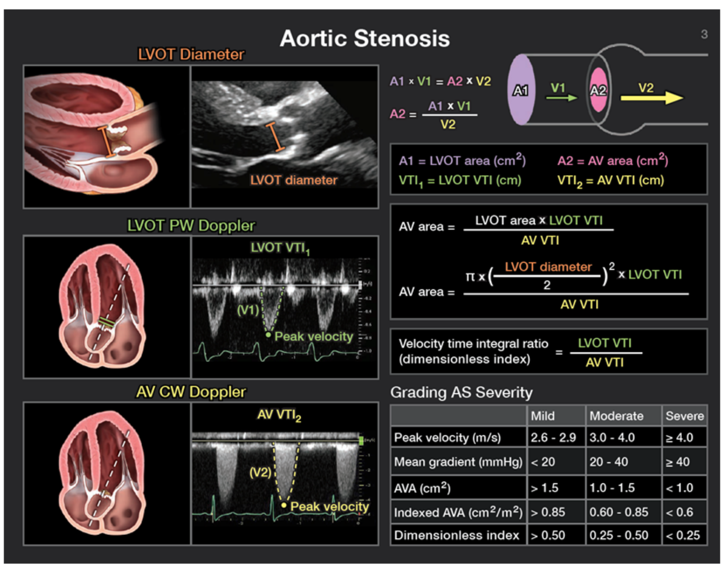
Future: Combining Image Identification with Measurements: Aortic Stenosis



	Mild	Moderate	Severe
Peak velocity (m/s)	2.6 - 2.9	3.0 - 4.0	≥ 4.0
Mean gradient (mmHg)	< 20	20 - 40	≥ 40
AVA (cm^2)	> 1.5	1.0 - 1.5	< 1.0
Indexed AVA (cm^2/m^2)	> 0.85	0.60 - 0.85	< 0.6
Dimensionless index	> 0.50	0.25 - 0.50	< 0.25

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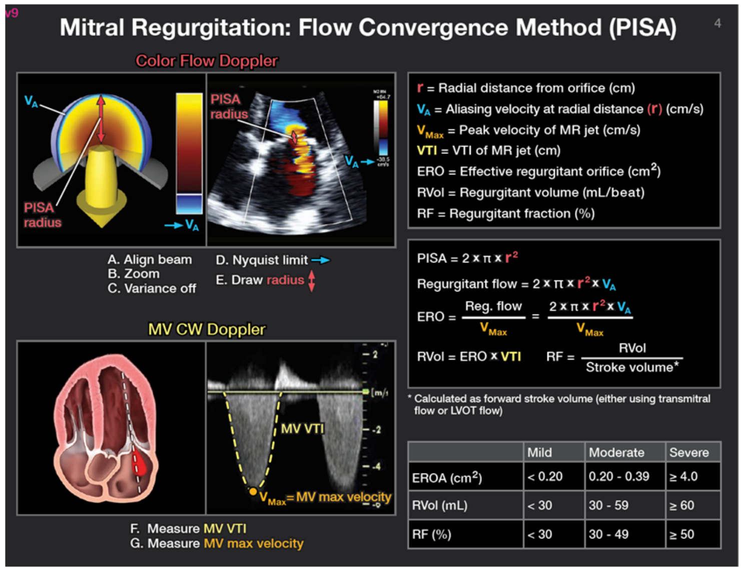
Narang A et al. Echocardiography Formula Review Guide: Native Valves and Intracardiac Pressures. 2019.

Future: Combining Image Identification with Measurements: Mitral Regurgitation



	Mild	Moderate	Severe
EROA (cm^2)	< 0.20	0.20 - 0.39	≥ 4.0
RVol (mL)	< 30	30 - 59	≥ 60
RF (%)	< 30	30 - 49	≥ 50

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Narang A et al. Echocardiography Formula Review Guide: Native Valves and Intracardiac Pressures. 2019.

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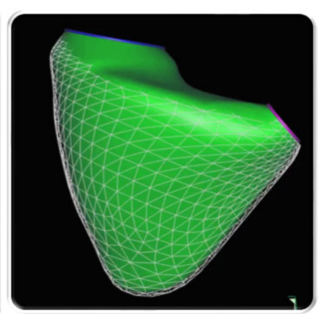
Chamber Quantification

ASE American Society of Echocardiography
Heart & Circulation Ultrasound Specialists
EACVI

Recommendations for Cardiac Chamber Quantification by Echocardiography in Adults: An Update from the American Society of Echocardiography and the European Association of Cardiovascular Imaging

Roberto M. Lang, MD, FASE, FESC, Luigi P. Badano, MD, PhD, FESC, Victor Mor-Avi, PhD, FASE, Jonathan Afilalo, MD, MSc, Anderson Armstrong, MD, MSc, Laura Ernande, MD, PhD, Frank A. Flachskampf, MD, FESC, Elyse Foster, MD, FASE, Steven A. Goldstein, MD, Tatiana Kuznetsova, MD, PhD, Patrizio Lancellotti, MD, PhD, FESC, Denisa Muraru, MD, PhD, Michael H. Picard, MD, FASE, Ernst R. Rietzschel, MD, PhD, Lawrence Rudski, MD, FASE, Kirk T. Spencer, MD, FASE, Wendy Tsang, MD, and Jens-Uwe Voigt, MD, PhD, FESC

J Am Soc Echocardiogr 2015;28:1-39
Eur Heart J Cardiovasc Imaging. 2015 Mar;16(3):233-71.



J Am Soc Echocardiogr 2015;28:1-39
Eur Heart J Cardiovasc Imaging. 2015 Mar;16(3):233-71.

