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Office of Research and Development

AI and Health

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Disclosures

Anant Madabhushi, PhD

Picture Health – Co-Founder, Equity Holder

Aiforia Inc, SimbioSys - Scientific Advisory Board

Elucid Bioimaging Inc. – Stock

Astrazeneca, Bristol Myers-Squibb, Boheringer Ingelheim, Eli Lily – Sponsored Research

SimbioSys, Biohme, Castle Biosciences – Consulting

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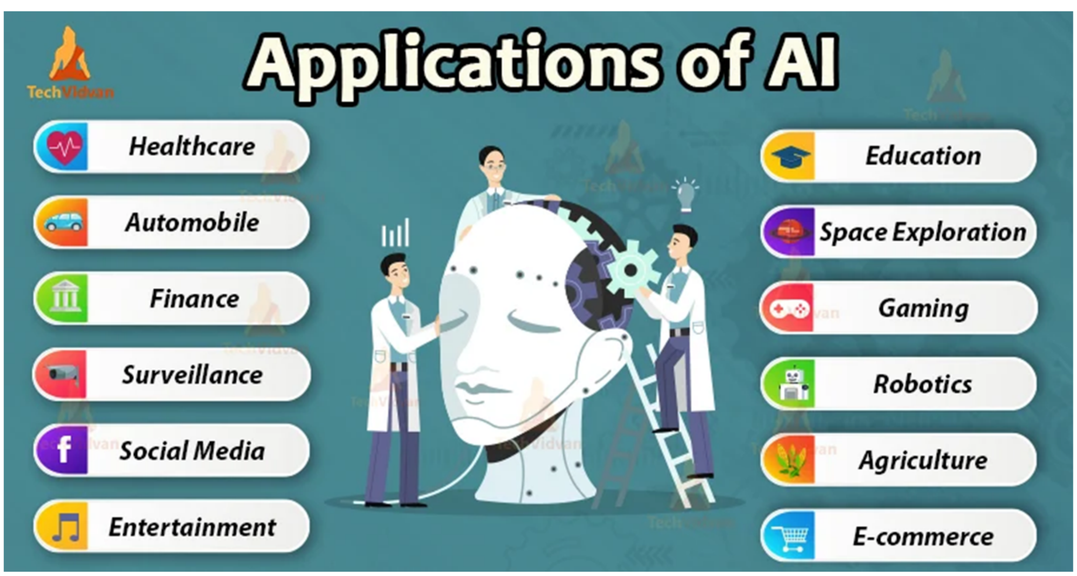
Anant Madabhushi
2,015 Tweets
Edit profile
Anant Madabhushi
@anantm
Artificial Intelligence, Cancer imaging, Digital pathology, radiomics, pathomics, precision medicine

@anantm

3


Applications of AI
Healthcare
Automobile
Finance
Surveillance
Social Media
Entertainment
Education
Space Exploration
Gaming
Robotics
Agriculture
E-commerce

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Role of AI and Computational Imaging in developing Better Diagnostic, Prognostic, and Predictive Tools

Diagnostic: *Identifying presence of disease*

Prognostic: *Predicting Disease Outcome, progression*

Predictive: *Predicting Response to treatment*

Precision Medicine*: Using Prognostic and Predictive Tools for Tailoring Therapy for a given patient based off specific risk profile*

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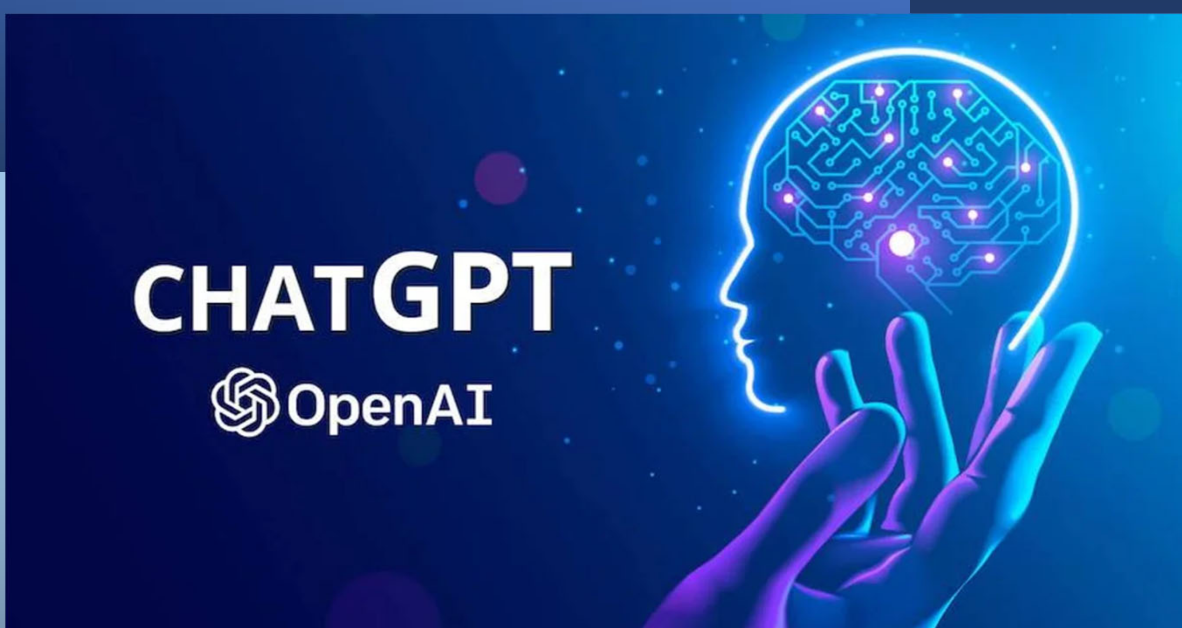

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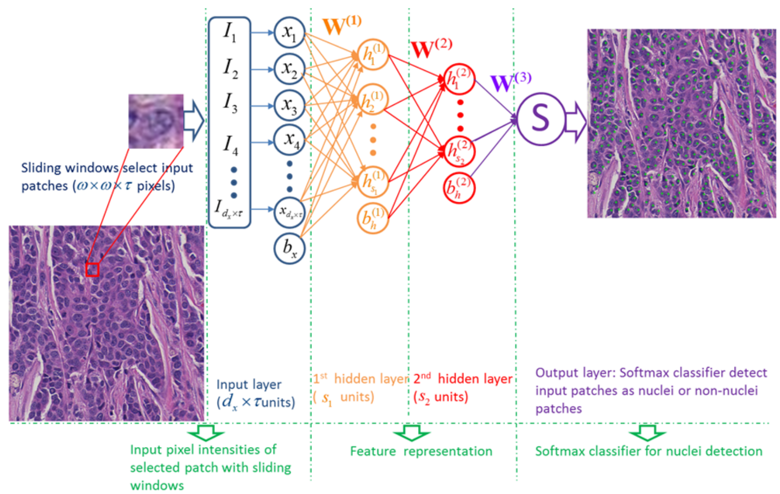
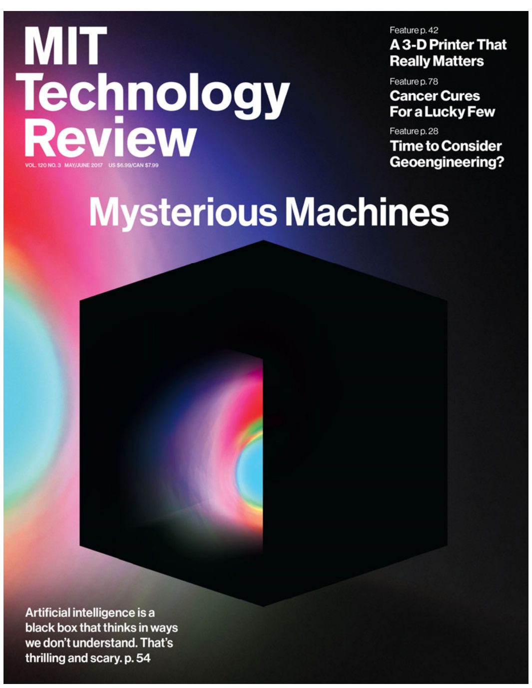
Deep Learning in Medicine



***Xu J**, et al.* "Stacked Sparse Autoencoder (SSAE) based Framework for Nuclei Patch Classification on Breast Cancer Histopathology", ISBI2014.
***Xu J**, et al.* "Stacked Sparse Autoencoder (SSAE) for Nuclei Detection on Breast Cancer Histopathology". *IEEE Trans. on Medical Imaging,* 2015
*Zhang X, Dou H, **Xu J,** Zhang S,* "Fusing Heterogeneous Features for the Image-Guided Diagnosis of Intraductal Breast Lesions", *IEEE Journal of Biomedical and Health Informatics,* 2015
Lu C, Xu H, ***Xu J***, Mandal M, and Madabhushi A, "Multiple Passes Adaptive Voting for Nuclei Detection in Histopathlogical Images", *IEEE Journal of Biomedical and Health Informatics, (Under Preparing)*

7



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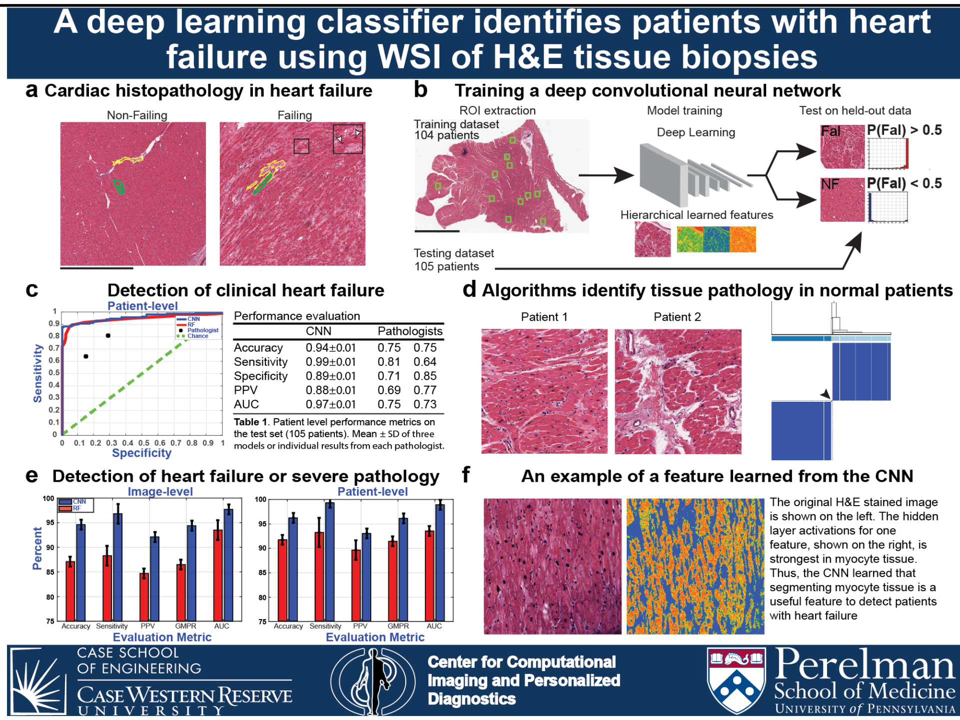

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Business | Technology

Is there a smarter path to artificial intelligence? Some experts hope so

Originally published June 24, 2018 at 5:00 pm | *Updated June 25, 2018 at 12:59 am*

But now some scientists are asking whether deep learning is really so deep after all.

In recent conversations, online comments and a few lengthy essays, a growing number of AI experts are warning that the infatuation with deep learning may well breed myopia and overinvestment now — and disillusionment later.

"There is no real intelligence there," said Michael I. Jordan, a professor at the University of California, Berkeley, and the author of an essay published in April intended to temper the lofty expectations surrounding AI. "And I think that trusting these brute-force algorithms too much is a faith misplaced."

More on AI

IBM's robot debater is ready to convince you that you're wrong

IBM pits computer against human debaters

10

Husky or Wolf? Using a Black Box Learning Model to Avoid Adoption Errors

Past Tides

August 24, 2017 By Wendy Wolfson

Say you want to adopt a dog, from a picture, and you task your machine learning system to classify the image as either a husky, which would be safe to adopt, or a wolf, which probably is not a good idea. Can you get that photograph classified with certainty? "Because researchers don't have insights into what is going on they can easily be misled," said Sameer Singh, assistant professor in the UCI Department of Computer Science. "Classification is core to machine learning," said Singh, describing 'black box' machine learning predictions at the Association for Computing Machinery (ACM) July 12 meeting at the Cove. Machine learning is pervasive in our lives—from email to games. "It's in our phones," said Singh, a machine learning and natural language processing expert. "It is in our houses. It is basically everywhere."One of his students created a wolf/dog classifier in a few hours that seemed to work—at first.

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Please Stop Explaining Black Box Models for High-Stakes Decisions

catastrophic harm to society. There is a way forward – it is to design models that are inherently interpretable.

Abstract

Black box machine learning models are currently being used for high stakes decision-making throughout society, causing problems throughout healthcare, criminal justice, and in other domains. People have hoped that creating methods for explaining these black box models will alleviate some of these problems, but trying to *explain* black box models, rather than creating models that are *interpretable* in the first place, is likely to perpetuate bad practices and can potentially cause catastrophic harm to society. There is a way forward – it is to design models that are inherently interpretable.

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Considerations in Building AI Tools for Precision Medicine

Interpretability – Black box versus hand-crafted

Affordability – Frugal Precision Medicine

Equitable – Does it work across populations?

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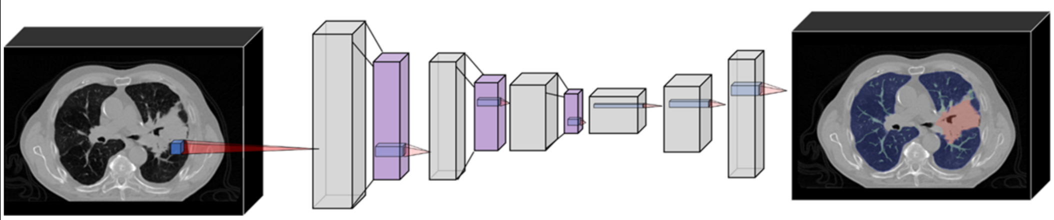
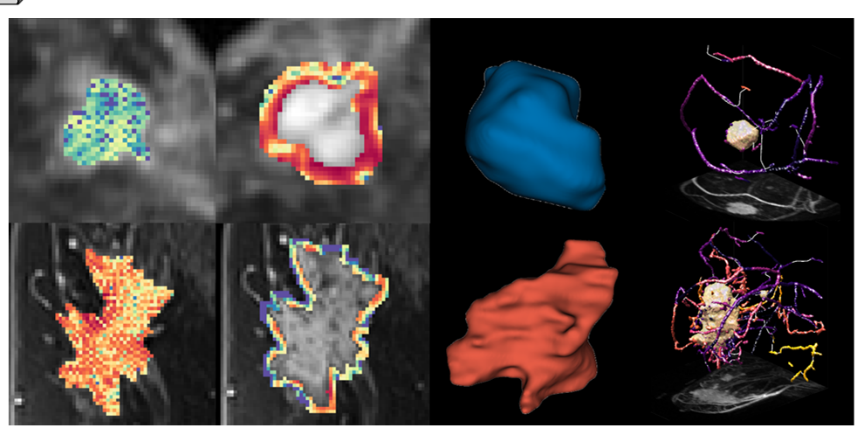
Handcrafted Features - Radiology



Segmentation of tumor, vessels, parenchyma

Mining the tumor and tumor habitat for interpretable, non-invasive radiomic biomarkers



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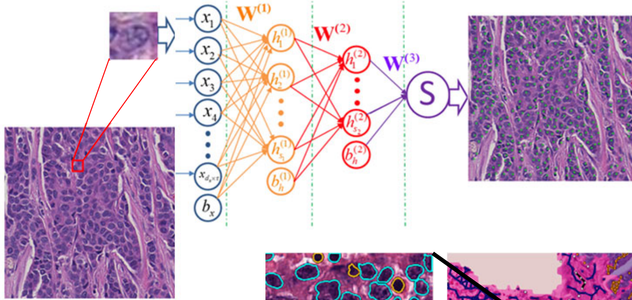
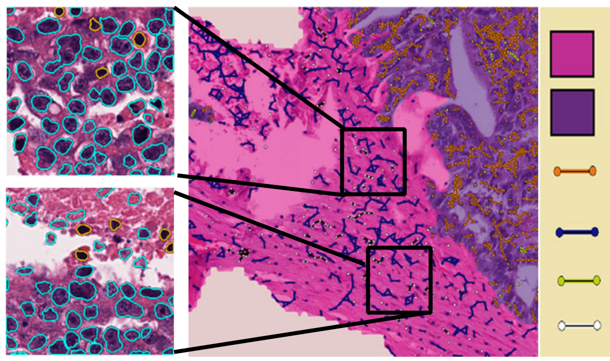
Handcrafted Features - Digital Pathology



Deep learning-based mapping of cells, tissues, and structures on histopathology images

Mining the TIME and histologic primitives for AI-powered interpretable biomarkers



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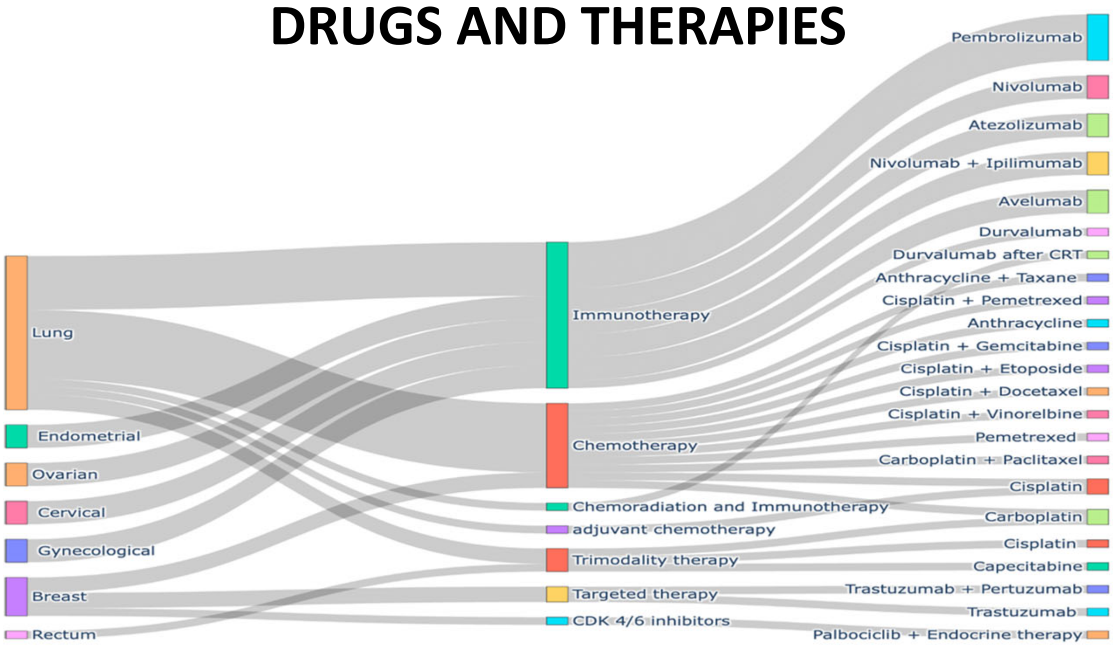
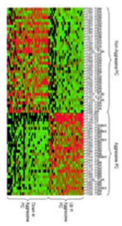
DRUGS AND THERAPIES

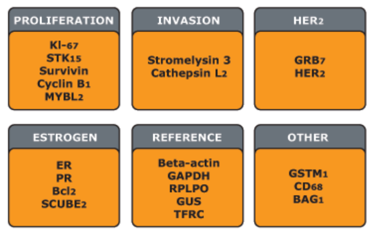


16

Which cancer patients will receive added benefit from chemotherapy?



Oncotype DX molecular assay (Genomic Health, Inc.)
- For early stage (LN-), ER+ patients
- Recurrence Score (RS) between 0-100
- Predicts:
  - Likelihood for 10-year distant recurrence
  - Expected benefit from adjuvant chemotherapy



Recurrence Score= +0.47 x HER2 Group Score
-0.34 x ER Group Score
+1.04 x Proliferation group Score
+0.10 x Invasion Group Score
+0.05 x CD68
-0.08 x GSTM1
-0.07 x BAG1

Paik et al., N Engl J Med 2004 351: 2817-2826

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Collagen fiber detection

Epithelium segmentation

Collagen vectors in tumor-associated stroma

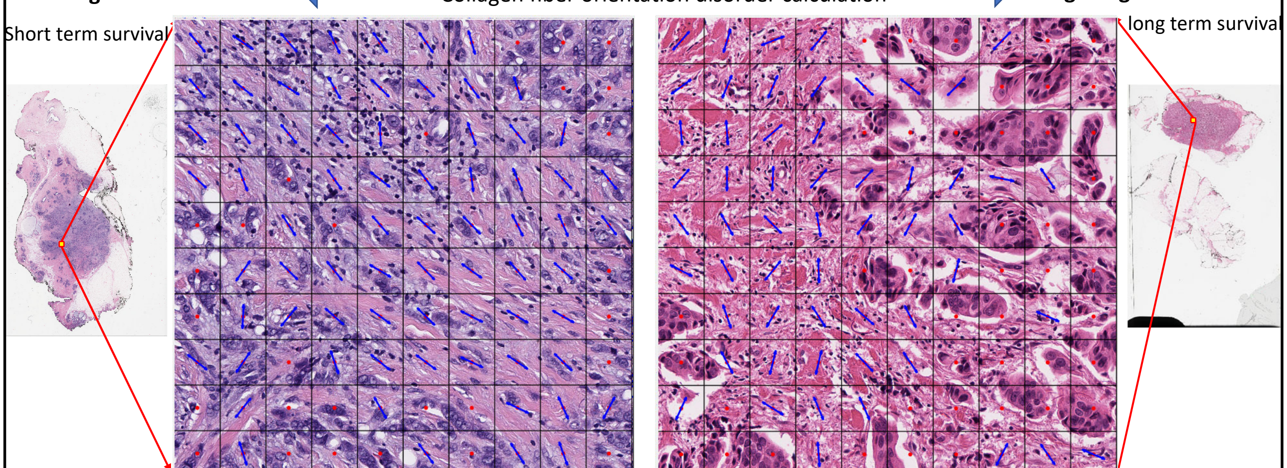
Collagen fiber orientation disorder calculation

Low degree of disorder

Short term survival

High degree of disorder

long term survival



Li et al, npj Breast Cancer, 2021

18

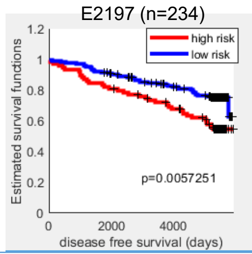
Disorder of collagen fiber orientation associated with risk of recurrence in ER+ breast cancers in ECOG-ACRIN E2197 & TCGA

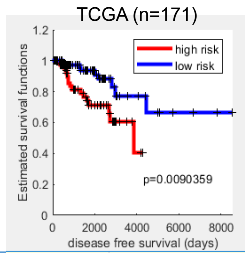
Unmet Clinical Need

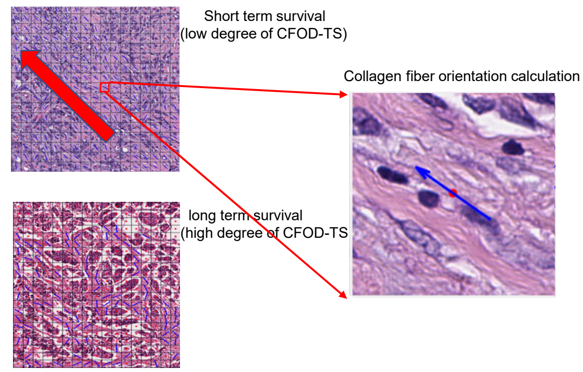
- Early stage ER+ breast cancer (BC) is the most common type of breast cancer in the United States
- Predicting the likelihood of recurrence for patients helps physicians plan more tailored treatment strategy to improve survival rate.

Results:

- Collagen Fiber Orientation Disorder in Tumor associated Stroma (CFOD-TS) was independently prognostic for ER+ BCs in E2197 and TCGA.







Take away:

Over-expression of CFOD-TS independently associated with lower likelihood of recurrence and could potentially serve as a prognostic marker of outcome for ER+ invasive breast cancer.

CASE SCHOOL OF ENGINEERING
CASE WESTERN RESERVE UNIVERSITY

The Center for Computational Imaging & Personalized Diagnostics

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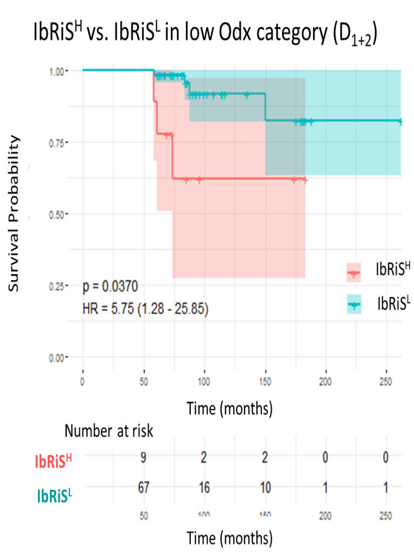
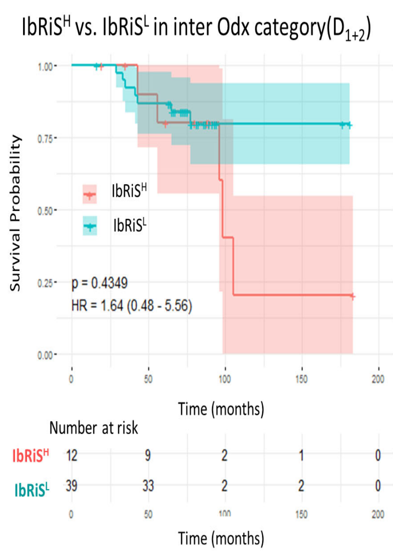
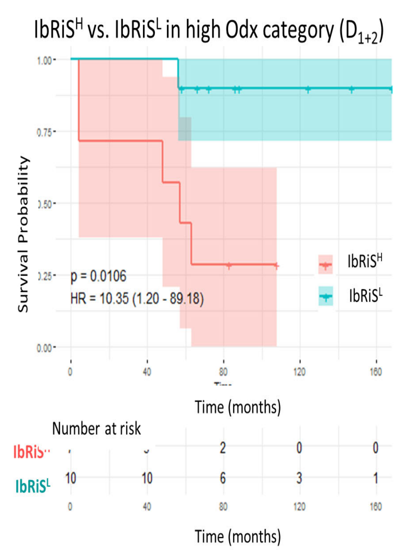
IbRiS adds prognostic value to Oncotype DX Risk Categories in in Estrogen Receptor Positive (ER+) Breast Cancer







Under Review

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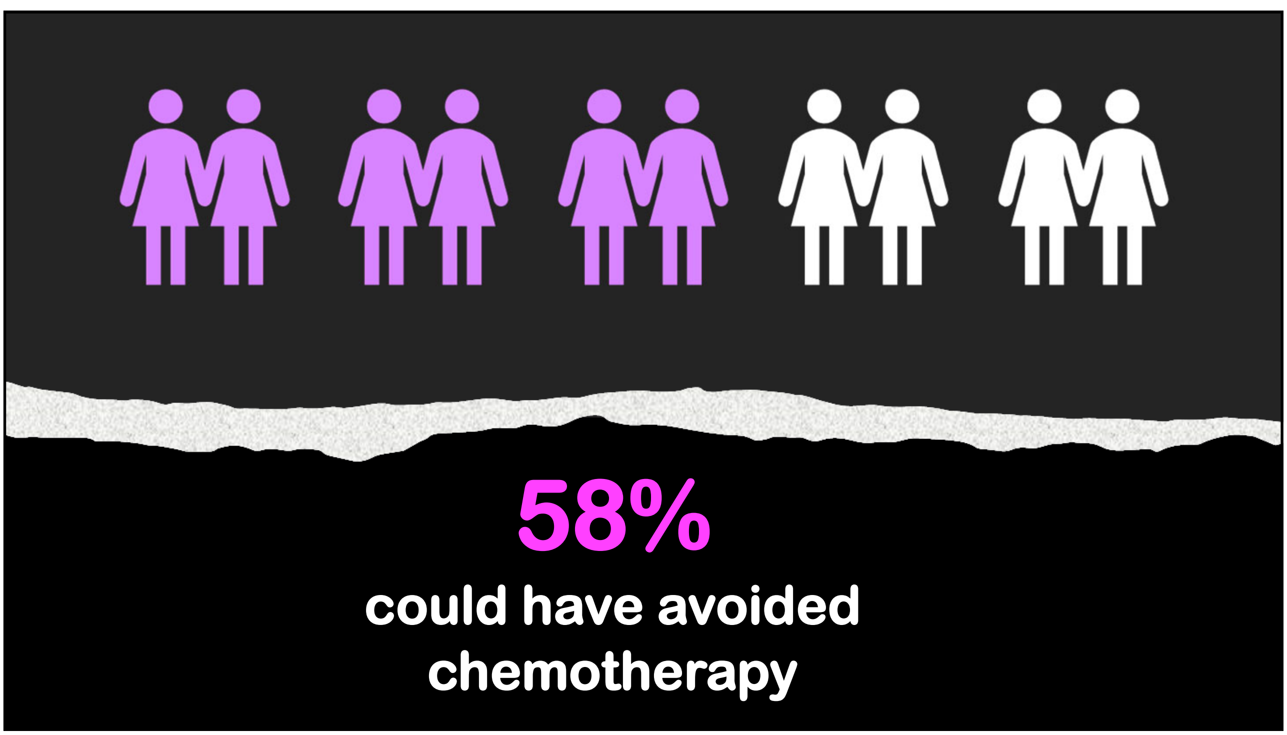
12%
more women needed chemotherapy

21


58%
could have avoided
chemotherapy

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Original Investigation FREE

January 21, 2021

Association of Race/Ethnicity and the 21-Gene Recurrence Score With Breast Cancer-Specific Mortality Among US Women

Kent F. Hoskins, MD[1,2]; Oana C. Danciu, MD[1,2]; Naomi Y. Ko, MD, MPH, AM[3]; Gregory S. Calip, PharmD, MPH, PhD[4,5,6]

» Author Affiliations | Article Information

JAMA Oncol. 2021;7(3):370-378. doi:10.1001/jamaoncol.2020.7320

Conclusions and Relevance In this cohort study, Black women in the US were more likely to have a high-risk recurrence score and to die of axillary node-negative breast cancer compared with non-Hispanic White women with comparable recurrence scores. The Oncotype DX Breast Recurrence Score test has lower prognostic accuracy in Black women, suggesting that genomic assays used to

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Computerized image analysis reveals differences in early-stage ER+ breast cancer phenotype of South Asian and North American women

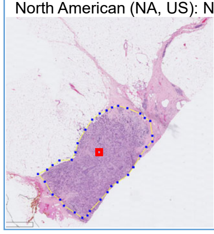
Unmet Clinical Need

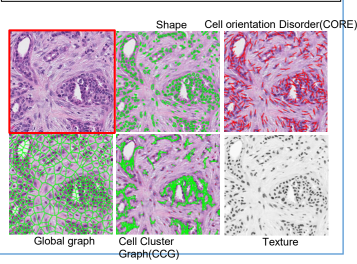
- Racial/ethnic disparity in incidence and mortality in breast cancers.
- Indian women more likely to be diagnosed with advanced breast cancer despite lower incidence than American women.
- The studies of digital pathology in breast cancer prognosis were mostly focused on American women.

Methods and Results

Data Description → Extraction of nuclear morphological features

South Asian (SA, Indian): N=69
North American (NA, US): N=121





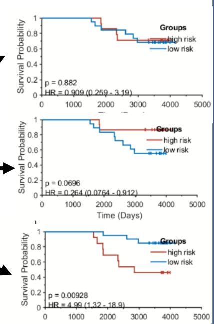
Model construction on training set → Validation on SA in testing set

Model trained with North American (MNA)

Model trained with North American + South Asian (MNA+SA)

Model trained with South Asian(MSA)

Model validation on South Asian



Take away:

Prognostic ability of the computational pathology based models for South Asian women with breast cancer could be significantly improved by taking into account of population-specific information.

Li et al San Antonio 2021

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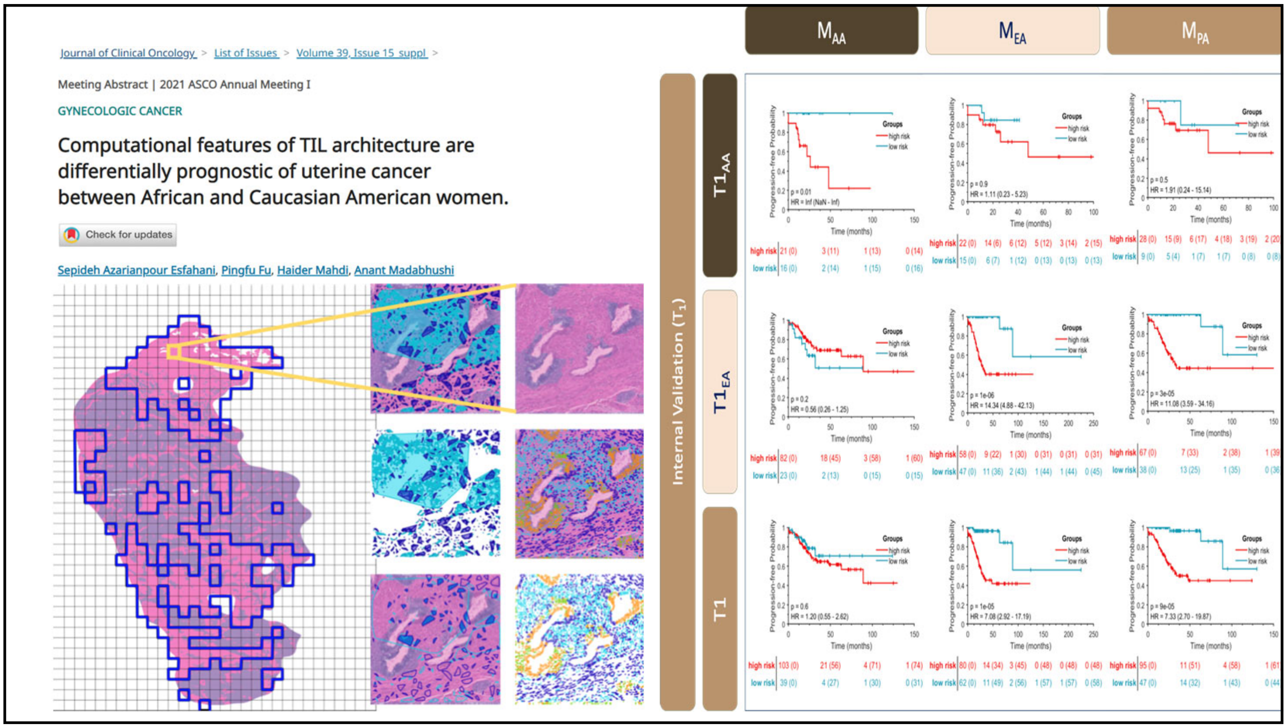

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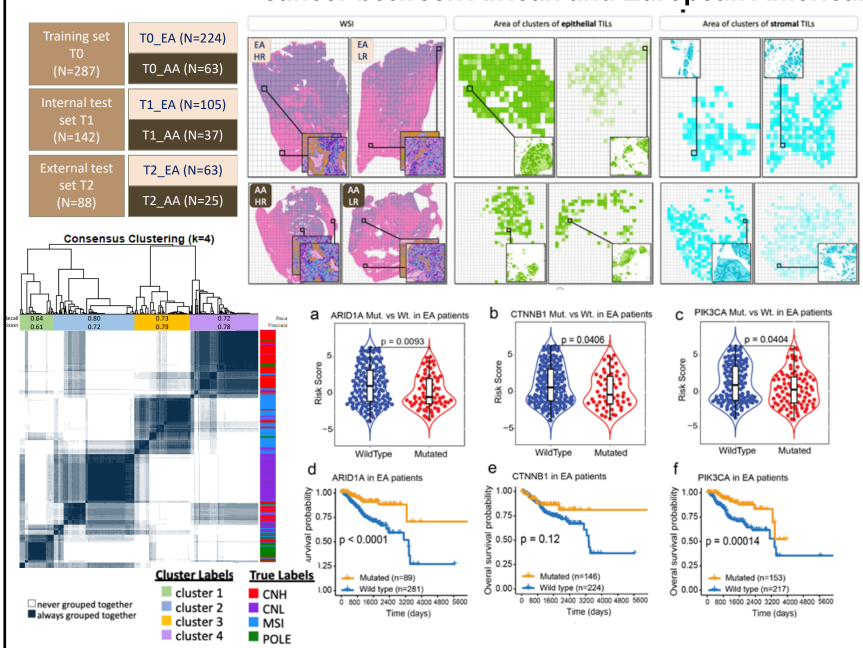
Computational features of Immune architecture are differentially prognostic of uterine cancer between African and European American women



- Features describing the immune cell architecture extracted from the tumor epithelial nests and surrounding stroma are associated with progression free survival of endometrial cancer
- African American-specific model: Concordance index=0.86, p=0.04, HR=6.52 (1.05-40.68)
- European American-specific model: Concordance index=0.93, p=1e-6, HR=14.34, CI=[4.88-42.13]
- Immune-related feature expression possibly captures underlying genomic variations

Takeaways

- The model yielded optimal performance when trained and validated on the same racial group.
- Population-agnostic model was not prognostic when validated on population subsets
- strong association with existing molecularly defined subtypes of endometrial cancer (CNH, CNL, MSI, POLE)

Azarianpour, ASCO, 2021

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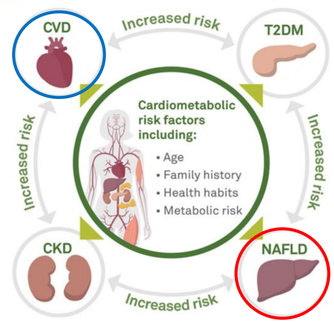
Machine Learning-Based Hepatic Fat Assessment on CT

Cardiovascular disease is strongly associated with type 2 diabetes, chronic kidney disease, and nonalcoholic fatty liver disease.

- CAC scans contain portions of the liver and spleen
  - ➢ Opportunity for liver fat evaluation: Hepatic Steatosis (HS).



Pipeline:

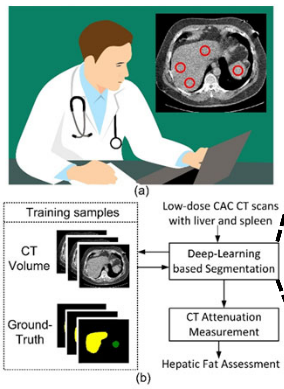
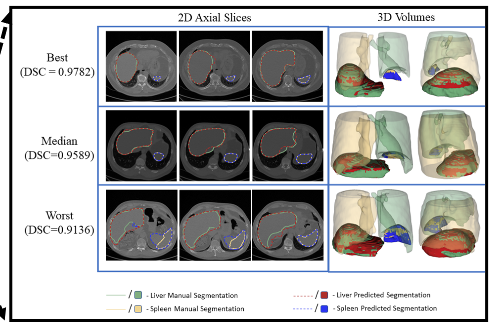


Figure: Hepatic Fat Assessment (a) Manual ROI method (b) Deep learning-based automatic method.



Results:

Table. Performance of the CT attenuation estimation methods against the expert human reader.

Seg. Method	CT Attenuation Estimation	Liver	Liver-to-spleen
nnUnet	Slice-based	0.98	0.95
	Volumetric based	0.96	0.92

Modanwal, Gourav, Jonathan R. Walker, Sadeer Al-Kindi, Sanjay Rajagopalan, and Anant Madabhushi. "Machine Learning-Based Hepatic Fat Assessment in Low-Dose Coronary Artery Calcium Scans is Correlated With Human Reader Assessment." *Circulation 142, no. Suppl_3* (2020): A16796-A16796.

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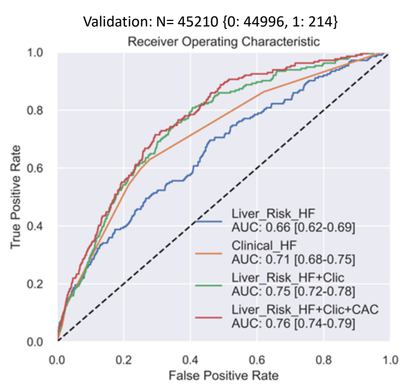
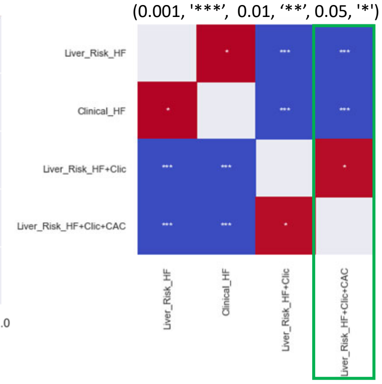
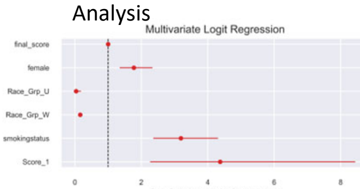
Liver Radiomics Predicts MACE Events – Large Validation



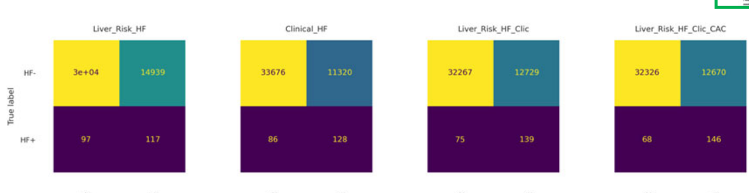
DeLong's Test (P-Value)
(0.001, '***', 0.01, '**', 0.05, '*')



Linear Discriminant Analysis



Odds of HF are 1.56 times higher for females compared to males



Performance on Holdout Validation

	Accuracy	Bal Acc.	AUC	SENS	SPEC
Liver_Risk	0.67	0.61	0.66	0.55	0.67
Clinical	0.72	0.68	0.71	0.63	0.72
Liver_Risk+Clinical	0.72	0.68	0.75	0.65	0.72
Liver_Risk+Clinical+CAC	0.72	0.70	0.76	0.68	0.72

*Clinical factors included are 'Age', 'female', 'Race_Grp', and 'smoking_status'

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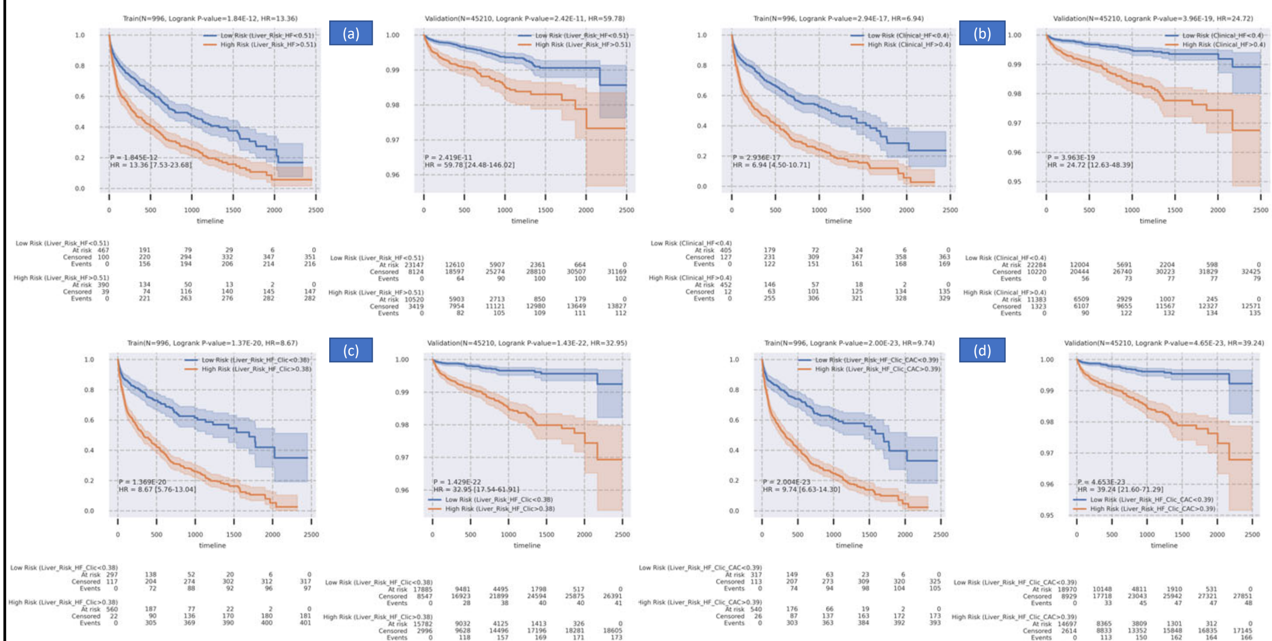
The risk threshold value was selected by maximizes Youden's J statistic



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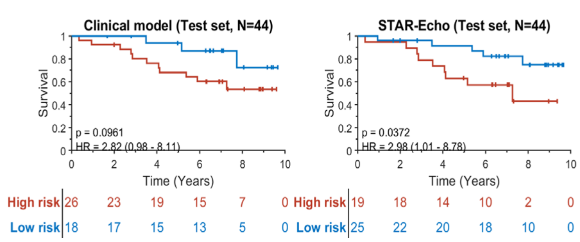
STAR-Echo: Spatiotemporal Echocardiography analysis for Prognosis of Major Adverse Cardiovascular Event (MACE) in Chronic Kidney Disease (CKD) patients

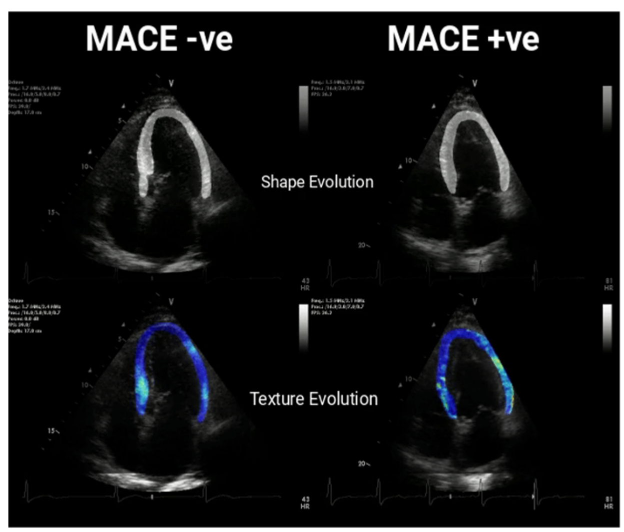
- Longitudinal changes in Echo, over a heartbeat cycle, are prognostic of downstream MACE outcomes in CKD patients.