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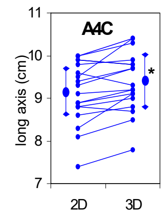
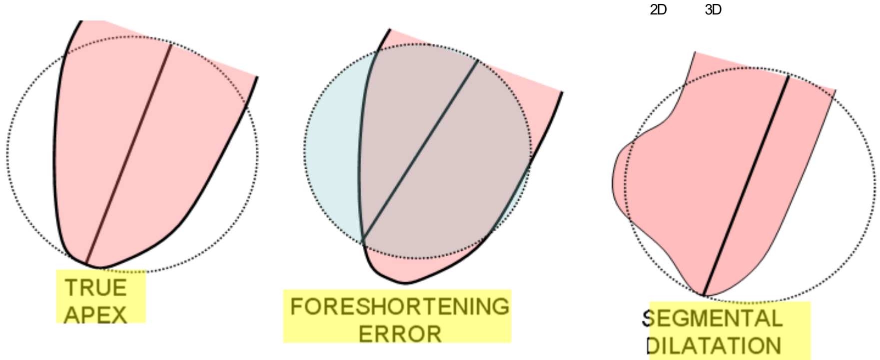
Why is 3D Echocardiography More Accurate?





Mor-Avi V, Lang RM, et al. *Circulation* 2004. 110: 1814-1818

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2

Limitations to the Implementation of 3D Echocardiography

- Time-consuming
- Requires training in 3DE analysis
- Accuracy varies with expertise
- Reproducibility varies among individuals and institutions

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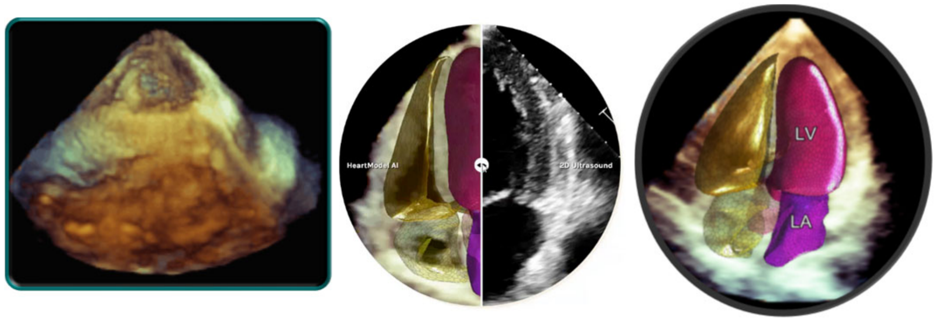
Slide 46

2 change to text, limitations and
Wendy Tsang, 6/25/2013

Real-Time Automated 3D TTE Left Heart Chamber Quantification



Tsang W, Mor-Avi V, Lang et al. *JACC Cardiovasc Imaging.* 2016 Jul;9(7):769-782.

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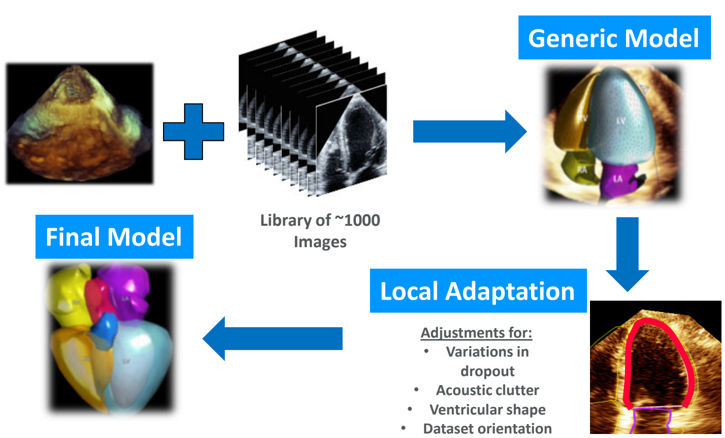
Heart Model Overview



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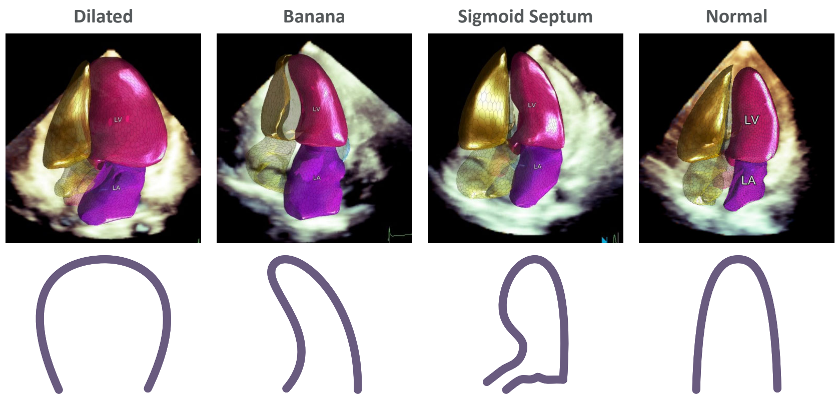
Real-Time Automated Transthoracic Three-Dimensional Echocardiographic Left Heart Chamber Quantification using an Adaptive Analytics Algorithm



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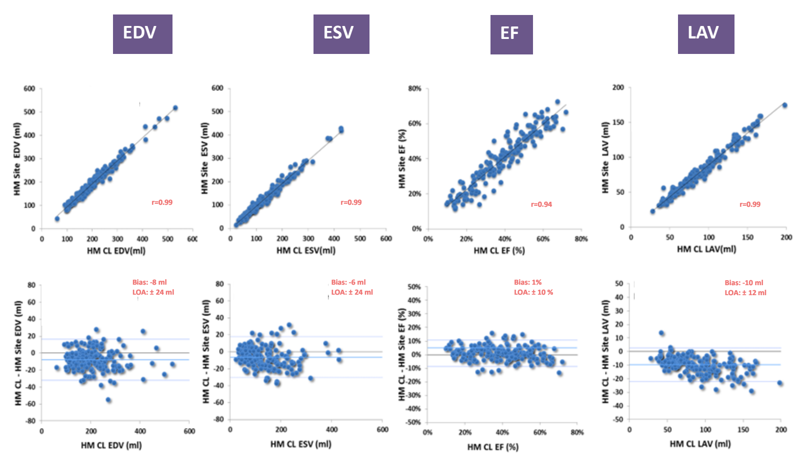
Heart Model with Corrections (Sites vs. Core Lab)