Model Performance

Result	AUC	*p - value*	*Hazard Ratio*
Clinical Model (EF, BNP & NT-proBNP)	0.66 *[0.5 - 0.83]*	0.096	2.82 *[0.98 - 8.11]*
STAR-Echo	**0.71** ***[0.53 - 0.89]***	**0.037**	**2.98** ***[1.01 - 8.78]***

EF: Ejection Fraction; BNP & NT-proBNP: B-type and N-terminal pro-B-type natriuretic peptide





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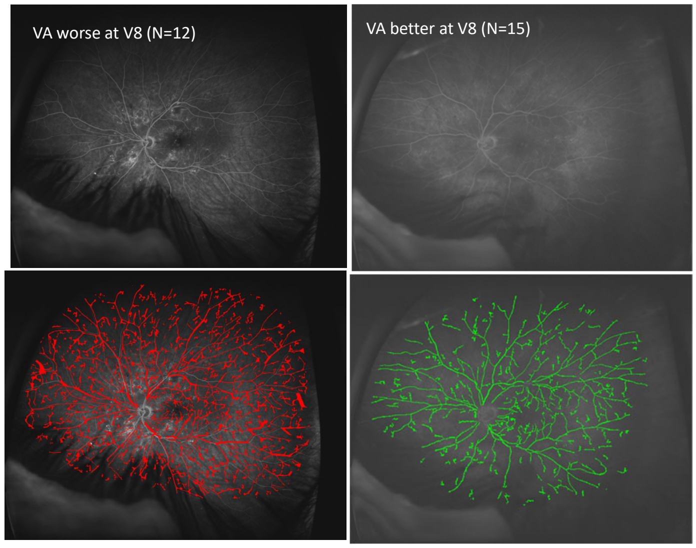
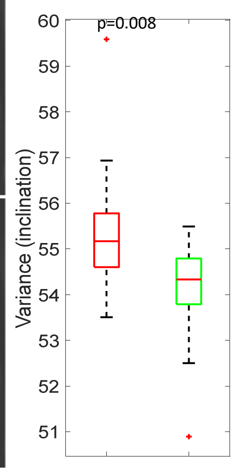
Vessel tortuosity predicts treatment response in Diabetic eye disease





- Extracted 5 hough transform-based vasculature features
- Top discriminating feature: variance of theta in hough parameter space
- AUC using machine learning classifier (Random Forests) in 3-fold cv: 0.65+/- 0.05

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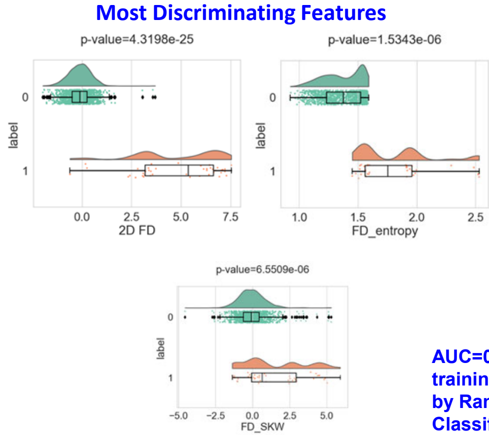
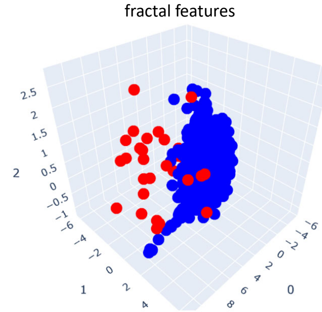
Association between Retinal Vascular Features with Alzheimer's Disease

Number of Patients =1353;
Number of Images =1806
Number of Baseline Images (N)=1587[Control=1545, AD (including MCI and other subgroups)=42]
Excluded 25 MCI

Most Discriminating Features



Kernel PCA with RBF kernel on 15 fractal features



AUC=0.69±0.04 on training set (N=1270) by Random Forest Classifier

AUC=0.6 on validation set (N=317)

Unpublished. Do not distribute

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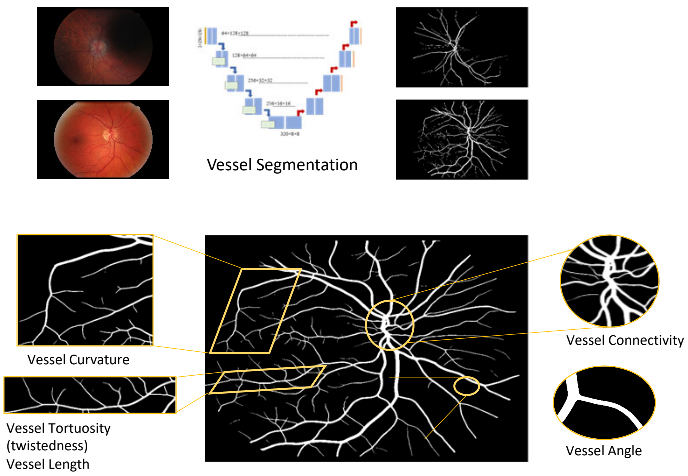
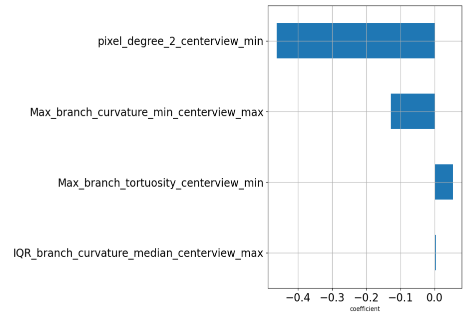
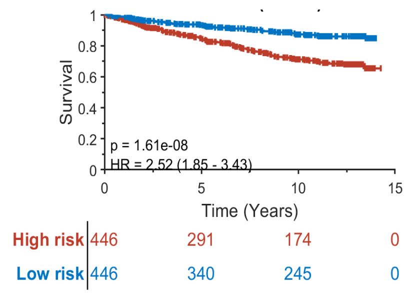
Predict Cardiovascular outcomes via Retinal Vessel features







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Take Away

- **AI is not magic –** Need to be thoughtful and intentional in developing algorithms.
- **Interpretability, reproducibility and equity are key considerations for AI.**
- Unsupervised and Supervised Based AI Approaches provide a trade off between not requiring domain knowledge and interpretability.
- Independent of type of approach, rigorous validation of the approaches is needed across different test sites.
- Creating carefully curated and representative training datasets for AI and nutrition will be critical.

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Acknowledgements

- R01CA268287A1
- U01CA269181
- R01CA26820701A1
- R01CA249992-01A1
- R01CA202752-01A1
- R01CA208236-01A1
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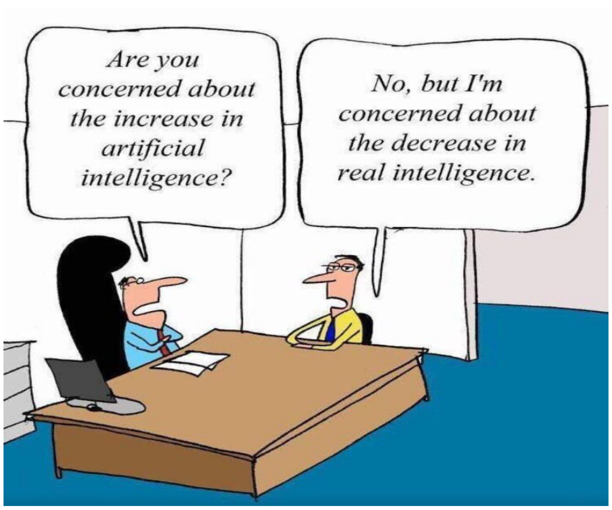
- 1R01HL15127701A1,
- R01HL15807101A1,
- 1R43EB028736-01
- IBX004121A
- W81XWH-19-1-0668
- W81XWH-20-1-0851
- W81XWH-20-1-0595)
- W81XWH-21-1-0345,
- W81XWH-21-1-0160,
- the Kidney Precision Medicine Project (KPMP) Glue Grant
- Sponsored research agreements from Bristol Myers-Squibb, Boehringer-Ingelheim, Eli-Lilly and Astrazeneca.

35



@anantm

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Ethics, Privacy, Bias and Trust in the Application of AI

Judy Gichoya, MD MS
Director, HITI Lab
Associate Professor, Department of Radiology
Emory University

HITI LAB

EMORY UNIVERSITY

1

Disclosures

- ACR
  - AI advisory council
- RSNA
  - Associate Editor - Radiology AI Trainee Editorial Board
  - CIRE Committee member
- SIIM
  - Co-chair – Research Committee
  - Board member
- HL7 and AHLI Board member
  - Association for Health Learning and Inference
- Softbrew LTD
  - Consulting on Global Health /Clinical informatics

- Funding
  - NBIB MIDRC / COVID -19 Data repository
  - Clairity Consortium
  - NIH AIM AHEAD pilot grant
  - RSNA Health disparities grant
  - DeepLook grant for AI validation
  - GE Edison grant for validating AI models
  - Harold Amos Faculty Award to study AI bias
  - Lacuna fund for creating diverse medical datasets

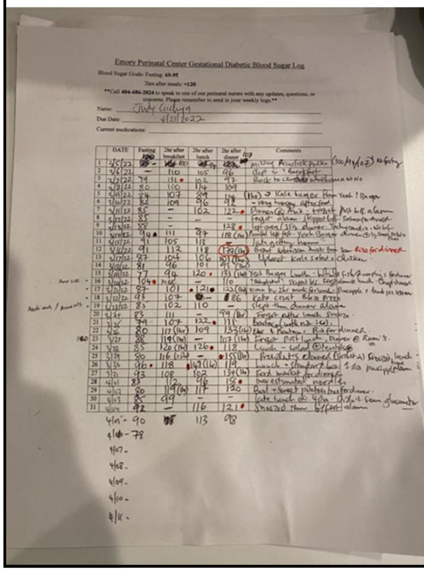
Last updated Sep 15th 2023

2

Original Investigation
August 17, 2021
Trends in Gestational Diabetes at First Live Birth by Race and Ethnicity in the US, 2011-2019
Nilay S. Shah, MD, MPH[1,2]; Michael C. Wang, BA[1]; Priya M. Freaney, MD[1,2]; et al

Screening for Gestational Diabetes
Updated Evidence Report and Systematic Review for the US Preventive Services Task Force
Jennifer Pillay, MSc[1]; Lois Donovan, MD[2]; Samantha Guitard, MSc[1]; et al

JAMA Patient Page
August 10, 2021
Screening for Gestational Diabetes
Jill Jin, MD, MPH[1]



3

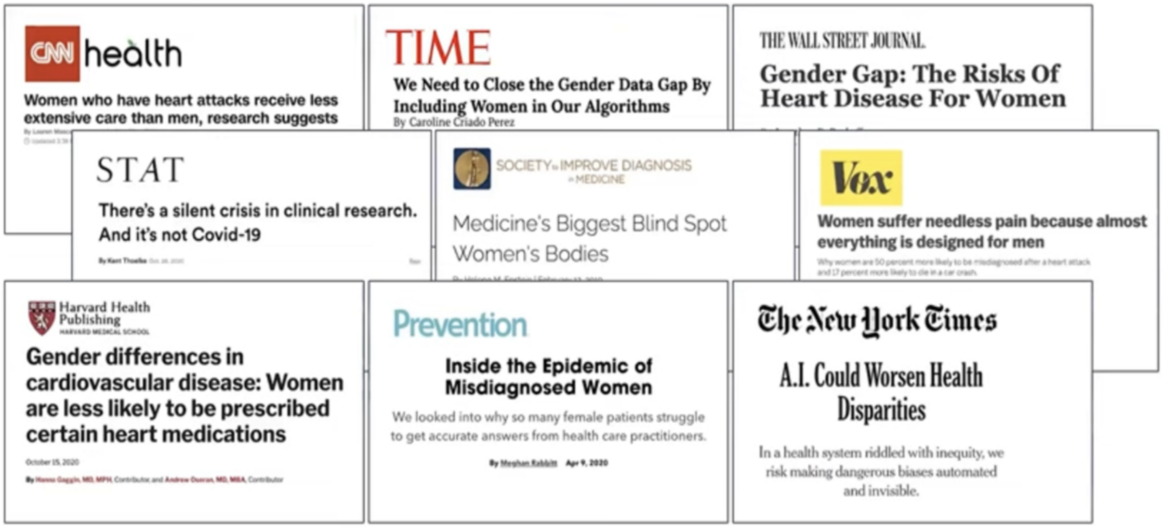
The Harm of **Not** Sharing Health Data

- NIH requires that women and underrepresented groups are included in clinical trials
- Exclusion of women, children, gender, race must be justified
- **Exclusion of pregnancy needs no justification**

> • "women and members of minority groups and their subpopulations must be included in all NIH-funded clinical research, *unless a clear and compelling rationale and justification establishes to the satisfaction of the relevant Institute/Center Director that inclusion is inappropriate* with respect to the health of the subjects or the purpose of the research"

4

Women: inequitable data access and literacy lead to expensive and adverse data outcomes



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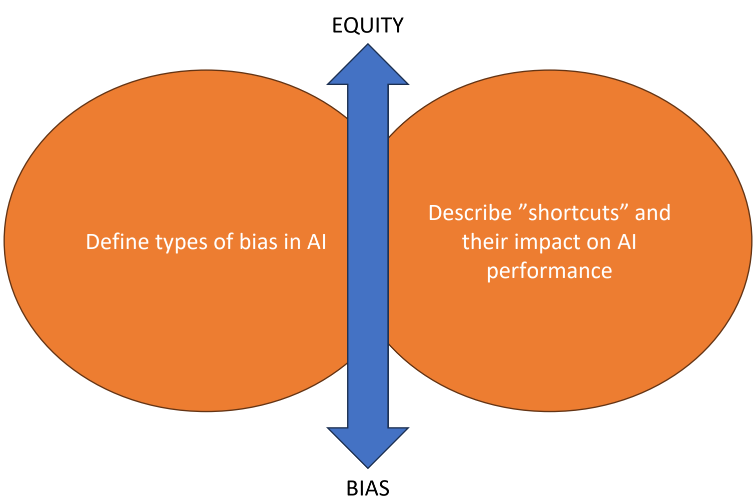
Objectives



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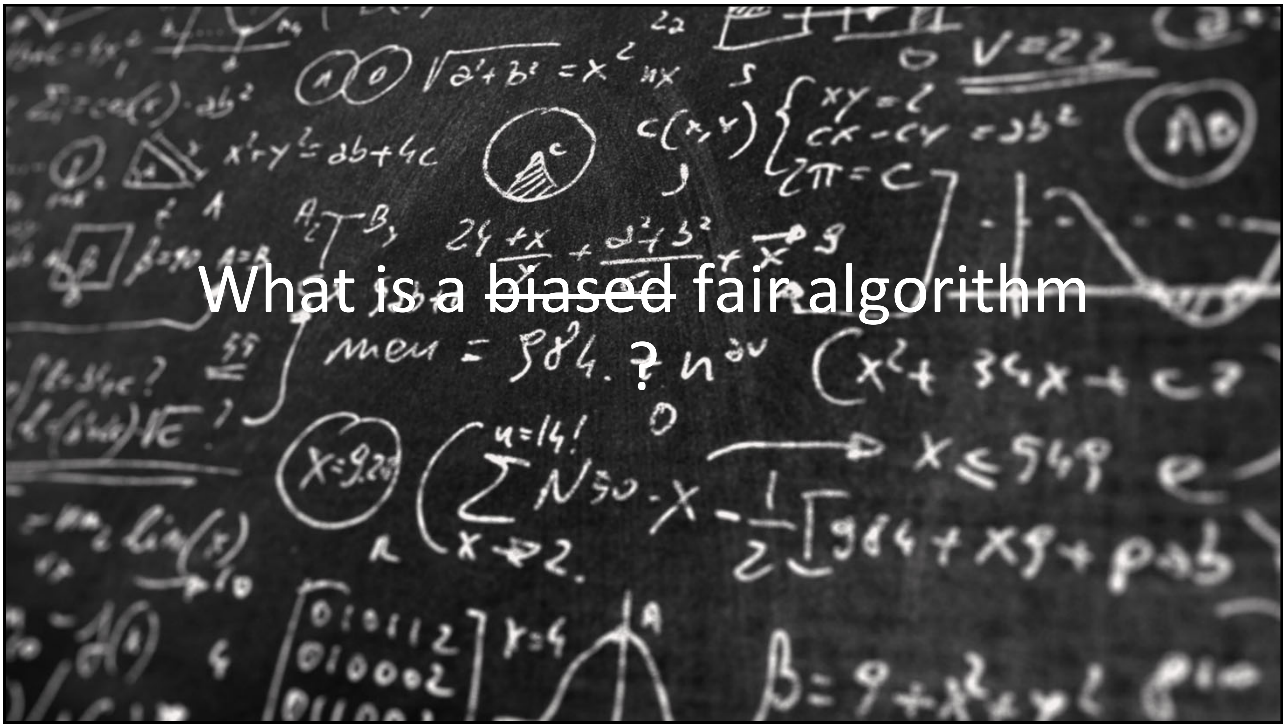

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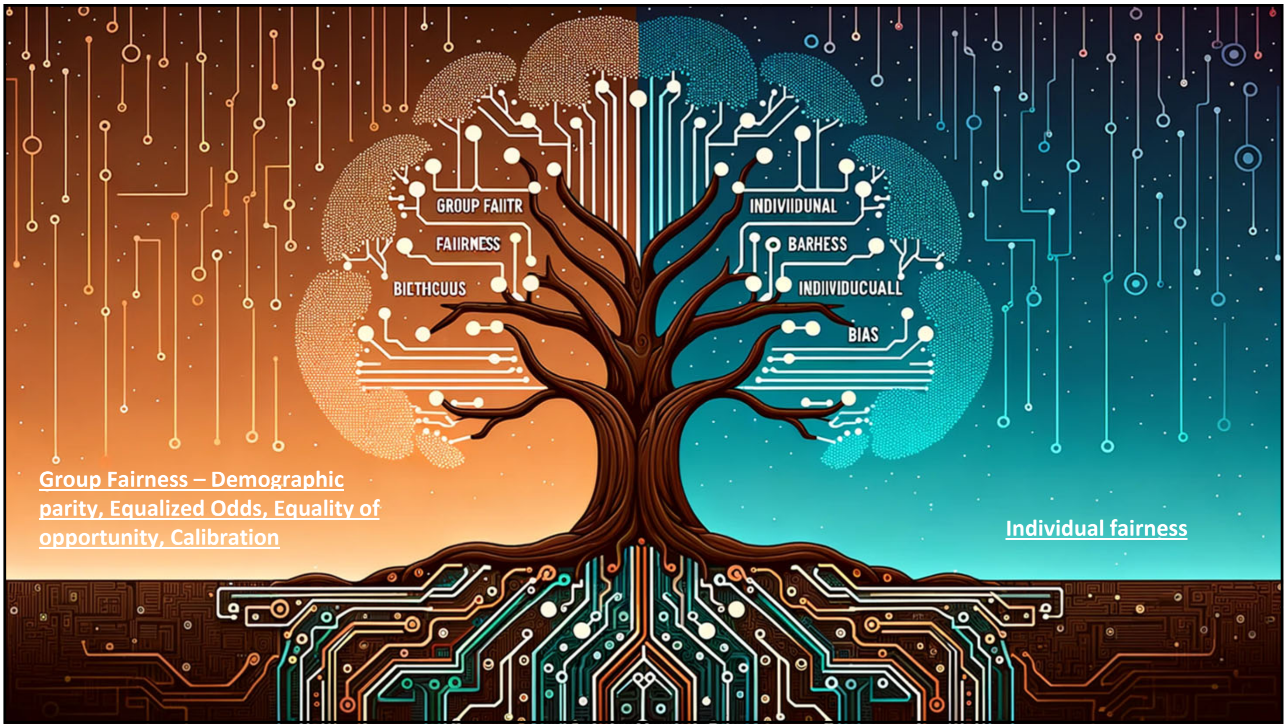

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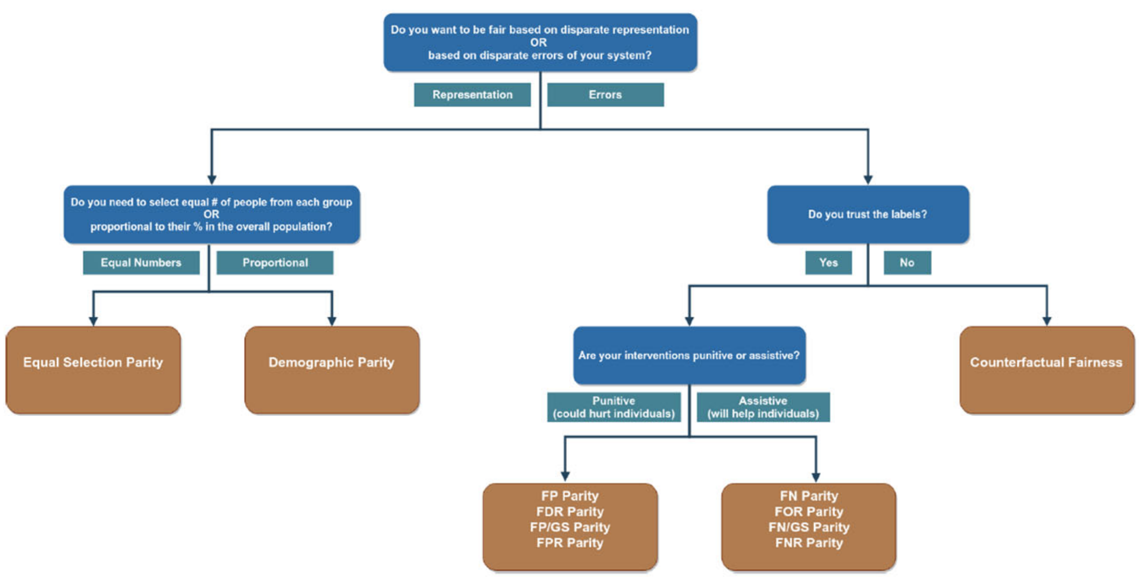
FAIRNESS TREE