Medvedofsky D, Mor-Avi…Lang RM. Eur Heart J Cardiovasc Imaging 2017

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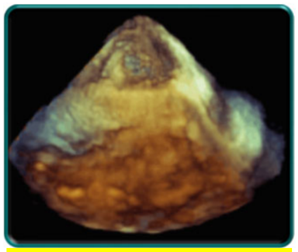
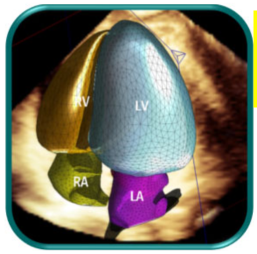
Fully Automated Cardiac Chamber Quantification

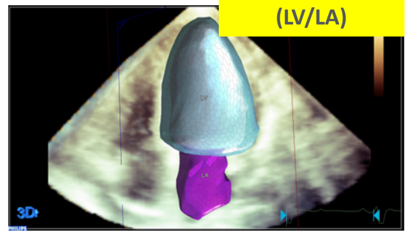


3D Full Volume Acquisition



Static ED and ES Volumes (LV/LA)

Dynamic Volume Curves (LV/LA)



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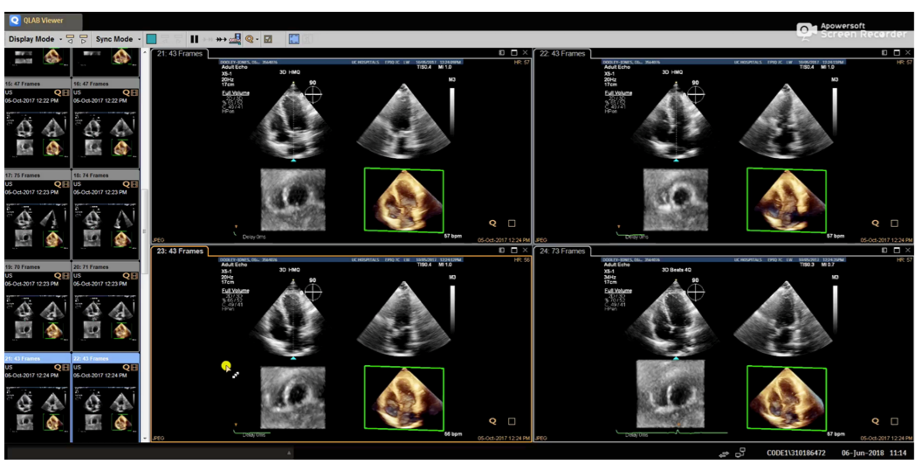
Heart Model Overview



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Possible Clinical Applications

- Heart failure admissions; response to GDMT, diuretics
- Cardio-oncology patients – precise quantification
- Discrepant evaluation of LV/LA
- Reduce need for cardiac MRI for chamber quantification

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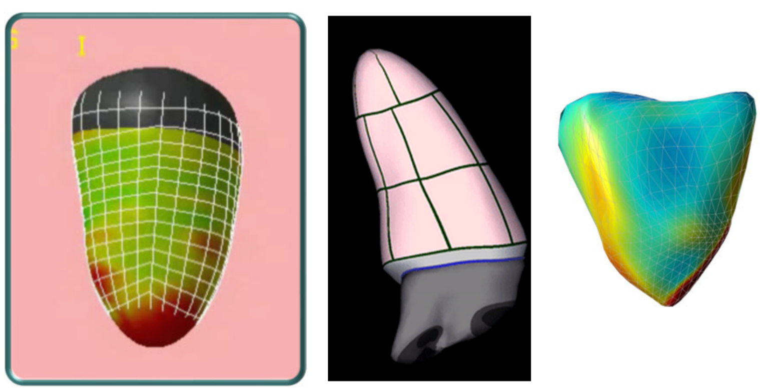
Dynamic Endocardial Surface Analysis



Morphological Shape Analysis, Remodeling in Disease, Response to Therapy, Strain

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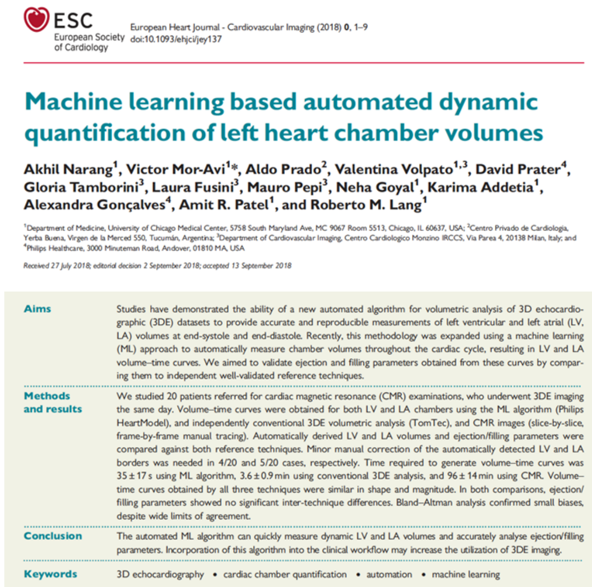

ESC European Society of Cardiology
European Heart Journal - Cardiovascular Imaging (2018) **0**, 1–9
doi:10.1093/ehjci/jey137

Machine learning based automated dynamic quantification of left heart chamber volumes

Akhil Narang[1], Victor Mor-Avi[1]*, Aldo Prado[2], Valentina Volpato[1,3], David Prater[4], Gloria Tamborini[3], Laura Fusini[3], Mauro Pepi[3], Neha Goyal[1], Karima Addetia[1], Alexandra Gonçalves[4], Amit R. Patel[1], and Roberto M. Lang[1]

[1]Department of Medicine, University of Chicago Medical Center, 5758 South Maryland Ave, MC 9067 Room 5513, Chicago, IL 60637, USA; [2]Centro Privado de Cardiologia, Yerba Buena, Virgen de la Merced 550, Tucumán, Argentina; [3]Department of Cardiovascular Imaging, Centro Cardiologico Monzino IRCCS, Via Parea 4, 20138 Milan, Italy; and [4]Philips Healthcare, 3000 Minuteman Road, Andover, 01810 MA, USA

Received 27 July 2018; editorial decision 2 September 2018; accepted 13 September 2018

Aims Studies have demonstrated the ability of a new automated algorithm for volumetric analysis of 3D echocardiographic (3DE) datasets to provide accurate and reproducible measurements of left ventricular and left atrial (LV, LA) volumes at end-systole and end-diastole. Recently, this methodology was expanded using a machine learning (ML) approach to automatically measure chamber volumes throughout the cardiac cycle, resulting in LV and LA volume–time curves. We aimed to validate ejection and filling parameters obtained from these curves by comparing them to independent well-validated reference techniques.

Methods and results We studied 20 patients referred for cardiac magnetic resonance (CMR) examinations, who underwent 3DE imaging the same day. Volume–time curves were obtained for both LV and LA chambers using the ML algorithm (Philips HeartModel), and independently conventional 3DE volumetric analysis (TomTec), and CMR images (slice-by-slice, frame-by-frame manual tracing). Automatically derived LV and LA volumes and ejection/filling parameters were compared against both reference techniques. Minor manual correction of the automatically detected LV and LA borders was needed in 4/20 and 5/20 cases, respectively. Time required to generate volume–time curves was 35 ± 17 s using ML algorithm, 3.6 ± 0.9 min using conventional 3DE analysis, and 96 ± 14 min using CMR. Volume–time curves obtained by all three techniques were similar in shape and magnitude. In both comparisons, ejection/filling parameters showed no significant inter-technique differences. Bland–Altman analysis confirmed small biases, despite wide limits of agreement.

Conclusion The automated ML algorithm can quickly measure dynamic LV and LA volumes and accurately analyse ejection/filling parameters. Incorporation of this algorithm into the clinical workflow may increase the utilization of 3DE imaging.

Keywords 3D echocardiography • cardiac chamber quantification • automation • machine learning

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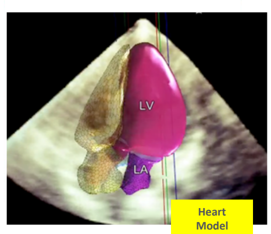
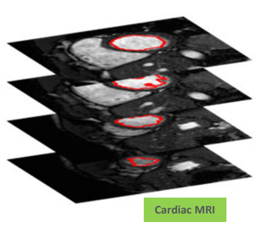
3D Echo Automated Quantification of LV and LA Volume-Time Curves: Comparison with MRI





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LV Curve Analysis

	Left Ventricle	CMR	Heart Model
Ejection Indices	End-systolic volume	76 ± 25	69 ± 21
	Stroke volume	100 ± 22	98 ± 23
	Ejection fraction	58 ± 9	59 ± 7
	Volume (50% ejection time)	123 ± 32	108 ± 29
Filling Indices	End-diastolic volume	175 ± 36	167 ± 36
	Filliing duration (%RR)	61 ± 7	57 ± 4
	Volume (25% filling time)	101 ± 35	91 ± 26
	Volume (50% filling time)	136 ± 40	123 ± 26
	Volume (75% filling time)	148 ± 40	141 ± 39
	Volume at diastasis	145 ± 41	133 ± 32
	Rapid filling volume	69 ± 27	64 ± 18
	Rapid filling fraction	0.68 ± 0.17	0.65 ± 0.11
	Atrial filling volume	31 ± 15	34 ± 13
	Atrial filling fraction	0.32 ± 0.17	0.35 ± 0.11

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LA Curve Analysis

	Left Atrium	CMR	Heart Model
Filling Indices	Maximum volume	86 ± 24	81 ± 25
	Filling duration (%RR)	45 ± 10	46 ± 7
	Filling fraction	49 ± 11	56 ± 12
	Volume (50% filling time)	68 ± 24	59 ± 22
Emptying Indices	Minimum volume	45 ± 24	36 ± 18
	Emptying duration (%RR)	55 ± 10	54 ± 7
	Volume (25% emptying time)	74 ± 26	67 ± 18
	Volume (50% emptying time)	68 ± 22	56 ± 18
	Volume (75% emptying time)	65 ± 22	52 ± 18
	Volume at diastasis	66 ± 22	55 ± 21
	Passive emptying volume	20 ± 9	26 ± 10
	Passive emptying fraction	0.49 ± 0.21	0.58 ± 0.14
	Active emptying volume	21 ± 11	19 ± 8
	Active emptying fraction	0.51 ± 0.21	0.42 ± 0.14

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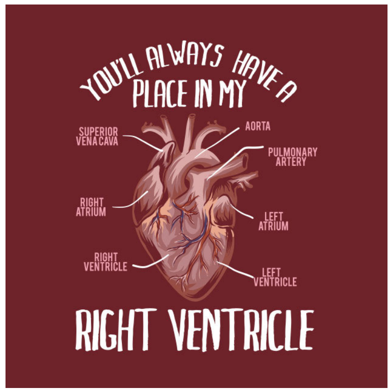
Don’t Forget the Right Ventricle!