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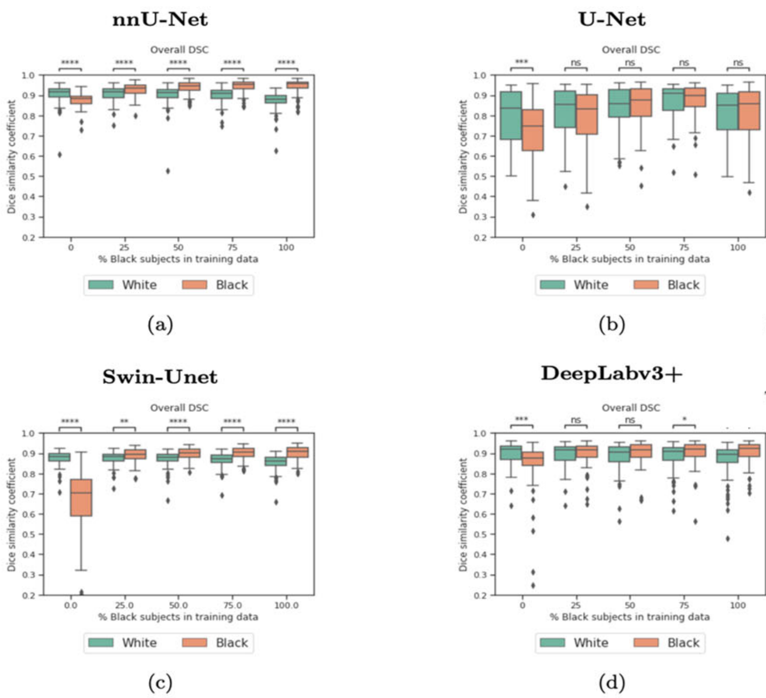
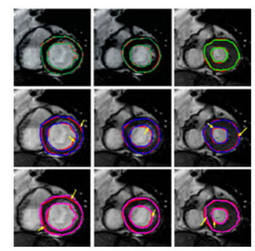


An investigation into the impact of deep learning model choice on sex and race bias in cardiac MR segmentation

Tiarna Lee[1], Esther Puyol-Antón[1,4], Bram Ruijsink[1,2], Keana Aitcheson[1], Miaojing Shi[3], and Andrew P. King[1]



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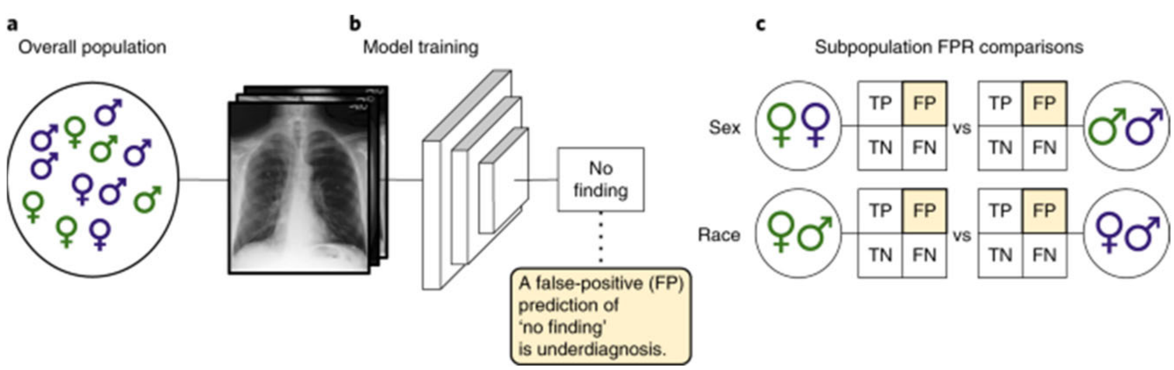
Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations

Laleh Seyyed-Kalantari[1,2], Haoran Zhang[3], Matthew B. A. McDermott[3], Irene Y. Chen[3] and Marzyeh Ghassemi[2,3]



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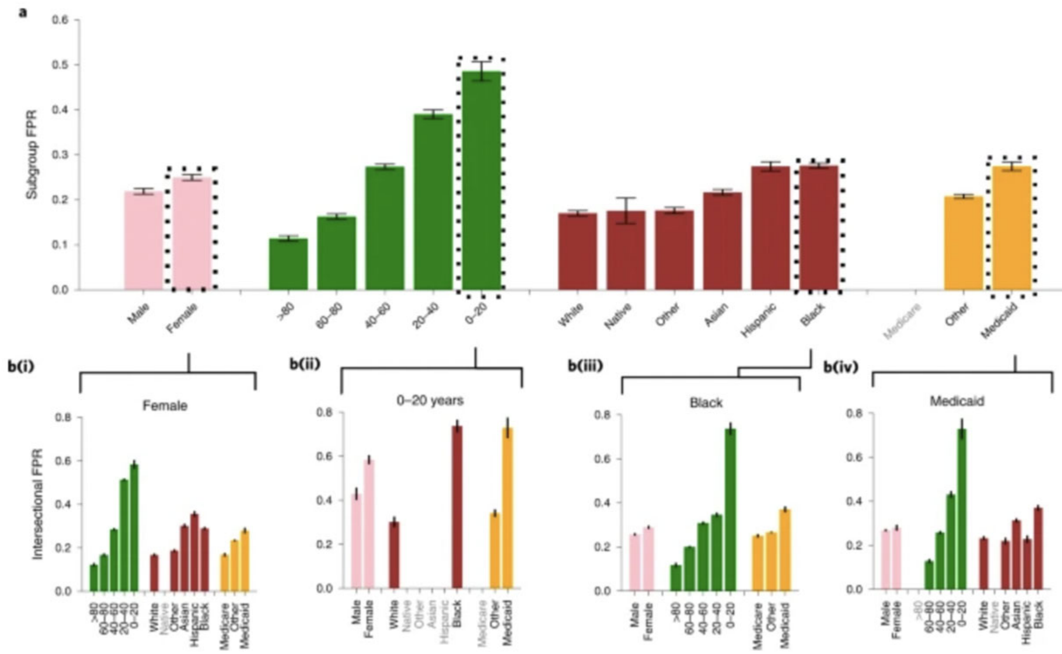
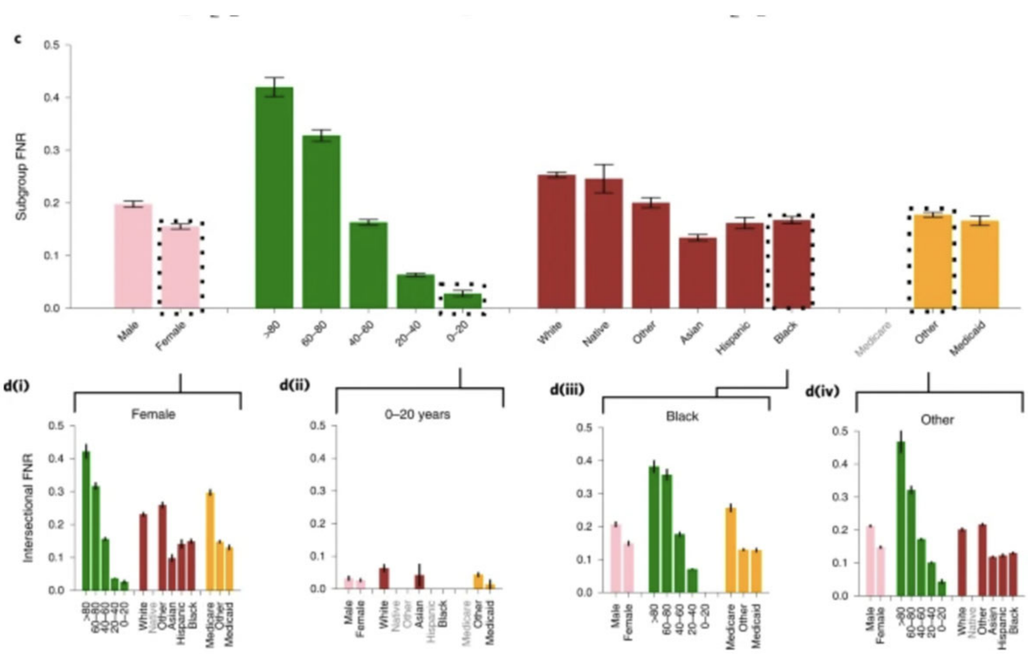


Seyyed-Kalantari. *et al.* Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations. *Nat Med* **27**, 2176–2182 (2021)

13

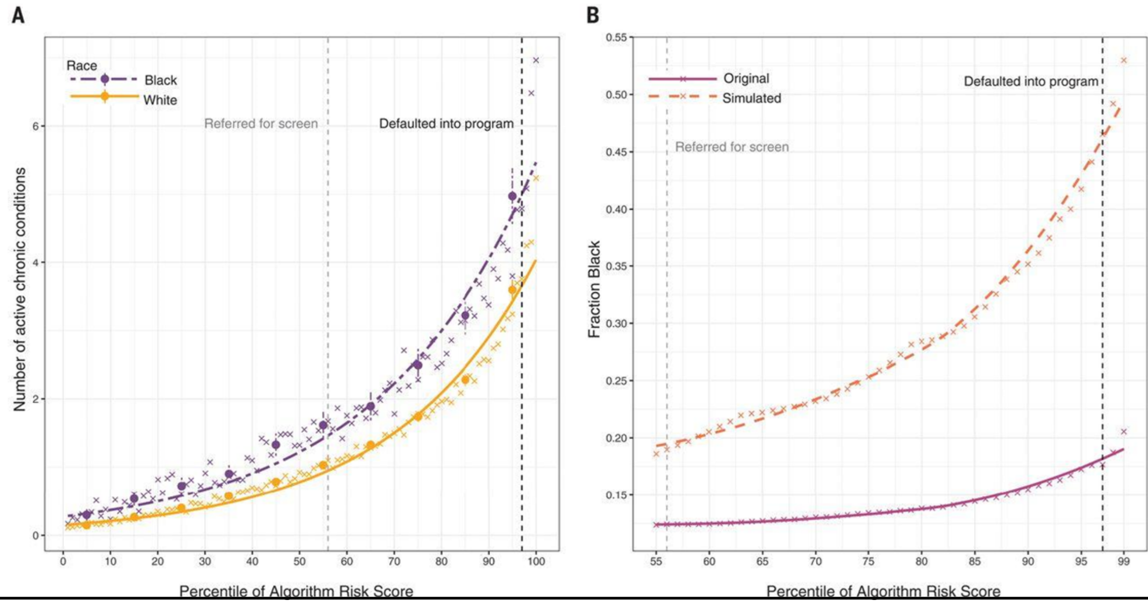


Seyyed-Kalantari. *et al.* Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations. *Nat Med* **27**, 2176–2182 (2021)

14

Dissecting racial bias in an algorithm used to manage the health of populations

ZIAD OBERMEYER, BRIAN POWERS, CHRISTINE VOGELI, AND SENDHIL MULLAINATHAN Authors Info & Affiliations



15

Automation Bias in Mammography: The Impact of Artificial Intelligence BI-RADS Suggestions on Reader Performance

Thomas Dratsch*, Xue Chen*, Mohammad Rezazade Mehrizi, Roman Kloeckner, Aline Mähringer-Kunz, Michael Püsken, Bettina Baeßler, Stephanie Sauer, David Maintz, Daniel Pinto dos Santos

Stage 1:

10 mammograms in random order with the correct diagnosis by the AI

10 Mammograms

Ground Truth		AI Suggestion		N
II	II	II	II	4
II	III	II	III	3
II	IV	II	IV	3

Stage 2:

40 mammograms in random order: 12/40 with an incorrect diagnosis and 28/40 with the correct diagnosis by the AI

12 Mammograms

Ground Truth		AI Suggestion		N
II	II	II	III	2
II	II	II	IV	2
II	III	II	II	2
II	III	II	IV	2
II	IV	II	II	2
II	IV	II	III	2

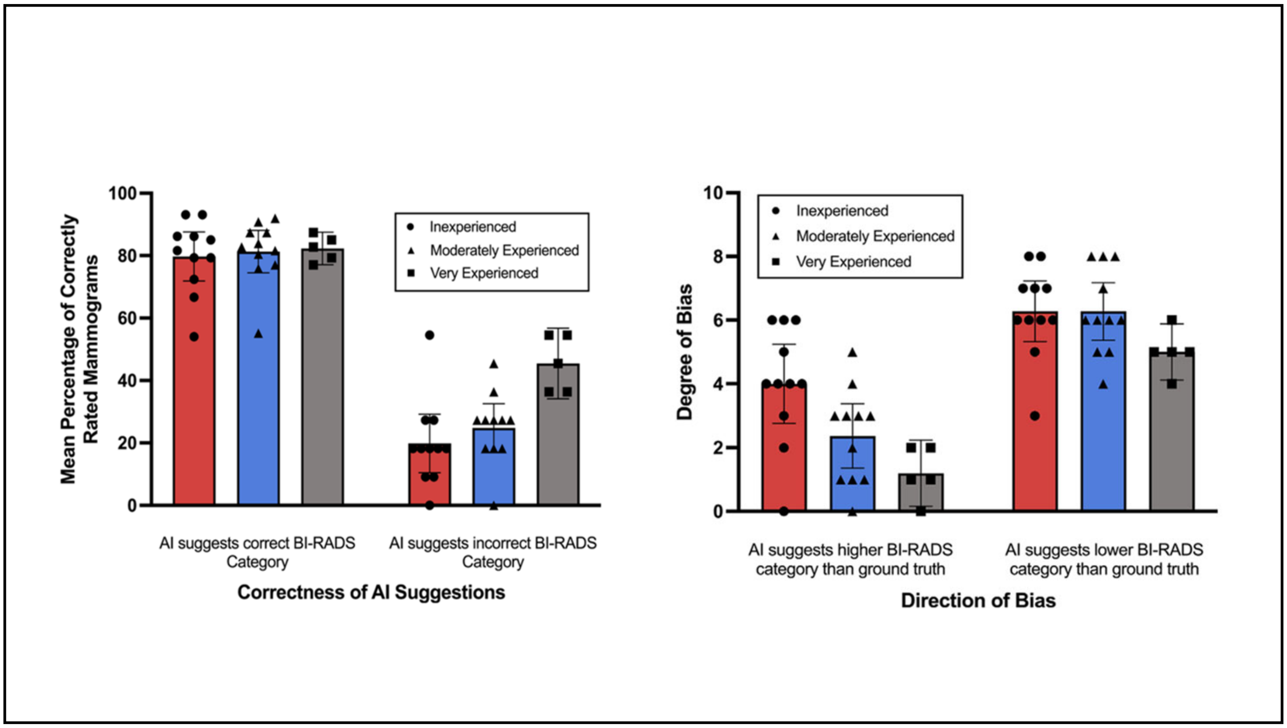
\+

28 Mammograms

Ground Truth		AI Suggestion		N
II	II	II	II	9
II	III	II	III	10
II	IV	II	IV	2
II	V	II	V	7

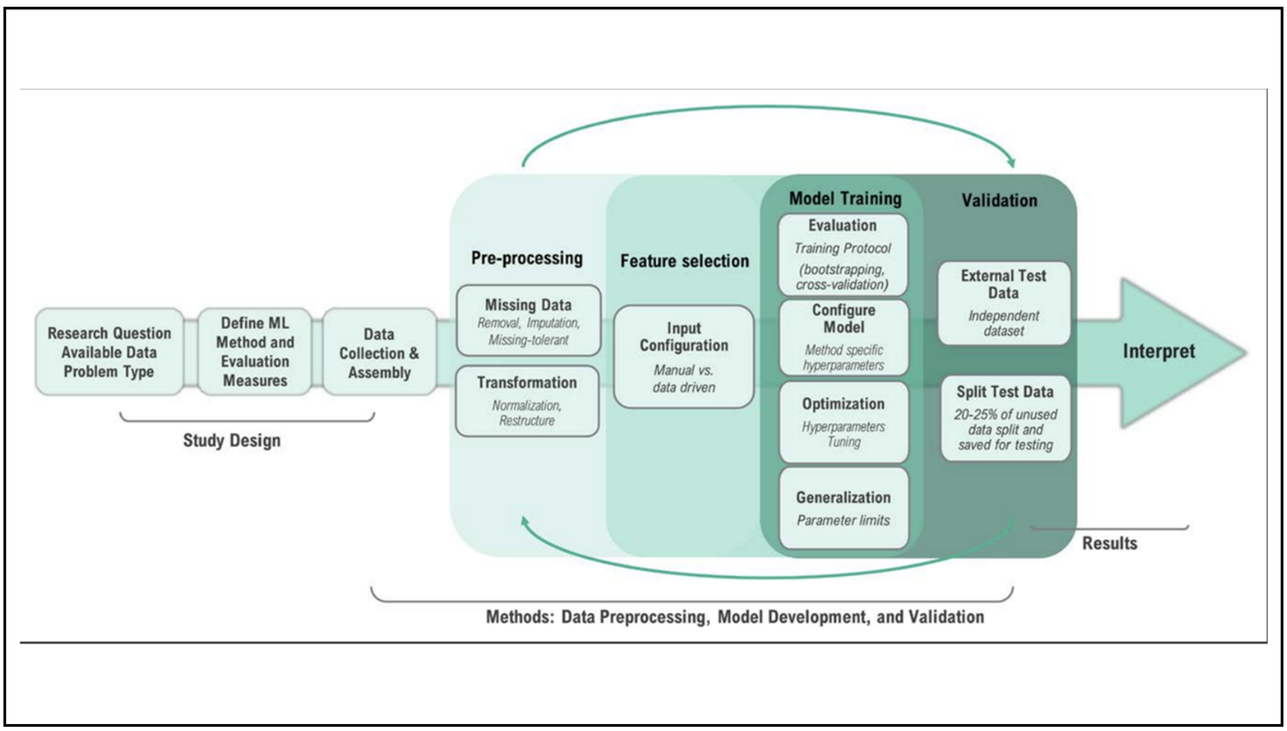
Total: 50 Mammograms

16



Mean Percentage of Correctly Rated Mammograms
100
80
60
40
20
0
Inexperienced
Moderately Experienced
Very Experienced
AI suggests correct BI-RADS Category
AI suggests incorrect BI-RADS Category
Correctness of AI Suggestions
Degree of Bias
10
8
6
4
2
0
AI suggests higher BI-RADS category than ground truth
AI suggests lower BI-RADS category than ground truth
Direction of Bias

17



Research Question
Available Data
Problem Type
Define ML Method and Evaluation Measures
Data Collection & Assembly
Study Design
Pre-processing
Missing Data
Removal, Imputation, Missing-tolerant
Transformation
Normalization, Restructure
Feature selection
Input Configuration
Manual vs. data driven
Model Training
Evaluation
Training Protocol (bootstrapping, cross-validation)
Configure Model
Method specific hyperparameters
Optimization
Hyperparameters Tuning
Generalization
Parameter limits
Validation
External Test Data
Independent dataset
Split Test Data
20-25% of unused data split and saved for testing
Interpret
Results
Methods: Data Preprocessing, Model Development, and Validation

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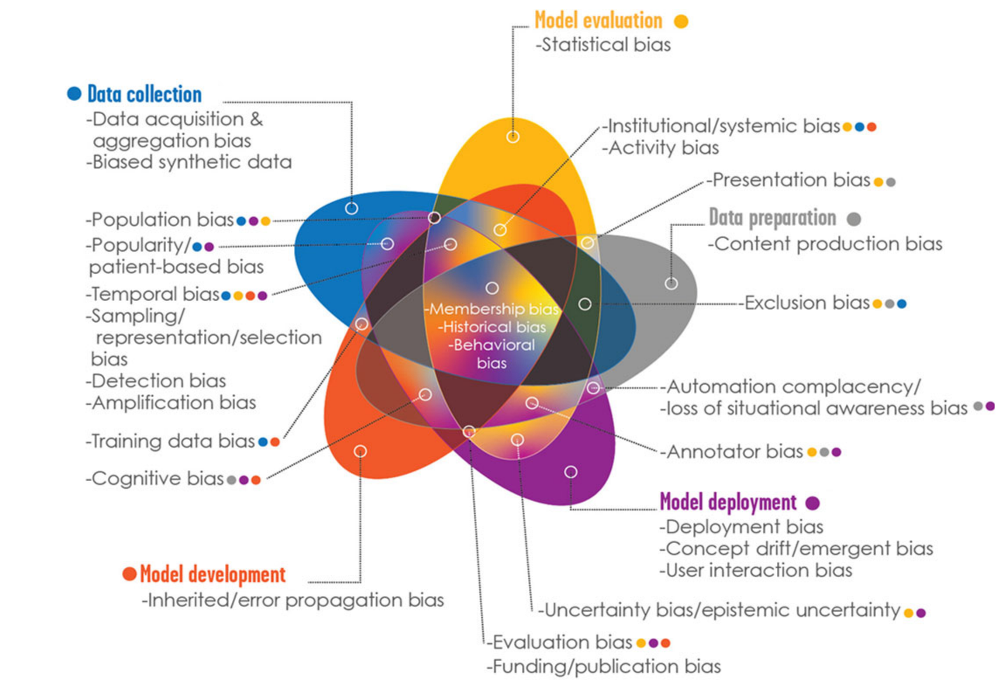

"Toward fairness in artificial intelligence for medical image analysis: identification and mitigation of potential biases in the roadmap from data collection to model deployment," J. Med. Imag. 10(6) 061104 (26 April 2023)