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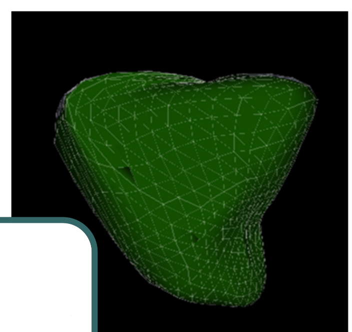
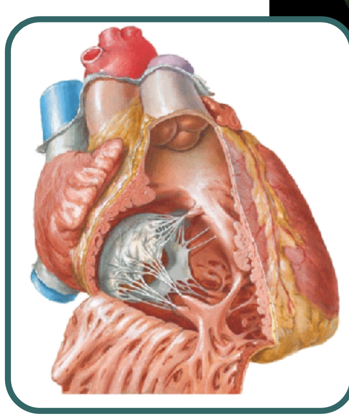
RV Anatomy and Contraction

- Complex crescent shape
- Thin-walled, compliant chamber
- Low pulmonary resistance / afterload
- Sensitive to changes in afterload
  - RV dilatation
  - RV hypertrophy





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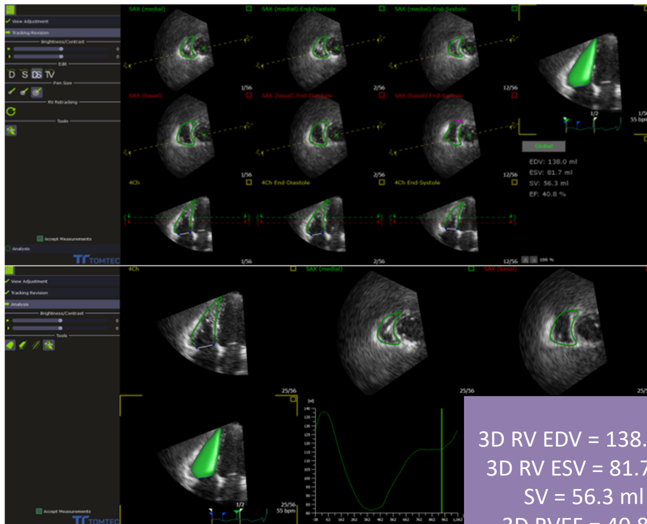
3D RV EF Automated Analysis



3D RV EDV = 138.0 ml
3D RV ESV = 81.7 ml
SV = 56.3 ml
3D RVEF = 40.8%

Genovese D…Narang, A, Lang RM. J Am Soc Echocardiogr. 2019 Aug;32(8):969-977.

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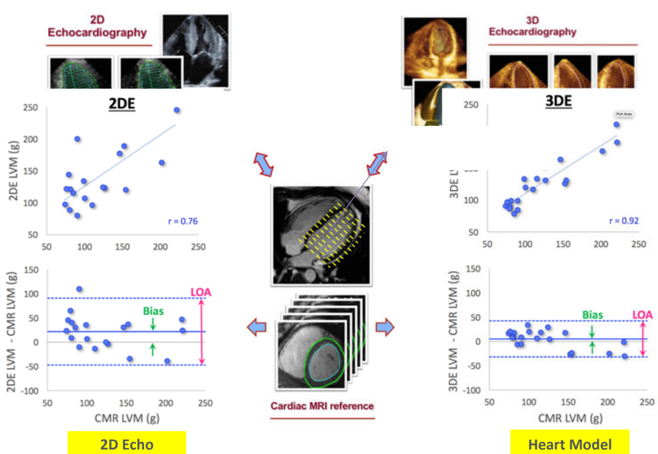
Automated Quantification of LV Mass



Volpato V…Narang A, Lang RM. Echocardiography. 2019 Feb;36(2):312-319.

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Real World AI Echocardiographic Analysis

ULTROMICS™

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WASE COVID Study

CLINICAL INVESTIGATIONS

ECHOCARDIOGRAPHY IN COVID-19 INFECTION

Echocardiographic Correlates of In-Hospital Death in Patients with Acute COVID-19 Infection: The World Alliance Societies of Echocardiography (WASE-COVID) Study

Ilya Karagodin, MD, Cristiane Carvalho Singulane, MD, Gary M. Woodward, PhD, Mingxing Xie, MD, PhD, FASE, Edwin S. Tucay, MD, FASE, Ana C. Tude Rodrigues, MD, Zuilma Y. Vasquez-Ortiz, MD, PhD, Azin Alizadehasl, MD, FASE, Mark J. Monaghan, PhD, Bayardo A. Ordonez Salazar, MD, Laurie Soulat-Dufour, MD, Atoosa Mostafavi, MD, Antonella Moreo, MD, Rodolfo Citro, MD, Akhil Narang, MD, Chun Wu, MD, PhD, Tine Descamps, PhD, Karima Addetia, MD, FASE, Roberto M. Lang, MD, FASE, and Federico M. Asch, MD, FASE, on behalf of the WASE-COVID Investigators[1], *Chicago, Illinois; Oxford and London, United Kingdom; Wuhan, People's Republic of China; Quezon City, Philippines; São Paulo, Brazil; Ciudad de Mexico, Mexico; Tehran, Iran; Paris, France; Milan and Salerno, Italy; and Washington, D.C.*

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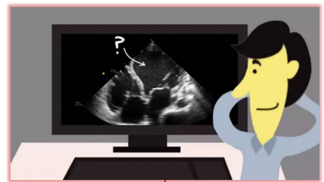
Echocardiography Workflow



Artificial Intelligence

Image acquisition

Artificial Intelligence

Automated chamber or parameter quantification; disease diagnosis

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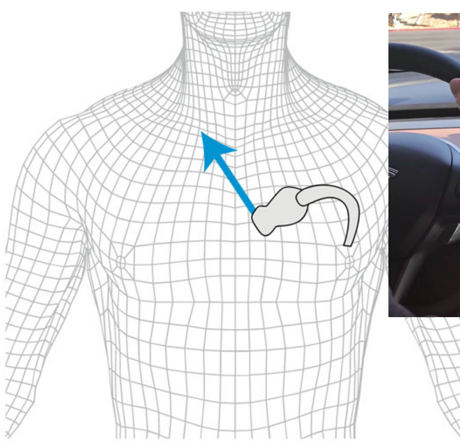
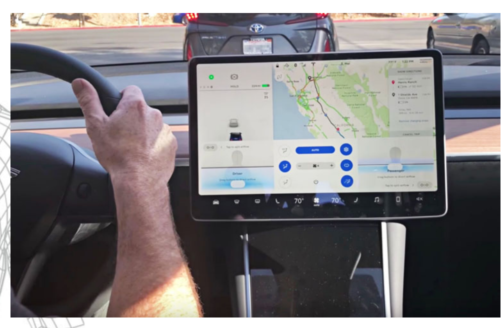
Can AI Guide Image Acquisition?