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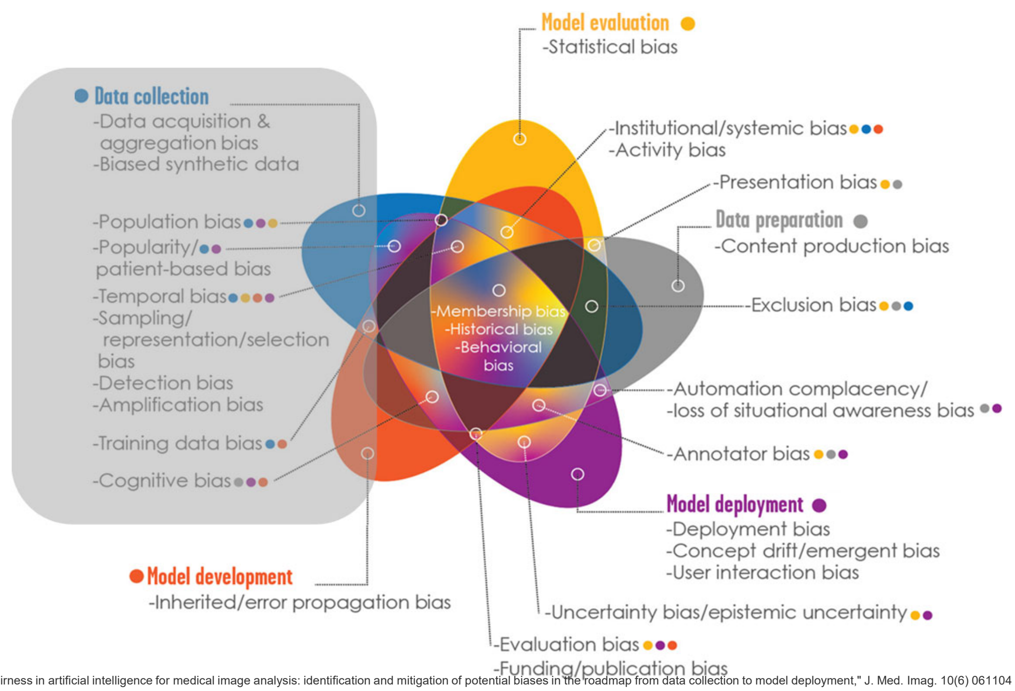

"Toward fairness in artificial intelligence for medical image analysis: identification and mitigation of potential biases in the roadmap from data collection to model deployment," J. Med. Imag. 10(6) 061104 (26 April 2023)

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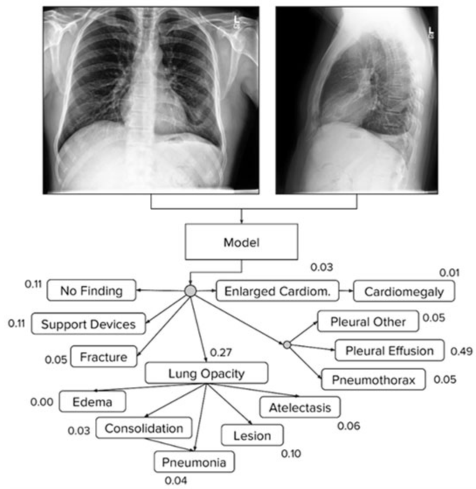
CXR Dataset Labels

Pathology	Positive (%)	Uncertain (%)	Negative (%)
No Finding	16627 (8.86)	0 (0.0)	171014 (91.14)
Enlarged Cardiom.	9020 (4.81)	10148 (5.41)	168473 (89.78)
Cardiomegaly	23002 (12.26)	6597 (3.52)	158042 (84.23)
Lung Lesion	6856 (3.65)	1071 (0.57)	179714 (95.78)
Lung Opacity	92669 (49.39)	4341 (2.31)	90631 (48.3)
Edema	48905 (26.06)	11571 (6.17)	127165 (67.77)
Consolidation	12730 (6.78)	23976 (12.78)	150935 (80.44)
Pneumonia	4576 (2.44)	15658 (8.34)	167407 (89.22)
Atelectasis	29333 (15.63)	29377 (15.66)	128931 (68.71)
Pneumothorax	17313 (9.23)	2663 (1.42)	167665 (89.35)
Pleural Effusion	75696 (40.34)	9419 (5.02)	102526 (54.64)
Pleural Other	2441 (1.3)	1771 (0.94)	183429 (97.76)
Fracture	7270 (3.87)	484 (0.26)	179887 (95.87)
Support Devices	105831 (56.4)	898 (0.48)	80912 (43.12)



CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison– https://arxiv.org/abs/1901.07031

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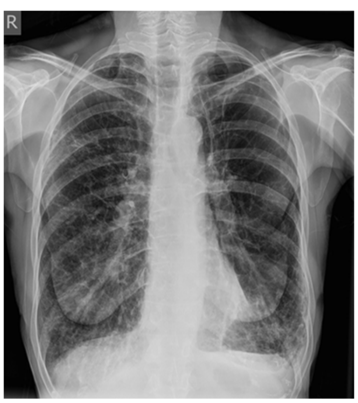
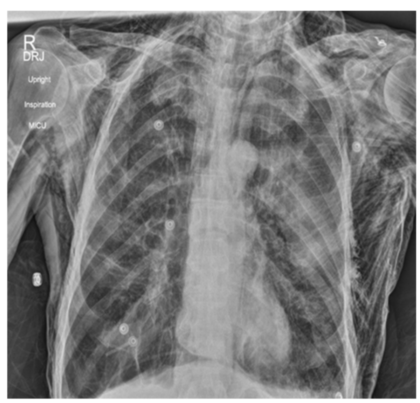
Hidden stratification

Pathology
Atelectasis
Cardiomegaly
Effusion
Infiltration
Mass
Nodule
Pneumonia
Pneumothorax
Consolidation
Edema
Emphysema
Fibrosis
Pleural Thickening
Hernia





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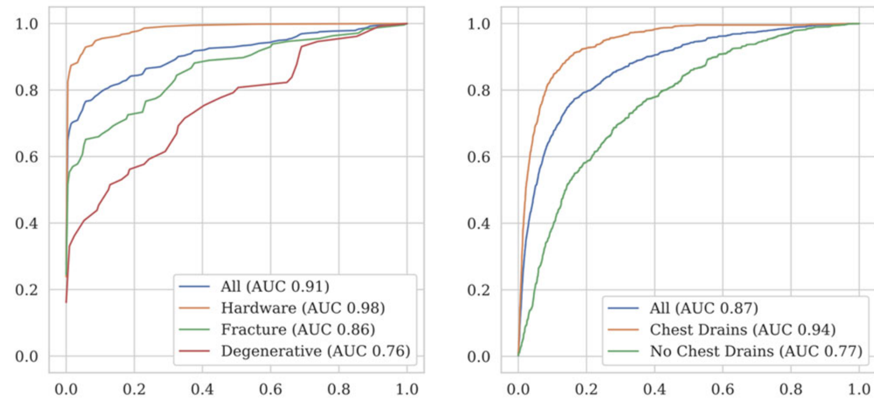
Hidden stratification



Hidden Stratification Causes Clinically Meaningful Failures in Machine Learning for Medical Imaging

Luke Oakden-Rayner, Jared Dunnmon, Gustavo Carneiro, Christopher Ré

23

Challenges with AI in diagnosis

Was there COVID-19 back in 2012? – Challenge for AI in Diagnosis with Similar Indications

Imon Banerjee, PhD[1,5], Priyanshu Sinha[2], Saptarshi Purkayastha, PhD[3], NazaninMashhaditafreshi, BSc[4], Amara Tariq, PhD[1], Jiwoong Jeong, MS[1], Hari Trivedi, MD[1,5], Judy W. Gichoya, MBChB MS[1,5]

[1]Department of Biomedical Informatics, Emory School of Medicine, Atlanta, USA;
[2]MentorGraphics Indian Pvt. Ltd., India;
[3]School of Informatics & Computing, Indiana University, Purdue University, Indianapolis, USA;
[4]Department of Computer Engineering, K. N. Toosi University of Technology, Tehran, Iran;
[5]Department of Radiology, Emory School of Medicine, Atlanta, USA

- "The models reported good to excellent performance on their internal datasets, however we observed from our testing that their performance dramatically worsened on external data."

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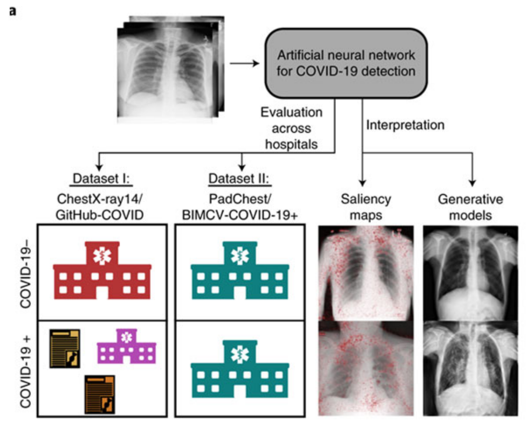
AI for radiographic COVID-19 detection selects shortcuts over signal

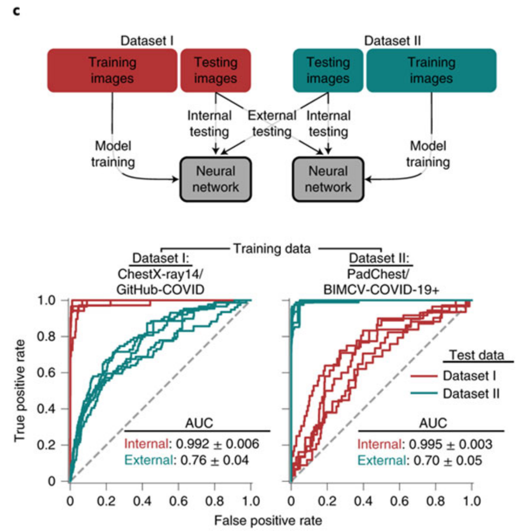
Alex J. DeGrave, Joseph D. Janizek & Su-In Lee

Nature Machine Intelligence 3, 610–619 (2021) | Cite this article



b

	Dataset I			Dataset II		
	Combined	Chest-X-ray14	GitHub-COVID	Combined	PadChest	BIMCV-COVID-19+
No. radiographs	112,528	112,120	408	97,866	96,270	1,596
No. patients	31,067	30,805	262	64,954	63,939	1,105
% COVID-19+	0.2	0	76.5	1.6	0	100
% AP images	39.9	40	26	5.6	4.7	58.1



https://www.nature.com/articles/s42256-021-00338-7

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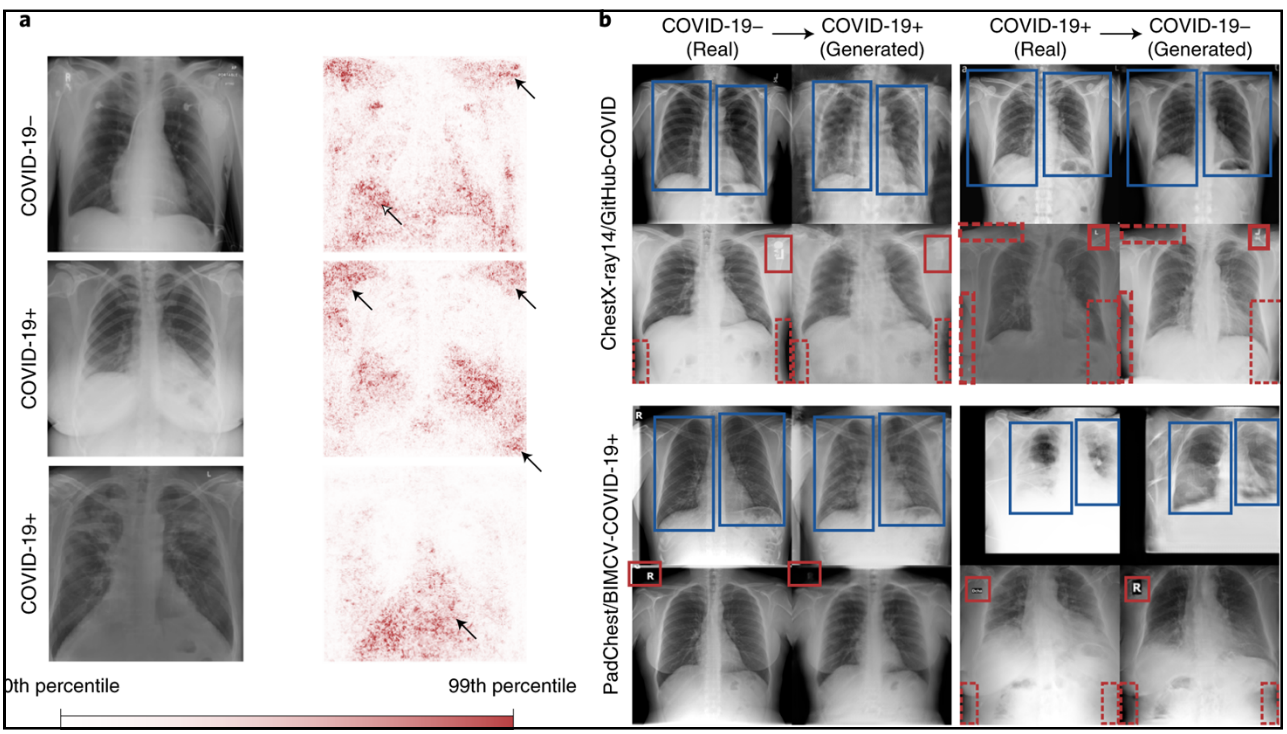

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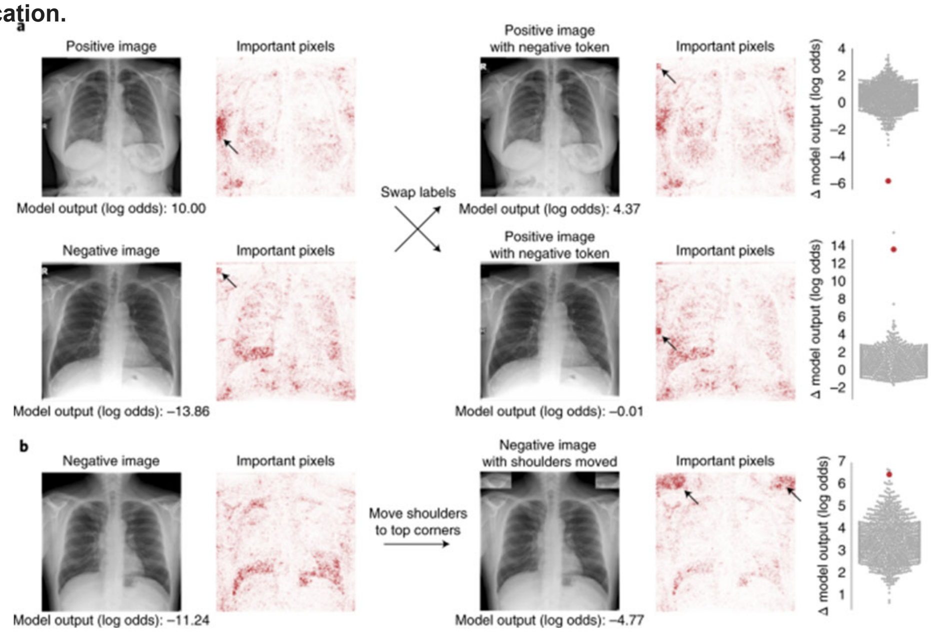
Experimental confirmation of insights from saliency maps and CycleGANs via radiograph modification.



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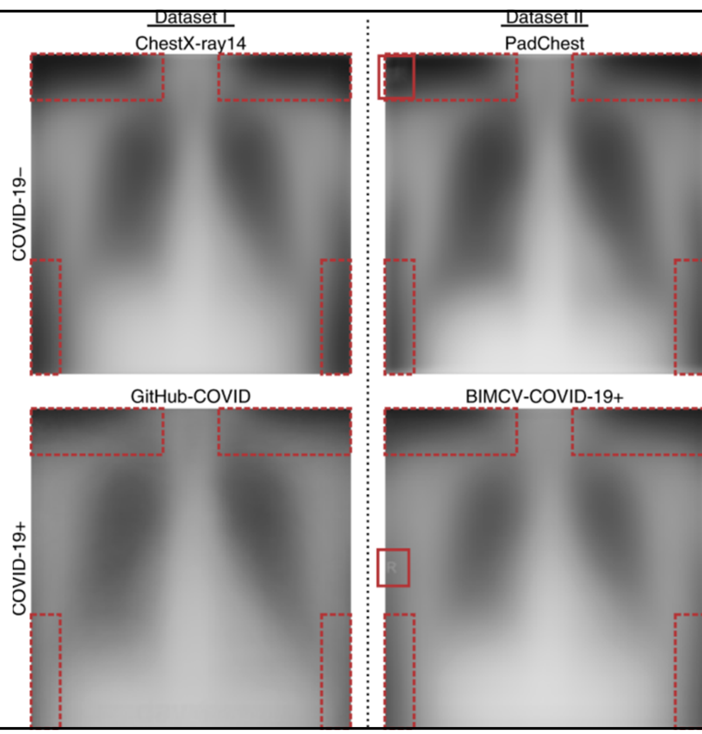

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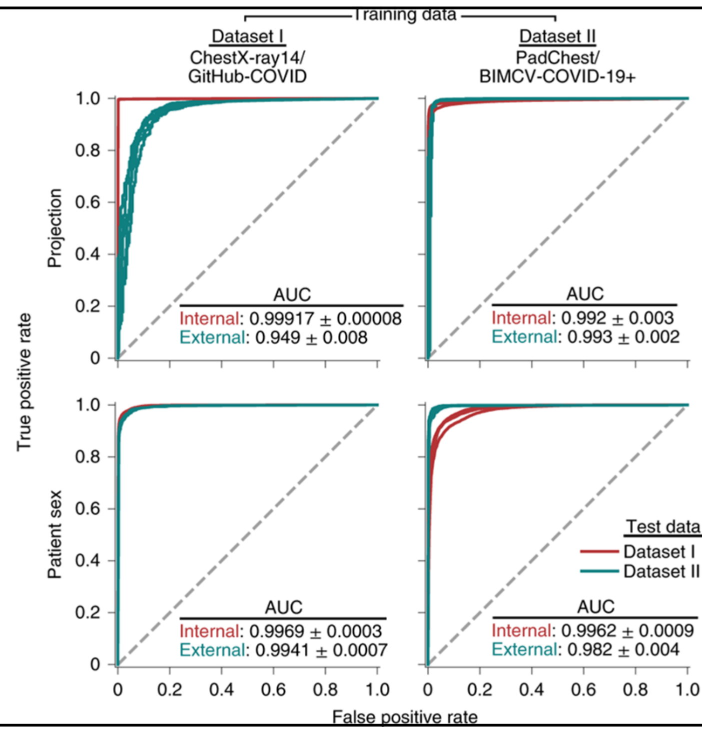

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Impact of multi-source data augmentation on performance of convolutional neural networks for abnormality classification in mammography

InChan Hwang[1] Hari Trivedi[2] Beatrice Brown-Mulry[1] Linglin Zhang[1] Vineela Nalla[3] Aimilia Gastounioti[4] Judy Gichoya[2] Laleh Seyyed-Kalanta Imon Banerjee[6] MinJae Woo[1*]

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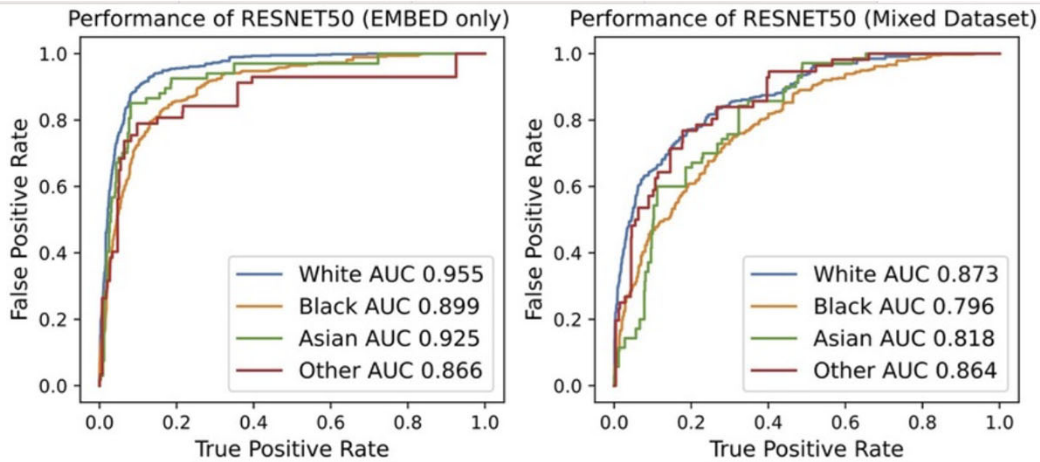
Impact of multi-source data augmentation on performance of convolutional neural networks for abnormality classification in mammography



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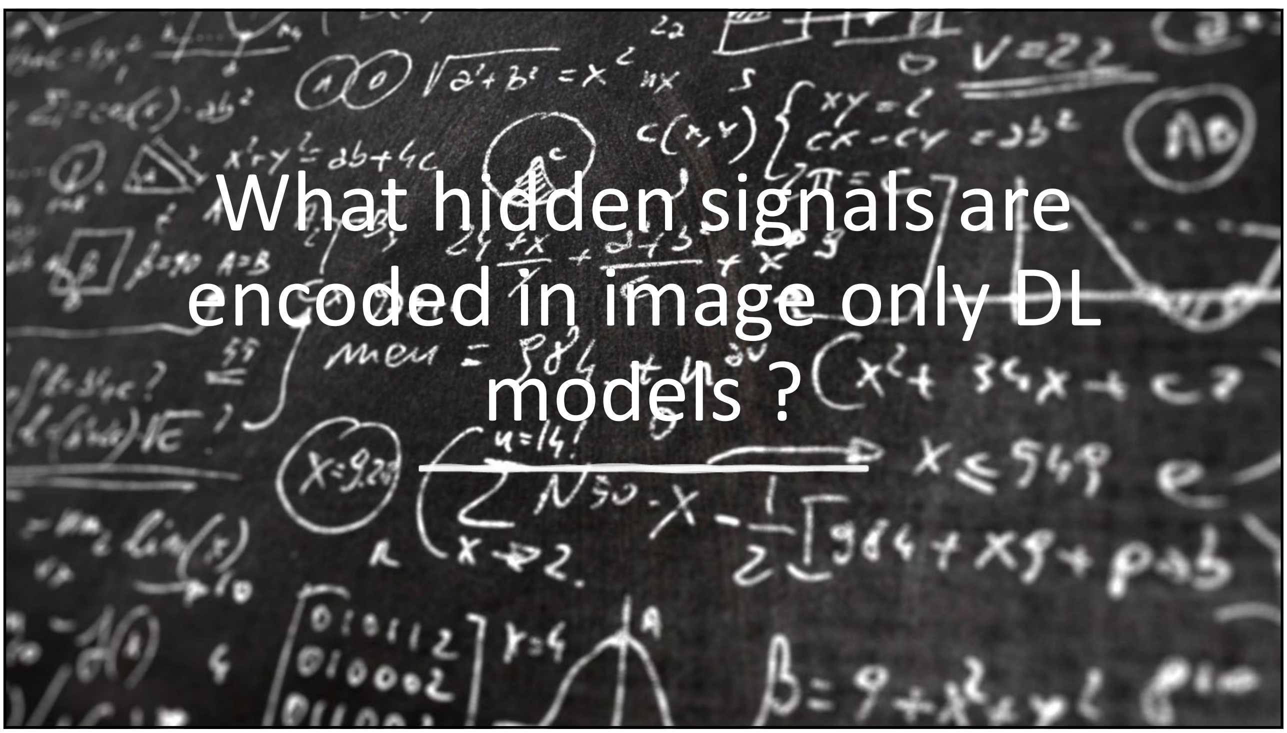