Caption Health

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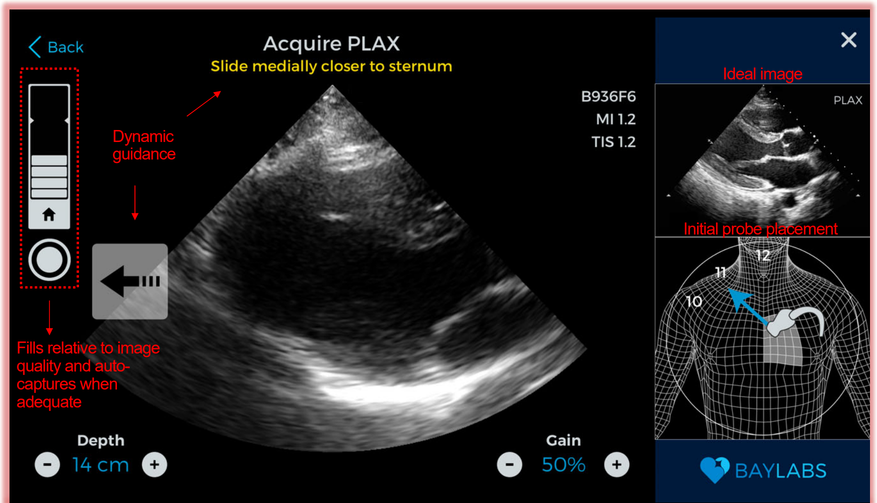
Deep-Learning Guidance of Image Acquisition



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Pivotal Study

- Prospective study at NMH and MHI
- **Objective:** Evaluate use of EchoGPS by novices who had no prior training in echocardiography
  - 8 RNs (4 at each site)
  - No prior echocardiography experience
  - Each RN underwent a short didactic session

Study Design

240 patients

- **RN** limited TTE using EchoGPS (10 views) Terason uSmart 3200T
- **Sonographer** limited TTE (10 views) Terason uSmart 3200T

Five level 3 expert echocardiographers, blindly and independently evaluated acquired images

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Subject Criteria

Inclusion Criteria

- Subjects already scheduled for a clinical echocardiogram
- ≥18 years old
- Inpatients or outpatients

Exclusion Criteria

- Unable to lay flat
- Patients experiencing known of suspected acute cardiac event (STEMI, unstable arrhythmia, shock, etc).
- Severe chest wall deformities
- History of pneumonectomy
- Unable to consent

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Pivotal Trial Demographics

- 240 patients recruited
- BMI
  - BMI <25: 35%
  - BMI 25-30: 32%
  - BMI >30: 33%
- Race
  - White: 77%
  - Black: 18%
- Mean age: 61 ± 16 years (20 - 91)
  - BMI <25: 35%
  - BMI 25-30: 32%
  - BMI >30: 33%
- Patients with any known cardiac abnormality: 64%

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Research

JAMA Cardiology | Original Investigation

Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use

Akhil Narang, MD; Richard Bae, MD; Ha Hong, PhD; Yngvil Thomas, MS; Samuel Surette, BS; Charles Cadieu, PhD;
Ali Chaudhry, MBA; Randolph P. Martin, MD; Patrick M. McCarthy, MD; David S. Rubenson, MD;
Steven Goldstein, MD; Stephen H. Little, MD; Roberto M. Lang, MD; Neil J. Weissman, MD; James D. Thomas, MD

Narang A et al. JAMA Cardiol. 2021;6(6):624-632.

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Pivotal Trial Results

Table 1. Proportion of Nurse-Acquired Artificial Intelligence–Guided Echocardiography of Sufficient Quality to Assess Core Cardiac Clinical Parameters in Population Scanned by Nurses[a]

End point	Clinical parameter examined by qualitative visual assessment	Performance goal, %	Total scans performed, No.	Scans of sufficient quality, No.	Scans of sufficient quality (95% CI)
1	Left ventricular size	80	240	237	98.8 (96.7-100)
2	Global left ventricular function	80	240	237	98.8 (96.7-100)
3	Right ventricular size	80	240	222	92.5 (88.1-96.9)
4	Nontrivial pericardial effusion	80	240	237	98.8 (96.7-100)

Table 2. Comparison of Nurse-Acquired and Sonographer-Acquired Studies for Primary and Secondary Clinical Parameters[a]

Image No.	Clinical parameter examined by qualitative visual assessment	No. (%) [95% CI]		Nurse-sonographer difference, percentage points
		Nurse examination	Sonographer examination	
1	Left ventricular size	232 (98.7) [96.3-99.7]	235 (100) [98.4-100.0]	−1.3
2	Global left ventricular function	232 (98.7) [96.3-99.7]	235 (100) [98.4-100.0]	−1.3
3	Right ventricular size	217 (92.3) [88.2-95.4]	226 (96.2) [92.9-98.2]	−3.9
4	Nontrivial pericardial effusion	232 (98.7) [96.3-99.7]	234 (99.6) [97.7-100.0]	−0.9
5	Right ventricular function	214 (91.1) [86.7-94.4]	226 (96.2) [92.9-98.2]	−5.1
6	Left atrial size	222 (94.5) [90.7-97.0]	234 (99.6) [97.7-100.0]	−5.1
7	Aortic valve	215 (91.5) [87.2-94.7]	228 (97.0) [94.0-98.8]	−5.5
8	Mitral valve	226 (96.2) [92.9-98.2]	233 (99.1) [97.0-99.9]	−2.9
9	Tricuspid valve	195 (83.0) [77.6-87.6]	217 (92.3) [88.2-95.4]	−9.3
10	Inferior vena cava size	135 (57.4) [50.9-63.9]	215 (91.5) [87.2-94.7]	−34.1