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1913 newspaper advertisement

Henrik Ibsen

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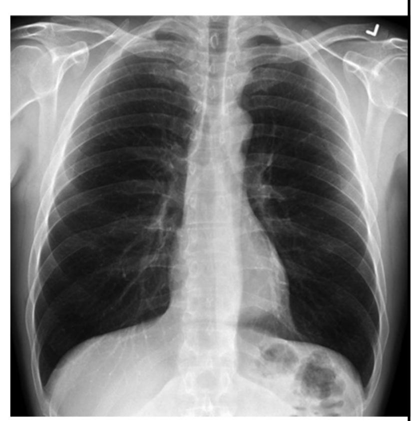
Judy is “Black”, F, 60 yrs (CXR age = 78 yrs), SDI 45, ICD codes – COPD, CHF, 15,000 USD



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ORIGINAL ARTICLE DATA SCIENCE | VOLUME 19, ISSUE 1, P184-191, JANUARY 01, 2022

Detecting Racial/Ethnic Health Disparities Using Deep Learning From Frontal Chest Radiography

Ayis Pyrros, MD • Jorge Mario Rodríguez-Fernández, MD • Stephen M. Borstelmann, MD • Judy Wawira Gichoya, MD • Jeanne M. Horowitz, MD • Brian Fornelli, MS • Nasir Siddiqui, MD • Yury Velichko, PhD • Oluwasanmi Koyejo, PhD • William Galanter, MD, PhD • Show less

DOI: https://doi.org/10.1016/j.jacr.2021.09.010 • Check for updates

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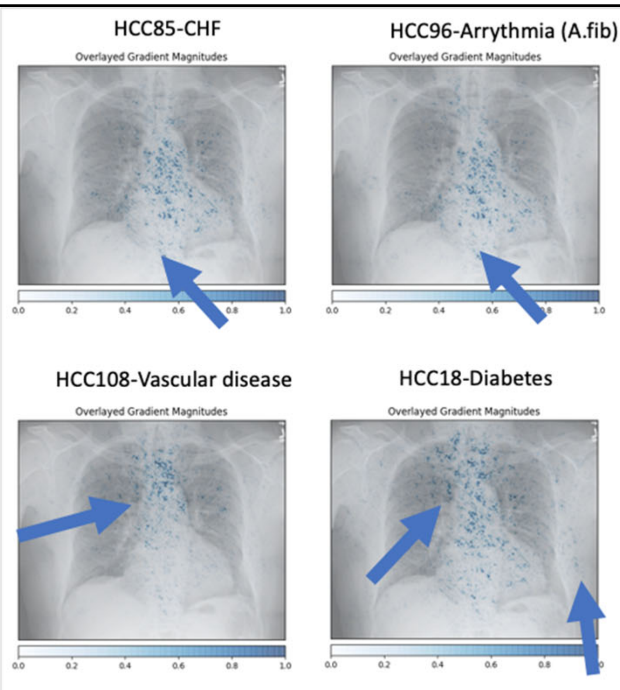

One CXR generates six HCC probabilities

- Cardiac arrythmia maps demonstrate subtle increased activation in the atrial regions
- CHF maps shows enlarged heart
- Vascular disease activation at the aortic knob
- COPD shows increased activation of the lungs
- Diabetes activation in the axillary soft-tissues and aorta

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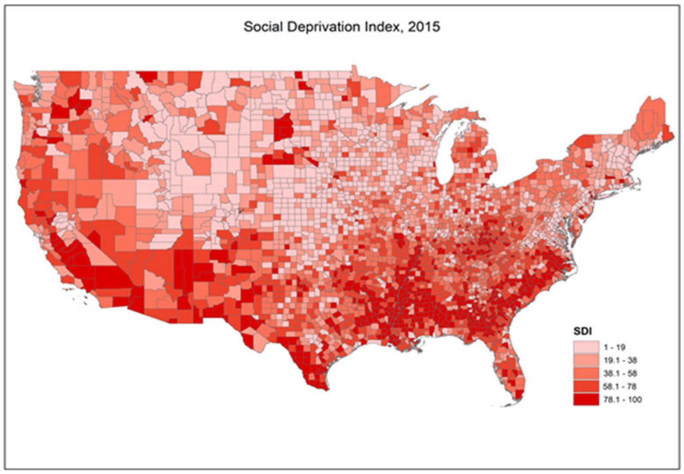
Social Deprivation Index



NONWHITE: ASIAN,BLACK, HISPANIC	AVEARGE AGE 48	
	SDI average 45, median 40, std 28	Social Deprivation Index
	252 (30%)	114 MALE
		138 FEMALE
WHITE	AVERAGE AGE 52	
	SDI average 27, median 21, std 23	Social Deprivation Index
	562 (70%)	275 MALE
		287 FEMALE

https://www.graham-center.org/maps-data-tools/social-deprivation-index.html

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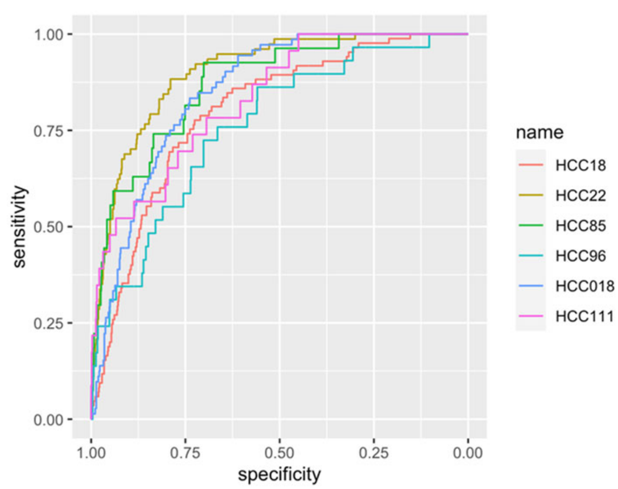
Results

- HCC18: Diabetes with Chronic Complications
  - Area under the curve: 0.80, 95% CI: 0.75-0.84 (DeLong)
- HCC22: Morbid Obesity
  - Area under the curve: 0.90, 95% CI: 0.87-0.93(DeLong)
- HCC85: Congestive Heart Failure
  - Area under the curve: 0.87, 95% CI: 0.81-0.94 (DeLong)
- HCC96: Cardiac Arrythmias
  - Area under the curve: 0.76, 95% CI: 0.67-0.85 (DeLong)
- HCC108: Vascular disease
  - Area under the curve: 0.85, 95% CI: 0.82-0.89 (DeLong)
- HCC111: Chronic obstructive pulmonary disease
  - Area under the curve: 0.83, 95% CI: 0.75-0.91 (DeLong)



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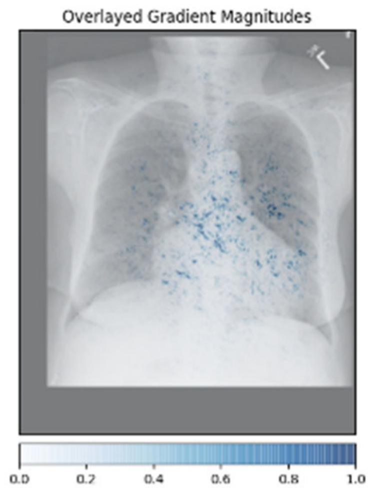
65-year-old self-reported Hispanic **Spanish** speaking woman, with COVID+, and **without a diagnosis for CHF**.



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Article | Open Access | Published: 07 July 2023

Opportunistic detection of type 2 diabetes using deep learning from frontal chest radiographs

Ayis Pyrros, Stephen M. Borstelmann, Ramana Mantravadi, Zachary Zaiman, Kaesha Thomas, Brandon Price, Eugene Greenstein, Nasir Siddiqui, Melinda Willis, Ihar Shulhan, John Hines-Shah, Jeanne M. Horowitz, Paul Nikolaidis, Matthew P. Lungren, Jorge Mario Rodríguez-Fernández, Judy Wawira Gichoya, Sanmi Koyejo, Adam E Flanders, Nishith Khandwala, Amit Gupta, John W. Garrett, Joseph Paul Cohen, Brian T. Layden, Perry J. Pickhardt & William Galanter

Nature Communications **14**, Article number: 4039 (2023) | Cite this article

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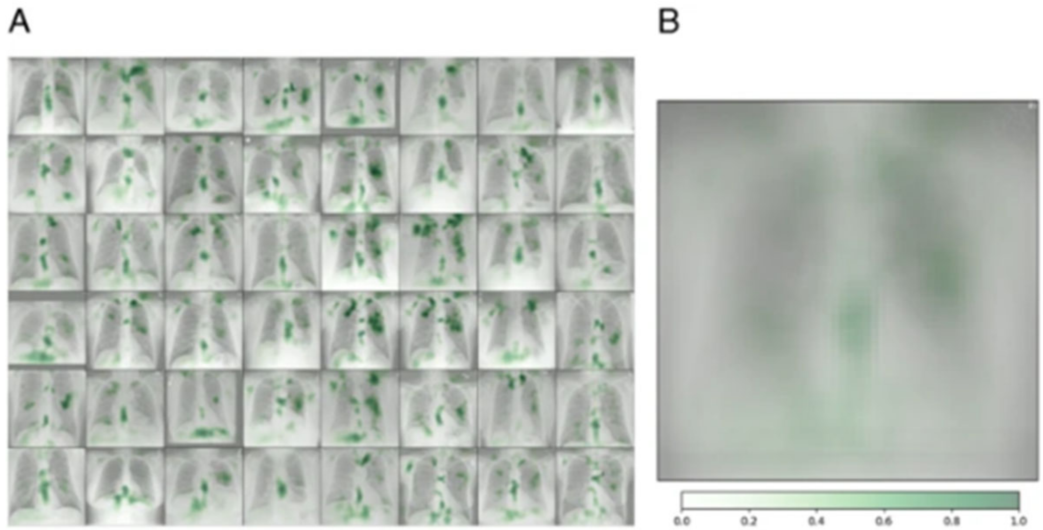
Opportunistic detection of type 2 diabetes using deep learning from frontal chest radiographs



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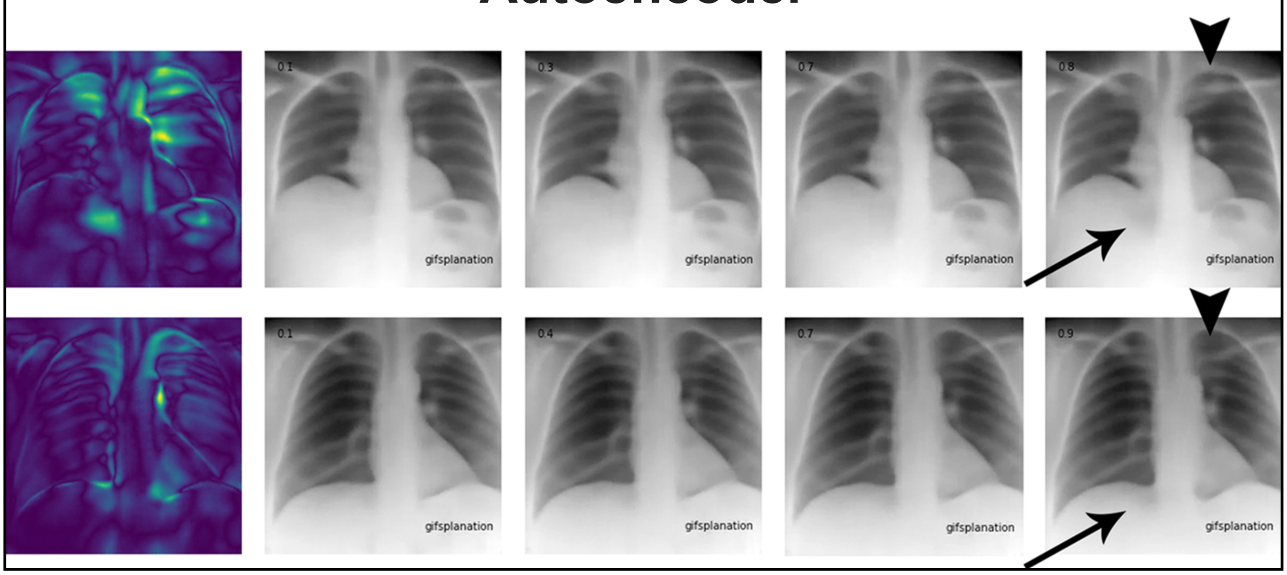
Gifsplanation using Latent Feature Autoencoder



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Prediction of future healthcare expenses of patients from chest radiographs using deep learning: a pilot study

Jae Ho Sohn, Yixin Chen, Dmytro Lituiev, Jaewon Yang, Karen Ordovas, Dexter Hadley, Thienkhai H. Vu, Benjamin L. Franc & Youngho Seo

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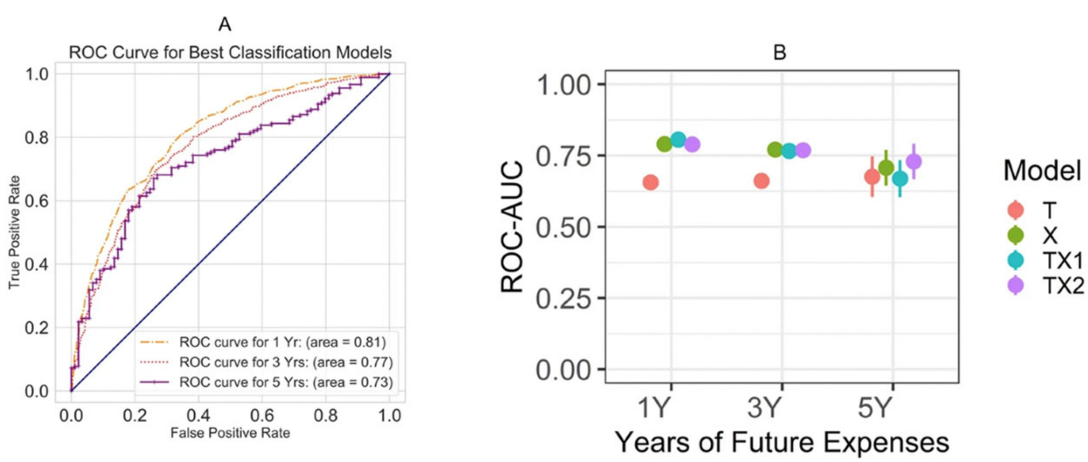
Article | Open Access | Published: 18 May 2022

Prediction of future healthcare expenses of patients from chest radiographs using deep learning: a pilot study

Jae Ho Sohn, Yixin Chen, Dmytro Lituiev, Jaewon Yang, Karen Ordovas, Dexter Hadley, Thienkhai H. Vu, Benjamin L. Franc & Youngho Seo



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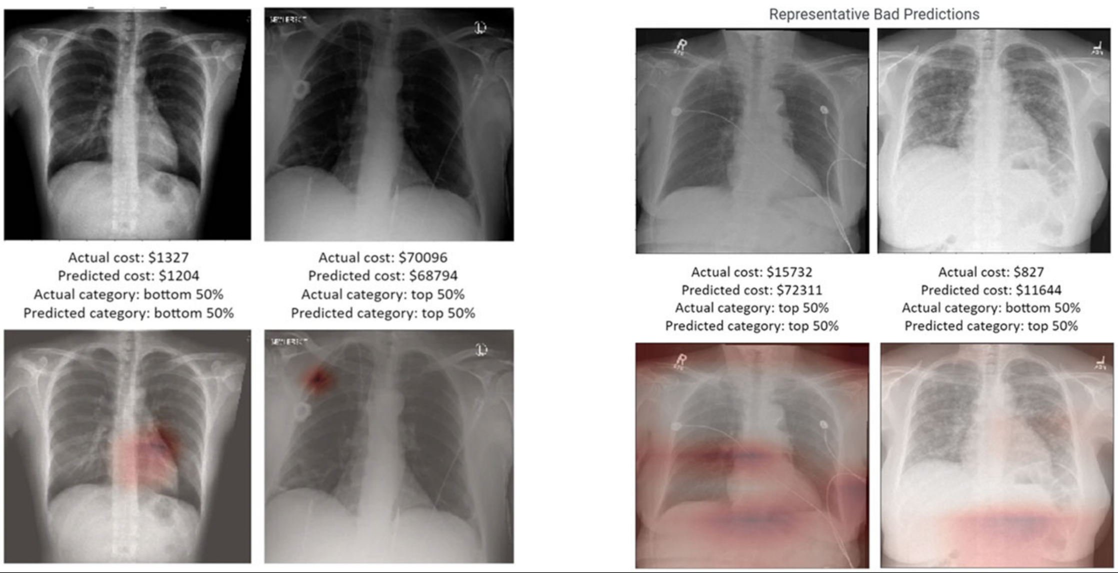
Prediction of future healthcare expenses of patients from chest radiographs using deep learning: a pilot study

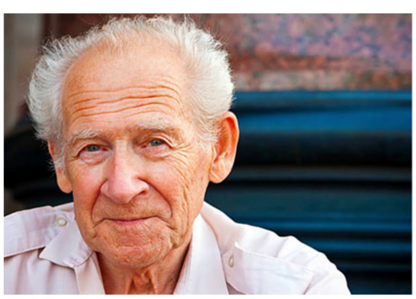


45

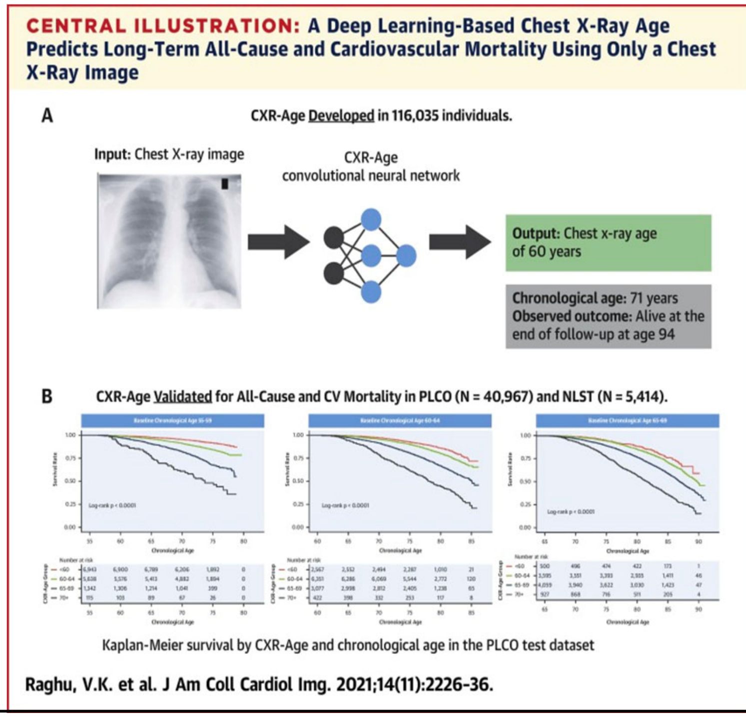
> JACC Cardiovasc Imaging. 2021 Nov;14(11):2226-2236. doi: 10.1016/j.jcmg.2021.01.008.
Epub 2021 Mar 17.

Deep Learning to Estimate Biological Age From Chest Radiographs

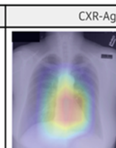
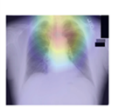
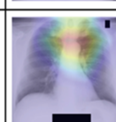
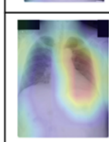
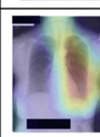
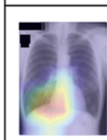
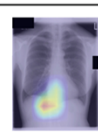
Vineet K Raghu [1], Jakob Weiss [2], Udo Hoffmann [3], Hugo J W L Aerts [4], Michael T Lu [3]



46



47

CXR-Age greater than chronological age		CXR-Age less than chronological age	
	Chronological age: 55 years CXR-Age: 68 years Interpretation: Central mediastinum and heart, with cardiomegaly and signs of pulmonary congestion. Outcome: Died of cardiomyopathy at age 60		Chronological age: 72 years CXR-Age: 64 years Interpretation: Central mediastinum and heart, in a patient with an unremarkable cardiac silhouette. Outcome: Alive at end of follow-up, age 85
	Chronological age: 62 years CXR-Age: 71 years Interpretation: Prominent upper mediastinum and aortic knob. Outcome: Died of a stroke at age 69		Chronological age: 71 years CXR-Age: 60 years Interpretation: Normal upper mediastinum and aortic knob. Outcome: Alive at end of follow-up, age 91
	Chronological age: 64 years CXR-Age: 74 years Interpretation: Prominent upper mediastinum/low neck Outcome: Died of ischemic heart disease at age 65		Chronological age: 73 years CXR-Age: 64 years Interpretation: Less prominent upper mediastinum and low neck. Outcome: Alive at end of follow-up, age 90
	Chronological age: 59 years CXR-Age: 69 years Interpretation: Dilated left heart and aortic knob. Outcome: Died of cancer at age 63.		Chronological age: 73 years CXR-Age: 64 years Interpretation: Normal left heart and aortic knob. Outcome: Alive at end of follow-up, age 93
	Chronological age: 55 years CXR-Age: 64 years Interpretation: Right cardiophrenic angle, including a prominent right atrium and slightly elevated right hemi diaphragm Outcome: Died of a respiratory illness at age 59		Chronological age: 65 years CXR-Age: 57 years Interpretation: Right cardiophrenic angle, with normal right atrial and diaphragmatic silhouettes. Outcome: Alive at end of follow-up, age 76

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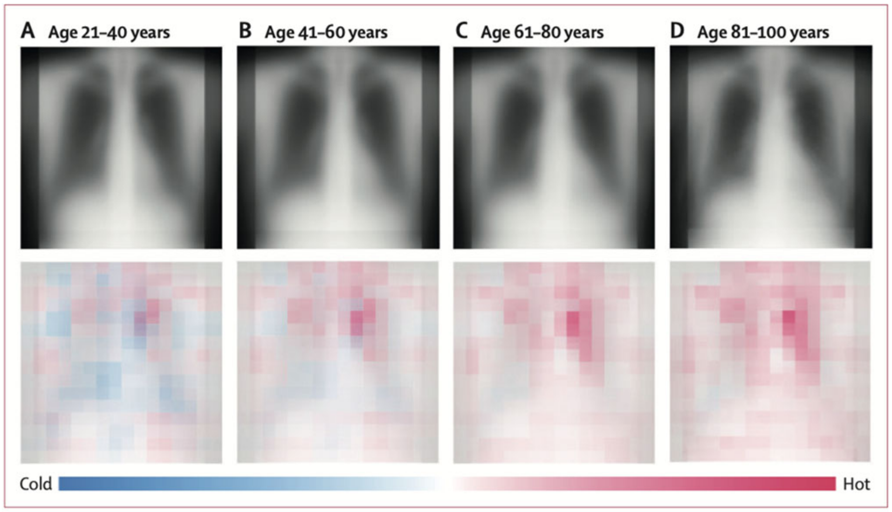
Chest radiography as a biomarker of ageing: artificial intelligence-based, multi-institutional model development and validation in Japan