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Case Example #1

- Patient 1121
- 63 year old female, BMI 15
- History of COPD, no known cardiac history
- No prior echocardiogram

All scans by nurse

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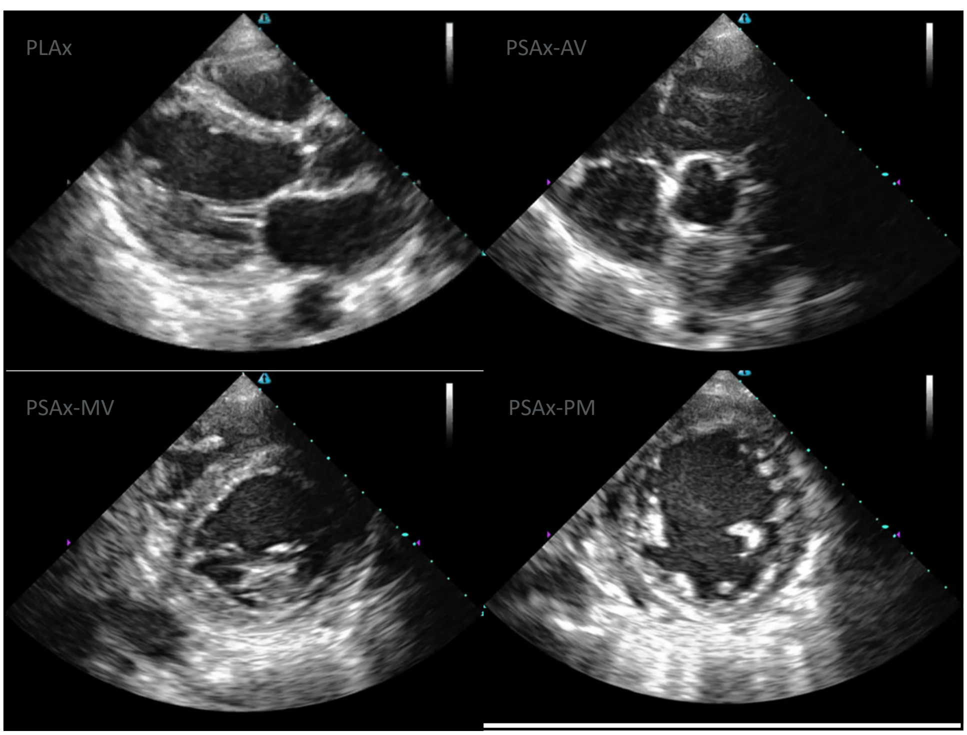

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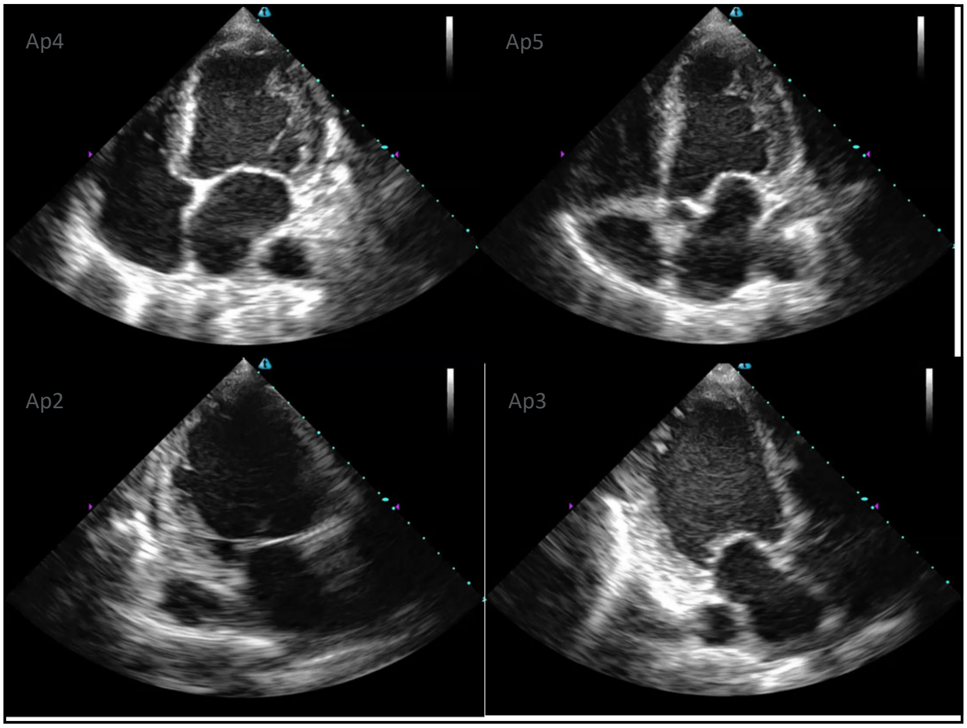

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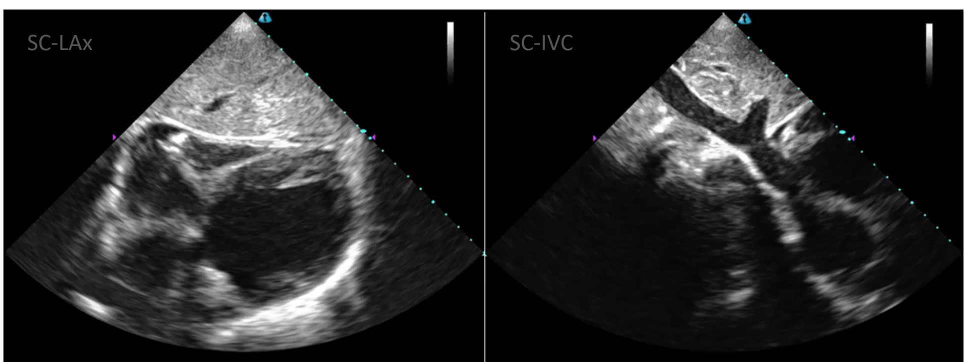