Yasuhito Mitsuyama, Toshimasa Matsumoto, Hiroyuki Tatekawa, Shannon L Walston, Tatsuo Kimura, Akira Yamamoto, Toshio Watanabe, Yukio Miki, Daiju Ueda



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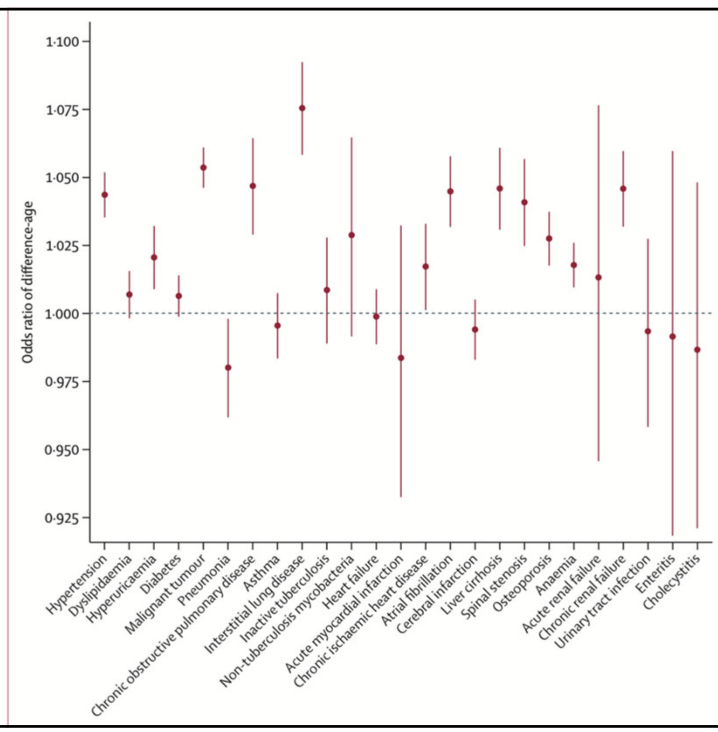

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The Lancet Digital Health

Volume 4, Issue 6, June 2022, Pages e406-e414

Articles

AI recognition of patient race in medical imaging: a modelling study

Judy Wawira Gichoya MD [a], Imon Banerjee PhD [c], Ananth Reddy Bhimireddy MS [a], John L Burns MS [d], Leo Anthony Celi MD [e, g], Li-Ching Chen BS [h], Ramon Correa BS [c], Natalie Dullerud MS [i], Marzyeh Ghassemi PhD [e, f], Shih-Cheng Huang [j], Po-Chih Kuo PhD [h], Matthew P Lungren MD [j], Lyle J Palmer PhD [k, l], Brandon J Price MD [m], Saptarshi Purkayastha PhD [d], Ayis T Pyrros MD [n], Lauren Oakden-Rayner MD [k], Chima Okechukwu MS [o] ... Haoran Zhang MS [i]

Show more

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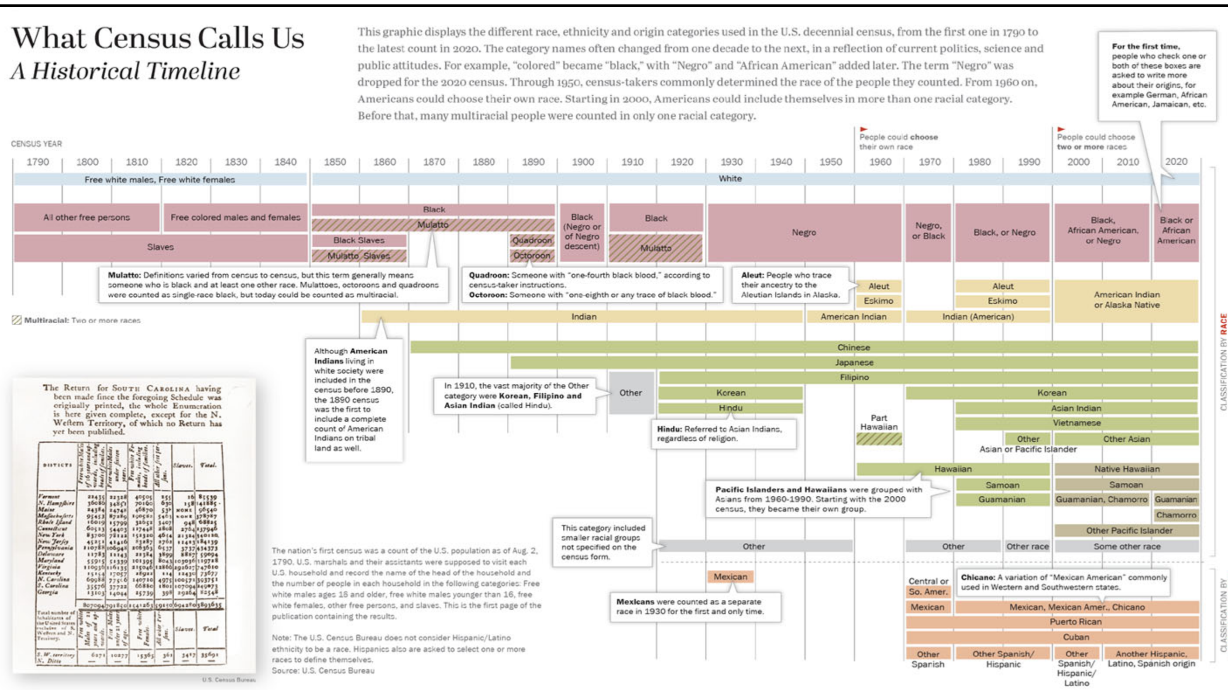

https://onlineexhibits.library.yale.edu/s/Census/page/introduction

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	MXR	CXP	EMX	NLST	RSPECT (Stanford subset)	EM-CT	DHA	EM-Mammo	EM-CS
Data type	Chest x-ray	Chest x-ray	Chest x-ray	Chest CT	Chest CT (PE protocol)	Chest CT	Digital radiography x-ray	Breast mammograms	Lateral c-spine x-ray
Number of patients (number of images)	53073 (228915)	65400 (223414)	90518 (227872)	512 (198475)	254 (72329)	560 (187513)	691 (691)	27160 (86669)	997 (10358)
Sex									
Female	27532 (51·9%)	29090 (44·5%)	48477 (53·6%)	184 (36·0%)	135 (53·1%)	286 (51·1%)	400 (49·2%)	27160 (100%)	535 (53·7%)
Male	25541 (48·1%)	36310 (55·5%)	42041 (46·4%)	328 (64·0%)	119 (46·9%)	274 (48·9%)	391 (56·6%)	0	462 (46·3%)
Race									
Black	8957 (16·9%)	3147 (4·8%)	42373 (46·8%)	241 (47·1%)	23 (9·1%)	403 (72·0%)	333 (48·2%)	13696 (50·4%)	247 (24·8%)
Asian	1935 (3·6%)	7096 (10·8%)	3293 (3·6%)	0	0	0	0	0	0
White	34035 (64·1%)	36765 (56·2%)	38071 (42·1%)	271 (53·0%)	231 (90·9%)	157 (28·0%)	358 (51·8%)	13464 (49·6%)	750 (75·2%)
Unknown	8146 (15·3%)	18420 (28·2%)	6781 (7·5%)	0	0	0	0	0	0
Dataset split									
Training, %	60·0%	60·0%	75·0%	78·0%	0	0	70·0%	60·0%	80·0%
Validation, %	10·0%	10·0%	12·5%	10·0%	0	0	10·0%	20·0%	10·0%
Test, %	30·0%	30·0%	12·5%	12·0%	100·0%	100·0%	20·0%	20·0%	10·0%

CXP=CheXpert dataset. DHA=Digital Hand Atlas. EM-CS=Emory Cervical Spine radiograph dataset. EM-CT=Emory Chest CT dataset. EM-Mammo=Emory Mammogram dataset. EMX=Emory chest x-ray dataset. MXR=MIMIC-CXR dataset. NLST=National Lung Cancer Screening Trial dataset. RSPECT=RSNA Pulmonary Embolism CT dataset.

Table 1: **Summary of datasets used for race prediction experiments**

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	Area under the receiver operating characteristics curve
Race detection in radiology imaging	
Chest x-ray (internal validation)*	
MXR (Resnet34, Densenet121)	0·97, 0·94
CXP (Resnet 34)	0·98
EMX (Resnet34, Densenet121, EfficientNet-B0)	0·98, 0·97, 0·99
Chest x-ray (external validation)*	
MXR to CXP, MXR to EMX	0·97, 0·97
CXP to EMX, CXP to MXR	0·97, 0·96
EMX to MXR, EMX to CXP	0·98, 0·98
Chest x-ray (comparison of models)†	
MXR, CXP, EMX	Multiple results (appendix p 26)
CT chest (internal validation)*	
NLST (slice, study)	0·92, 0·96
CT chest (external validation)*	
NLST to EM-CT (slice, study)	0·80, 0·87
NLST to RSPECT (slice, study)	0·83, 0·90
Limb x-ray (internal validation)*	
DHA	0·91
Mammography*	
EM-Mammo (image, study)	0·78, 0·81
Cervical spine x-ray*	
EM-CS	0·92

	Area under the receiver operating characteristics curve value for race classification		
	Asian (95% CI)	Black (95% CI)	White (95% CI)
Primary race detection in chest x-ray imaging			
MXR Resnet34	0·986 (0·984–0·988)	0·982 (0·981–0·983)	0·981 (0·979–0·982)
CXP Resnet34	0·981 (0·979–0·983)	0·980 (0·977–0·983)	0·980 (0·978–0·981)
EMX Resnet34	0·969 (0·961–0·976)	0·992 (0·991–0·994)	0·988 (0·986–0·989)
External validation of race detection models in chest x-ray imaging			
MXR Resnet34 to CXP	0·947 (0·944–0·951)	0·962 (0·957–0·966)	0·948 (0·945–0·951)
MXR Resnet34 to EMX	0·914 (0·899–0·928)	0·983 (0·981–0·985)	0·975 (0·973–0·978)
CXP Resnet34 to MXR	0·974 (0·971–0·977)	0·955 (0·952–0·957)	0·956 (0·954–0·958)
CXP Resnet34 to EMX	0·915 (0·901–0·929)	0·968 (0·965–0·971)	0·954 (0·951–0·958)
EMX Resnet34 to MXR	0·966 (0·962–0·969)	0·970 (0·968–0·972)	0·964 (0·962–0·965)
EMX Resnet34 to CXP	0·949 (0·946–0·952)	0·973 (0·970–0·977)	0·947 (0·945–0·950)
Race detection in non-chest x-ray imaging modalities: binary race detection (Black or White)			
NLST	0·92 (slice; 0·910–0·918), 0·96 (study; 0·926–0·982)	..	..
NLST to EM-CT	0·80 (slice; 0·796–0·800), 0·87 (study; 0·829–0·904)	..	..
NLST to RSPECT	0·83 (slice; 0·825–0·834), 0·90 (study; 0·836–0·958)	..	..
EM-Mammo	0·78 (slice; 0·773–0·786), 0·81 (study; 0·794–0·818)	..	..
EM-CS	0·913 (0·892–0·931)	..	..
DHA	0·87 (0·752–0·894)	..	..

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Model Attention

Assessing the Trustworthiness of Saliency Maps for Localizing Abnormalities in Medical Imaging

Nishanth Arun # 1, Nathan Gaw # 1, Praveer Singh 1, Ken Chang 1, Mehak Aggarwal 1, Bryan Chen 1, Katharina Hoebel 1, Sharut Gupta 1, Jay Patel 1, Mishka Gidwani 1, Julius Adebayo 1, Matthew D Li 1, Jayashree Kalpathy-Cramer 1

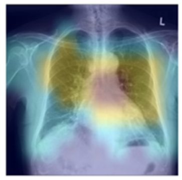
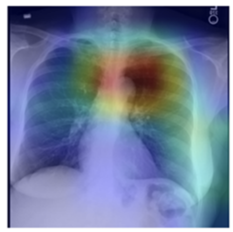
	Asian	Black	White
Accurate primary race prediction			
Accurate primary race prediction from the “no finding” class label			

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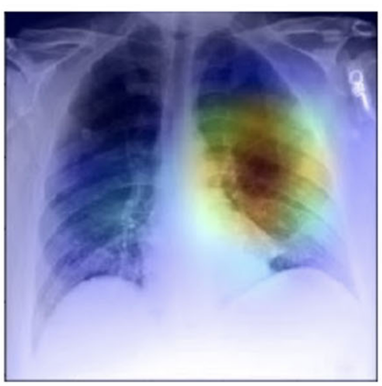
Image Obscuration



	Asian	Black	White
MXR Densenet121-Original	0.93	0.94	0.94
MXR Densenet121-Masked	0.88	0.79	0.79

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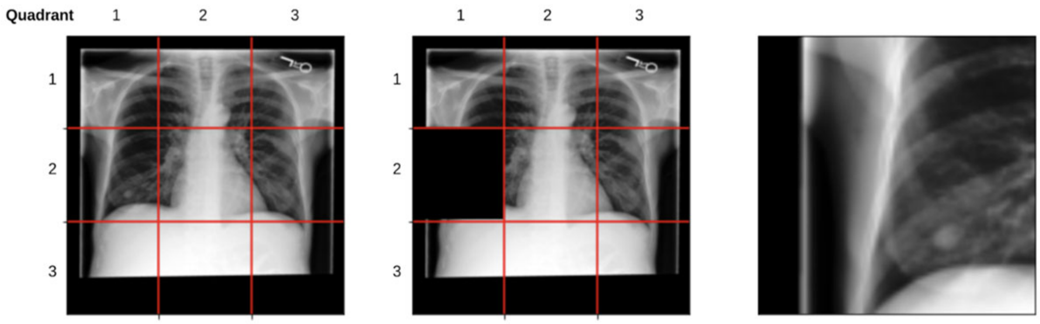
Patch Predictions and Exclusions



a) Original image b) Removing a patch c) Using only one patch

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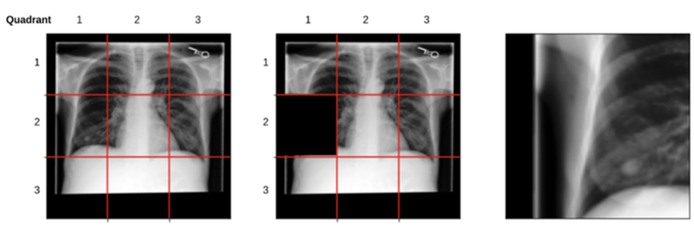
Patch Predictions and Exclusions



a) Original image b) Removing a patch c) Using only one patch

Patch exclusion

Quadrant	1	2	3
1	0.87	0.88	0.87
2	0.81	0.82	0.81
3	0.75	0.60	0.75

Single Patch Training

Quadrant	1	2	3
1	0.91	0.90	0.91
2	0.91	0.91	0.91
3	0.91	0.91	0.91

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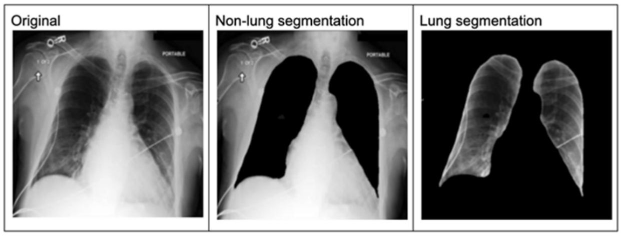
Anatomic segmentation



	Asian	Black	White
MXR Densenet121-Original	0.93	0.94	0.94
MXR Densenet121-Non lung	0.87	0.85	0.87
MXR Densenet121-Lung	0.68	0.74	0.73

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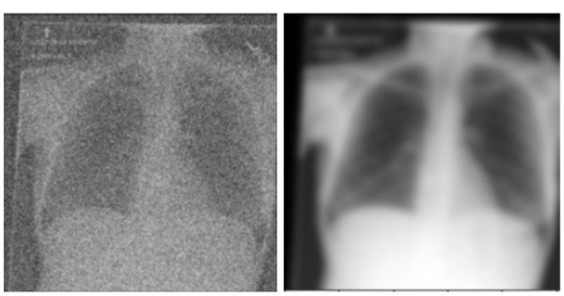
Image degradation experiments



	Asian	Black	White
MXR Densenet121-Original	0.93	0.94	0.94

MXR Densenet121-Noisy	0.64	0.72	0.70
MXR Densenet121-Blurred	0.59	0.64	0.62

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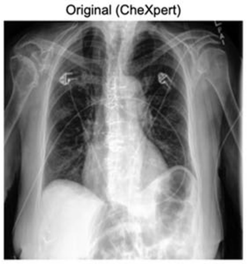
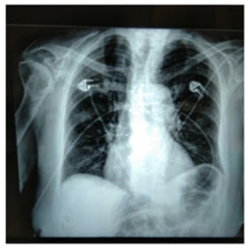
Image degradation experiments

Model trained on CheXphoto performance compared to CheXpert

Original (CheXpert)

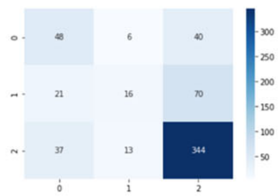


CheXphoto



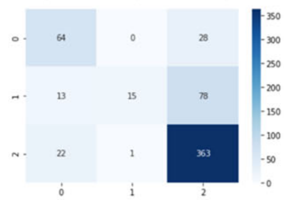
CheXphoto

	AUC
Asian	0.81
Black	0.77
White	0.80



CheXpert

	AUC
Asian	0.90
Black	0.94
White	0.89



CheXphoto: 10,000+ Photos and Transformations of Chest X-rays for Benchmarking Deep Learning Robustness

Nick A. Phillips, Pranav Rajpurkar, Mark Sabini, Rayan Krishnan, Sharon Zhou, Anuj Pareek, Nguyet Minh Phu, Chris Wang, Mudit Jain, Nguyen Duong Du, Steven QH Truong, Andrew Y. Ng, Matthew P. Lungren

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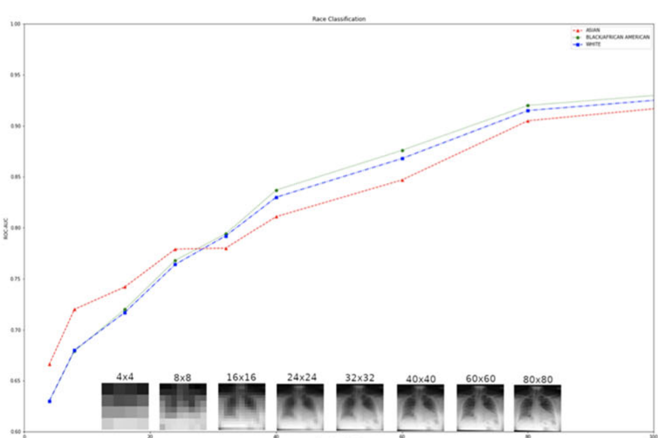
Image degradation experiments



Race	Resolution											
	4	8	16	24	32	40	60	80	160	240	320	512
Asian	0.66	0.72	0.74	0.78	0.78	0.81	0.85	0.90	0.95	0.96	0.97	0.98
Black	0.63	0.68	0.72	0.77	0.79	0.84	0.88	0.92	0.96	0.97	0.97	0.98
White	0.63	0.68	0.72	0.76	0.79	0.83	0.87	0.92	0.96	0.96	0.97	0.97

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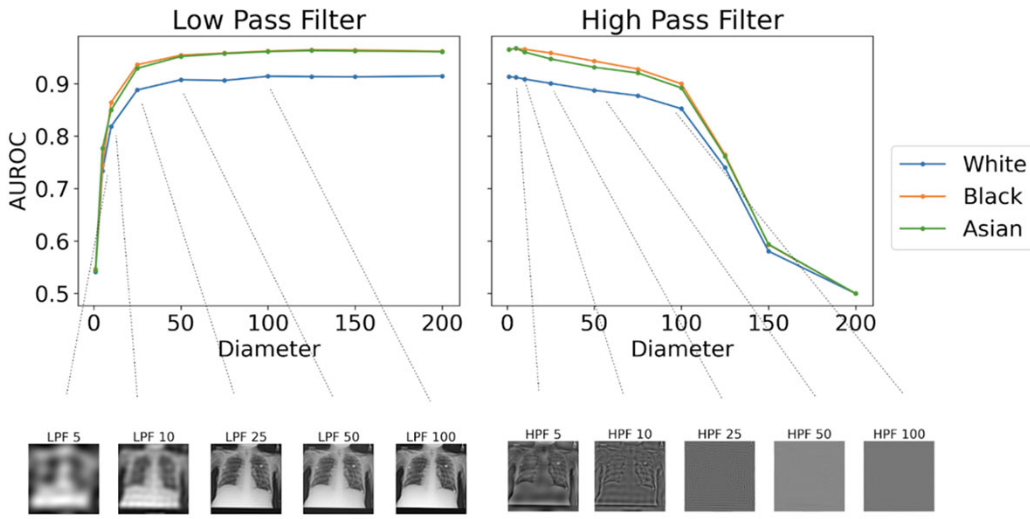
Image degradation experiments



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Performance across equipment

Race detection at **specific hospital** And specific manufacturer equipment

Hospital "1"

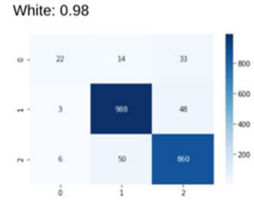
Carestream Portable X-ray machine

All views were AP

~55,000 training images

Internal test at same hospital with same equipment

Asian: 0.92
Black: 0.98
White: 0.98



Race detection at **specific hospital** And specific manufacturer equipment

Hospital "1"

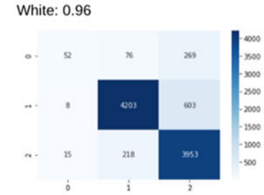
Carestream Portable X-ray machine

All views were AP

~55,000 training images

Test at other Emory hospitals with both Carestream & GE equipment

Asian: 0.86
Black: 0.97
White: 0.96



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Phantoms

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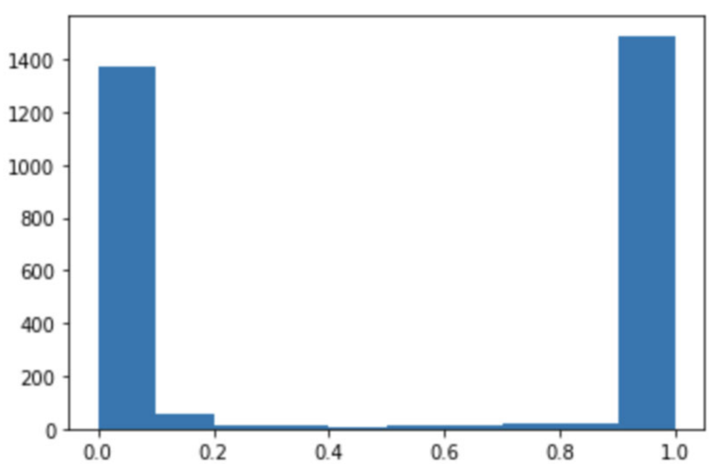
Phantoms



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Experiments on anatomic and phenotypic confounders

Experiments on anatomic and phenotypic confounders	
BMI*	
CXP	0·55, 0·52
Image-based race detection stratified by BMI†	
EMX, MXR	Multiple results (appendix p 24)
Breast density*	
EM-Mammo	0·54
Breast density and age*	
EM-Mammo	0·61
Disease distribution*	
MXR, CXP	0·61, 0·57
Image-based race detection for the no finding class*	
MXR	0·94
Model prediction after training on dataset with equal disease distribution†	
MXR	0·75
Removal of bone density features*	
MXR, CXP	0·96, 0·94
Impact of average pixel thresholds†	
MXR	0·50
Impact of age†	
MXR	Multiple results (appendix p 27)
Impact of patient sex†	
MXR	Multiple results (appendix p 28)
Combination of age, sex, disease, and body habitus*	
EMX (logistic regression model, random forest classifier, XGBoost model)	0·65, 0·64, 0.64

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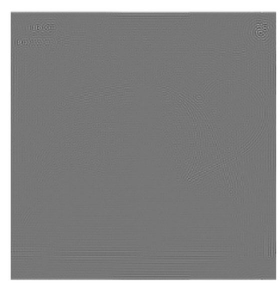
RECAP

The Lancet Digital Health
Available online 11 May 2022
In Press, Corrected Proof

Articles

AI recognition of patient race in medical imaging: a modelling study

Judy Wawira Gichoya MD [a], Imon Banerjee PhD [c], Ananth Reddy Bhimireddy MS [a], John L Burns MS [d], Leo Anthony Celi MD [e, g], Li-Ching Chen BS [h], Ramon Correa BS [c], Natalie Dullerud MS [i], Marzyeh Ghassemi PhD [e, f], Shih-Cheng Huang [j], Po-Chih Kuo PhD [h], Matthew P Lungren MD [j], Lyle J Palmer PhD [k, l], Brandon J Price MD [m], Saptarshi Purkayastha PhD [d], Ayis T Pyrros MD [n], Lauren Oakden-Rayner MD [k], Chima Okechukwu MS [o] ... Haoran Zhang MS [i]



1) Performance of deep learning models to detect race from medical images across modalities and external datasets
2) Assessment of possible anatomic and phenotype confounders such as body habitus and disease distribution
3) Investigation into underlying mechanisms by which AI models can recognize race.

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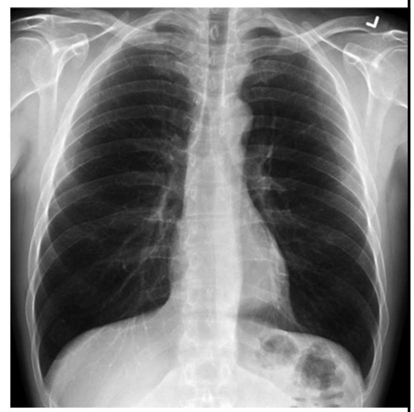
Judy is “Black”, F, 60 yrs (CXR age = 78 yrs), SDI 45, ICD codes – COPD, CHF, 15,000 USD



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Joint Statement on Enforcement Efforts Against Discrimination and Bias in Automated Systems

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The New York Times

OPINION

GUEST ESSAY

Lina Khan: We Must Regulate A.I. Here's How.

May 3, 2023

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Privacy and AI regulation

- Do we need consent for data sharing ?
- When / how to get consent ?
- IRBs empowered to protect patient privacy in the era of AI ?
- Can we sufficiently deidentify/anonymize patients ?
- Can patients opt out?
- Universal consent ? EMR versus patient pictures ?
- Accruing benefits
- NIH mandate for data sharing

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Ethics, Privacy, Bias and Trust in the Application of AI

Judy Gichoya, MD MS
Director, HITI Lab
Associate Professor, Department of Radiology
Emory University

HITI LAB

EMORY UNIVERSITY

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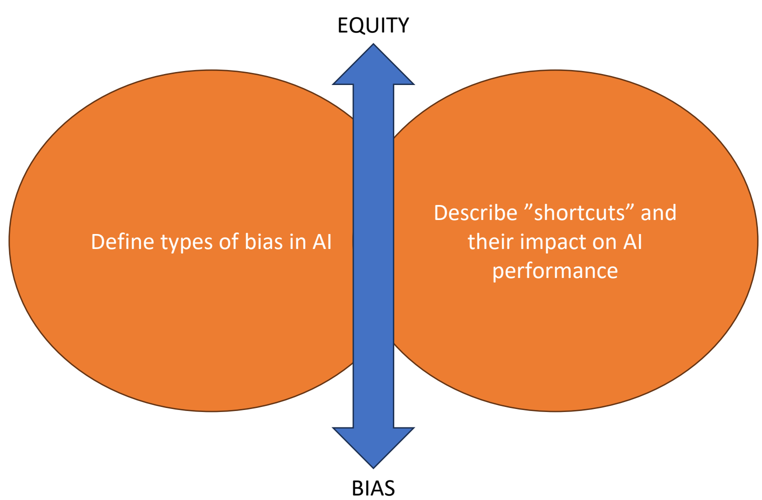
Objectives



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Ethics, Privacy, Bias and Trust in the Application of AI for precision nutrition

- What datasets ?
  - Labels?
  - Missing / Included ?
  - What signals will be encoded ?
  - What forms of data ?
- What ground truth ?
- **Communication of science** ?
- Validation in the real world setting ?
- Regulation
- Who will benefit ?
- Changing persona

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Lessons on data curation

- Clear problem definition at the onset
- Multiple criteria for cohort selection – CDW versus PACS CFIND versus department specific registries
- Obtain relevant metadata
- DICOM format preservation
- Datasets have an expiry date ****
- Datasets versioning – public release subset, RSNA challenge, Clairity consortium, AIM-AHEAD consortium, for profit FDA approval companies , research collaborators
- Distributed access – bring model to the data

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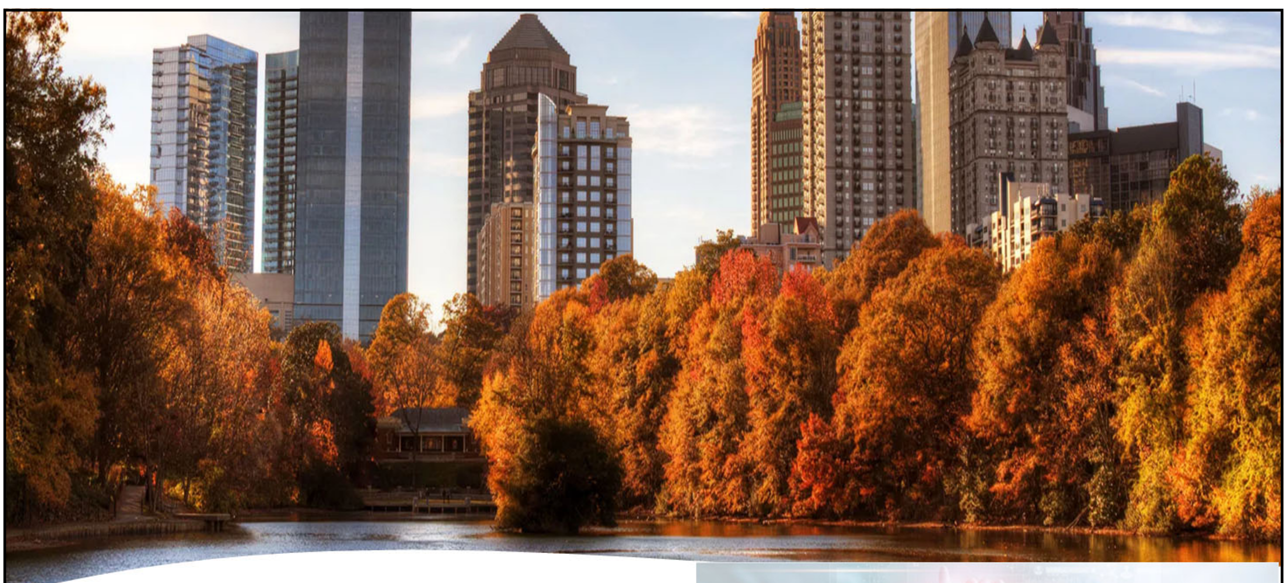

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Healthcare Innovation and Translational Informatics (HITI) Lab at Emory

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AI in Nutrition and Food Sciences: Promises and Challenges

Benoît Lamarche, PhD

INAF INSTITUT SUR LA NUTRITION ET LES ALIMENTS FONCTIONNELS

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Disclosures

None

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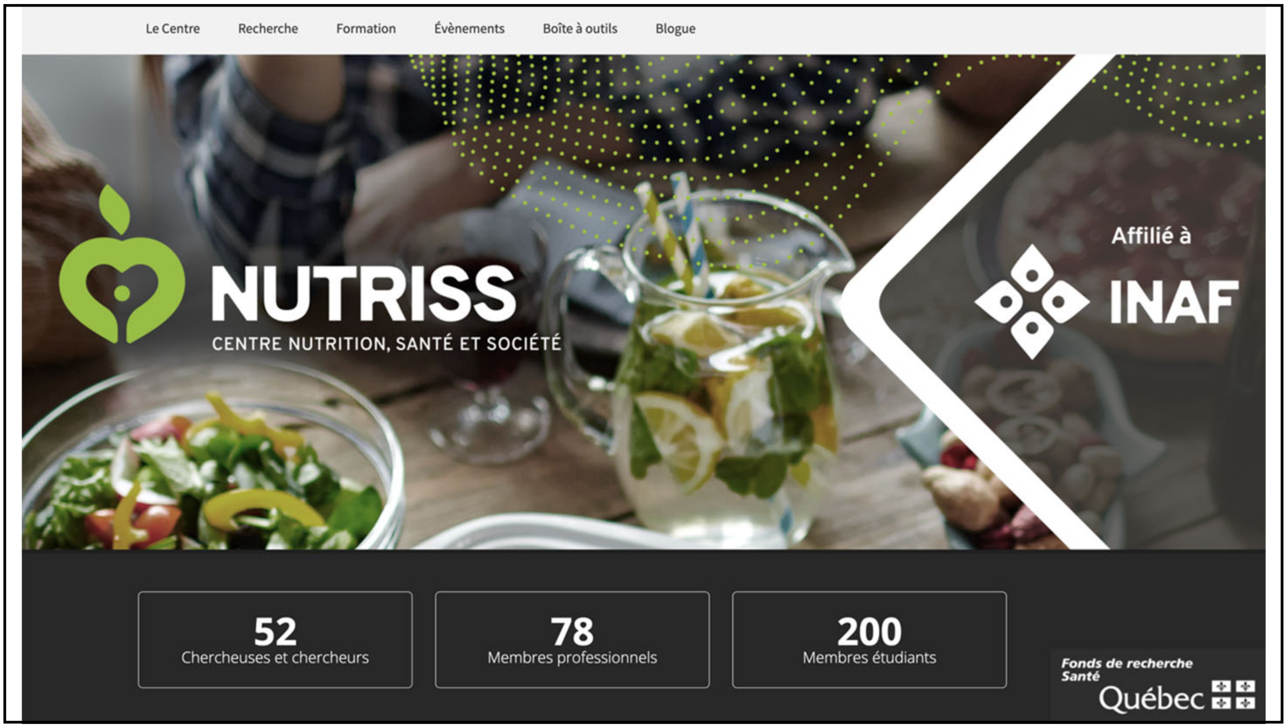

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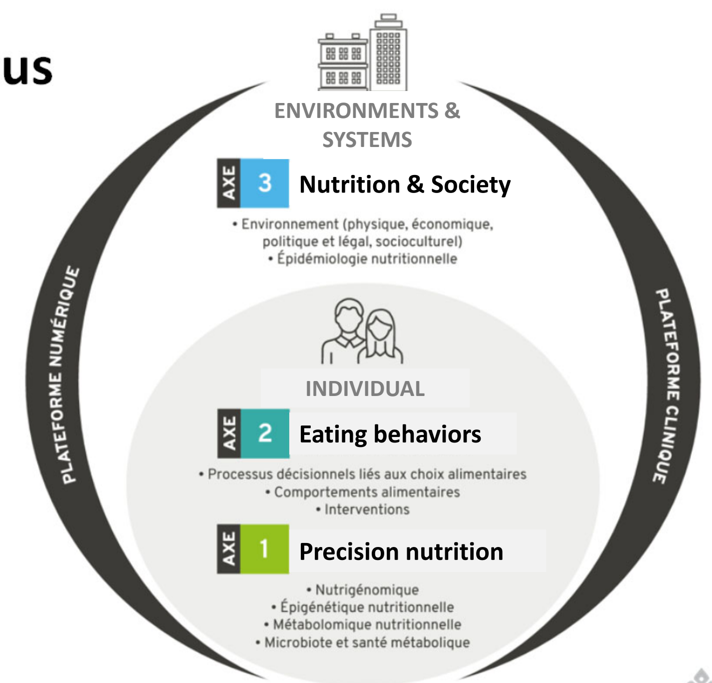
Research focus



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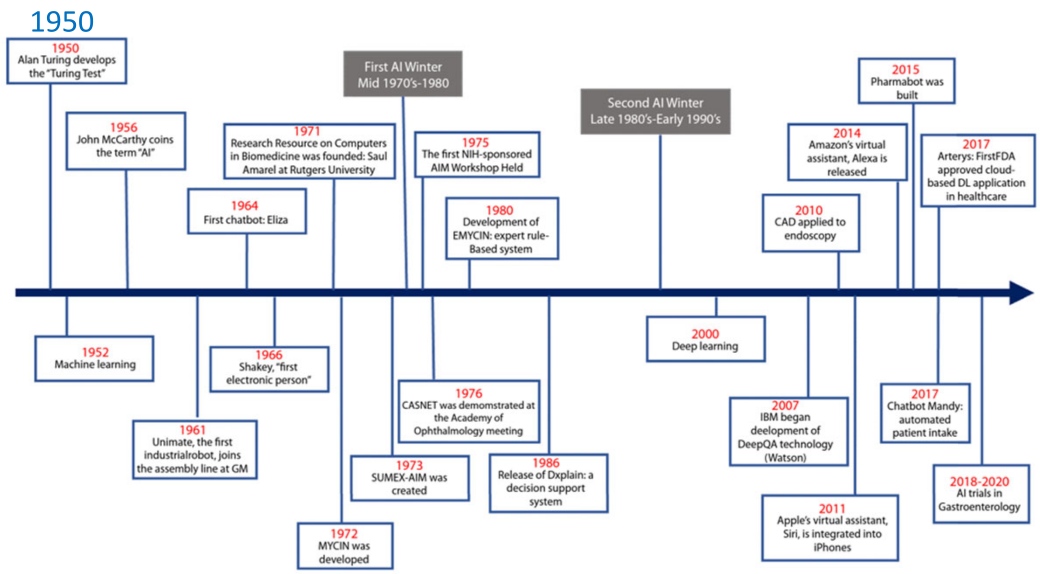
Time (2016) : Hungry Planet: What The World Eats (Canada)

5

AI in medicine **Kaul et al Gastronintestinal endoscopy 2020; 92(4):807+**



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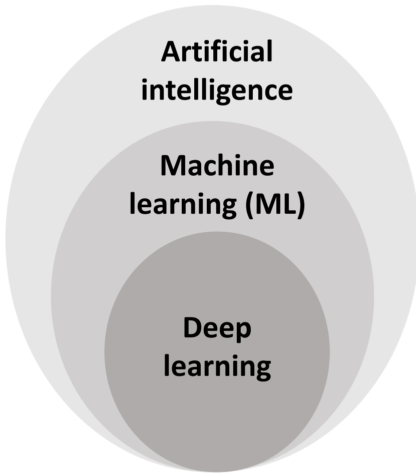
AI and machine learning

Côté et al., 2021; Morgenstern et al., 2021; Côté et al., 2022



Traditionnal approaches

Inputs → *Output*

Data
Model → Prediction

Machine learning approaches

Inputs → *Output*

Data
Results → **Model** - - -> Prediction

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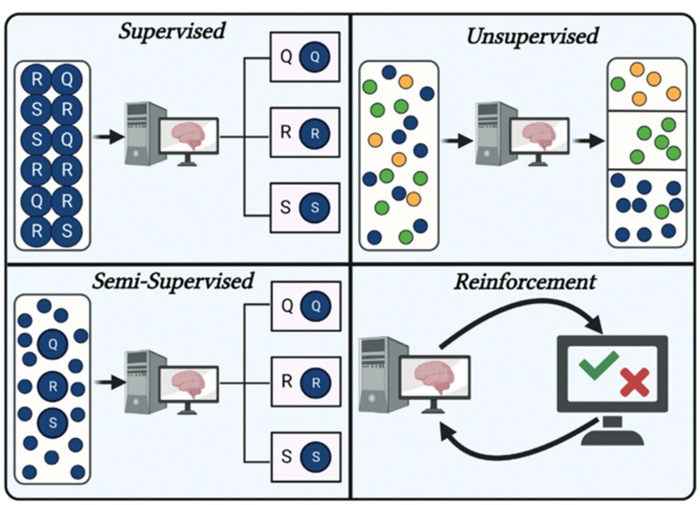
Machine learning

Kirk et al., Adv Nutr 2022;13:2573–2589.



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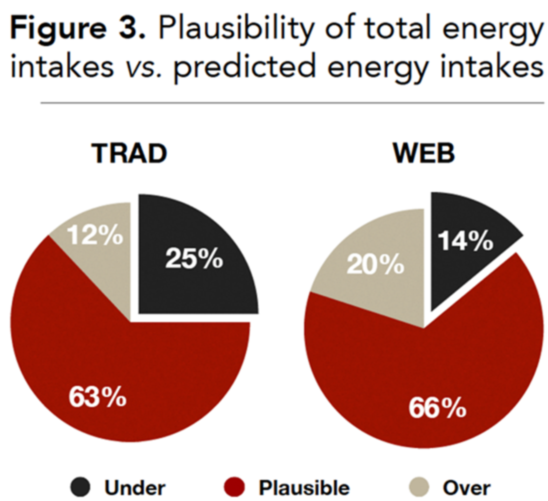
Garbage in, garbage out



Brassard et al, Frontiers Nutr 2020

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AI in nutrition

Promises

- Increased capacity to manage/analyse big data
  - –omics
  - precision nutrition
  - precision public health
- Dietary assessment
  - better understanding of dietary patterns
  - image-based methods
  - non image-based methods
- Predicting health outcomes
- Social media content analysis (NLP)

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AI in nutrition

Challenges

- Change of culture
- New vocabulary
- Standardization of methods
- Building capacity

https://www.analyticssteps.com/

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Are Machine Learning Algorithms More Accurate in Predicting Vegetable and Fruit Consumption Than Traditional Statistical Models? An Exploratory Analysis

Mélina Côté[1,2], Mazid Abiodoun Osseni[3,4], Didier Brassard[1,2], Élise Carbonneau[1,2], Julie Robitaille[1,2], Marie-Claude Vohl[1,2], Simone Lemieux[1,2], François Laviolette[1,3,4] and Benoît Lamarche[1,2]*

- Where are the P values?!?!
- Collinearity issues, multiple tests?
- « Hyperparameter optimisation » ?

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ICDAM 2023, Ireland

Objectives of the workshop

- Identify recent and emerging advances in methods for addressing the complexity of dietary patterns
- Elucidate benefits of the application of novel methods to our understanding of relationships between dietary patterns and health outcomes
- Identify priority methods that show the greatest promise for advancing the evidence on dietary patterns and health
- Identify barriers to advances in the development and application of methods for characterizing dietary patterns, and solutions to collectively overcome these barriers

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Extending methods in dietary patterns research

NCI/NIH Workshop 2016, Reedy et al, Nutrients 2018;10:571

Need to standardize dietary patterns methods and scores

Need to develop methods and models that fully capture the richness within the total dietary pattern

Need to evaluate the effect of measurement error in dietary patterns and develop methods to adjust for this error

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Capacity building

AI- Nutrition boot camp, NUTRISS-Sorbonne 2023

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Capacity building

AI- Nutrition boot camp, NUTRISS-Sorbonne 2023

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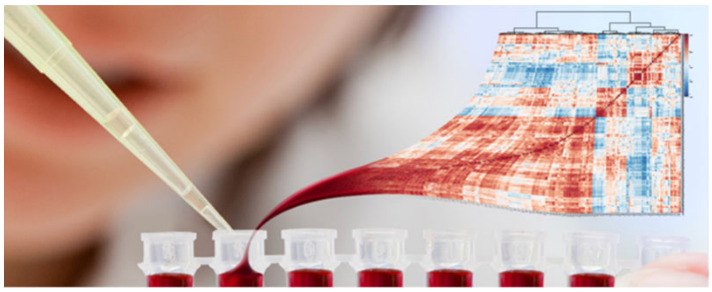
Machine Learning in Nutrition Research

Daniel Kirk,[1] Esther Kok,[1] Michele Tufano,[1] Bedir Tekinerdogan,[2] Edith JM Feskens,[1] and Guido Camps[1,3]
[1] Division of Human Nutrition and Health, Wageningen University and Research, Wageningen, The Netherlands; [2] Information Technology Group, Wageningen University and Research, Wageningen, The Netherlands; and [3] OnePlanet Research Center, Wageningen, The Netherlands

Adv Nutr 2022



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Canadian Science Publishing

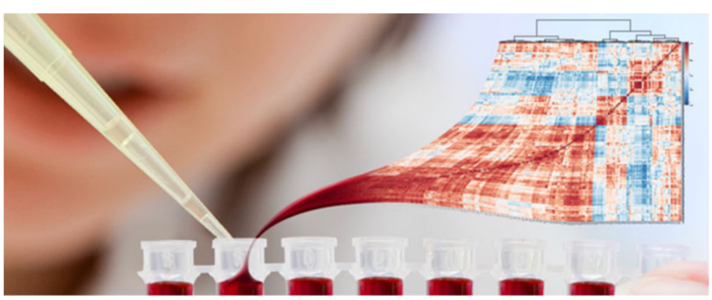
1

REVIEW

Artificial intelligence in nutrition research: perspectives on current and future applications

Mélina Côté and Benoît Lamarche

APNM 2021



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