Clinical TTE findings:

- **LVEF 17% w/ global dysfunction**
- **Grade 1 diastolic dysfunction**
- **Mild MR**

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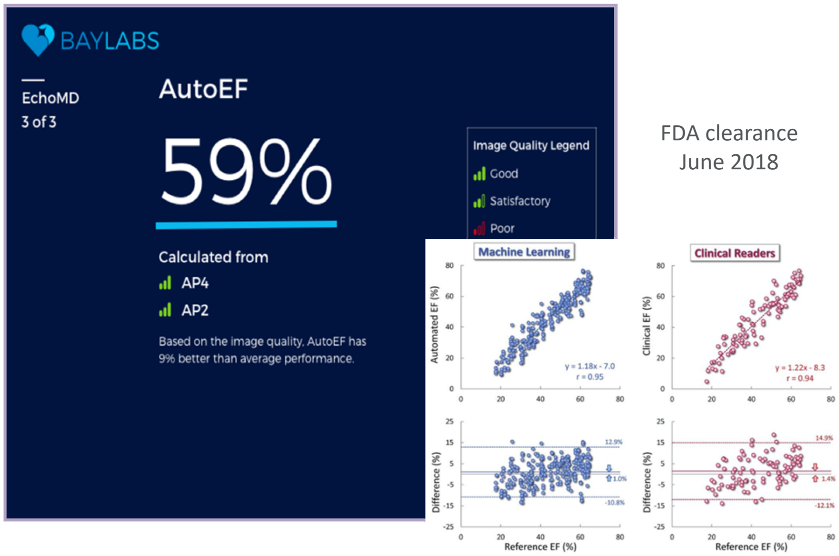
Combining AI Based Image Acquisition + Analysis



FDA clearance
June 2018

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Circ Cardiovasc Imaging. 2019 Sep;12(9):e009303.

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Potential Use for AI Based Image Acquisition

- Sonographers are a precious resource…
  - Resource-limited settings without ready access to sonographers/cardiologists
    - Rural environments
    - Developing world
  - Point of care setting
    - Emergency rooms, urgent care, oncology clinics, pre-operative clinics, intensive-care units

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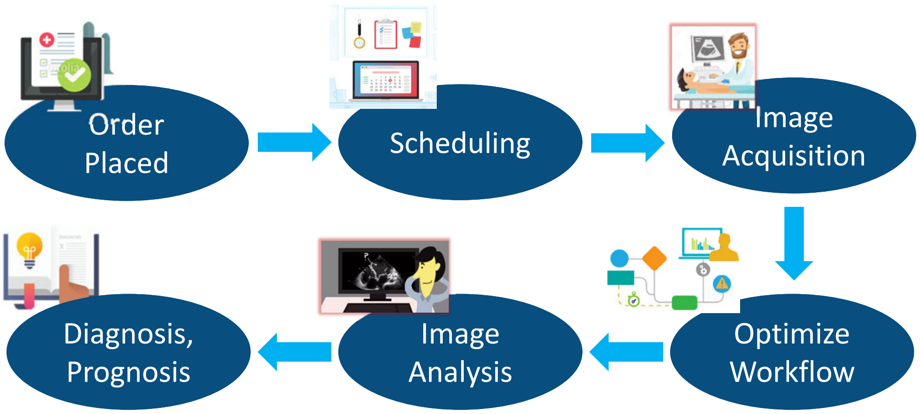
Summary of AI in Echocardiography



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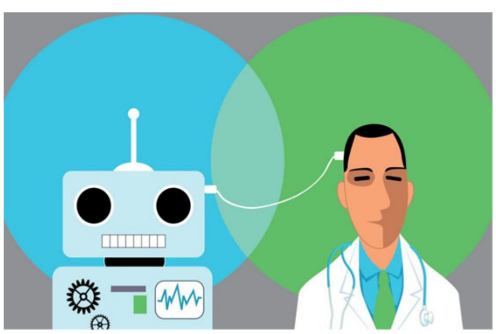
It's Not A Competition

"Artificial intelligence is a tool, not a threat."

-Rodney Brooks, PhD (Professor Emeritus in Robotics/AI @MIT)



"Human + Artificial Intelligence > Human Alone or Artificial Intelligence Alone"

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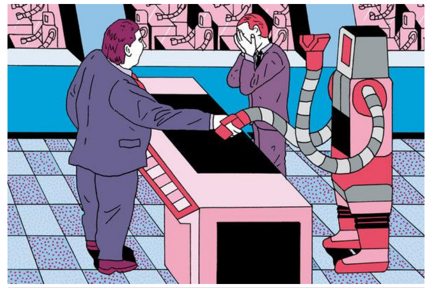
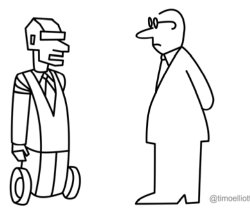
Thank You!

Acknowledgements

- Roberto Lang, MD
- James Thomas, MD
- Victor Mor-Avi, PhD
- Sanjiv Shah, MD
- Clyde Yancy, MD
- Charlie Davidson, MD
- Patrick McCarthy, MD
- Vera Rigolin, MD
- Echo Lab Colleagues



The Machines Are Coming!



"The good news is I have discovered inefficiencies. The bad news is that you're one of them."

Northwestern Medicine

AkhilNarangMD

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