JOHNS HOPKINS
MALONE CENTER *for*
ENGINEERING *in* HEALTHCARE

THE MALONE CENTER FOR ENGINEERING IN HEALTHCARE

AI for Human Health: Achieving the Promise While Avoiding the Perils

Gregory D. Hager, Director

Johns Hopkins University
Baltimore, MD USA

Johns Hopkins Malone Center *for* Engineering in Healthcare

Mission: To catalyze and accelerate the development, translation, and deployment of research-based innovations that advance the effectiveness and efficiency of health care.

AI, Machine Learning and Data Analytics

Develop tools for analytics and machine learning that advance decision support and improve prediction and process modeling for health care

Systems Optimization

Create better systems to streamline hospital operations, tackling problems such as emergency room crowding and scheduling issues

Technology & Devices

Pioneer new assistive technologies and medical devices for patients and care providers

User-Centered Design

Design future end-user technologies, including mobile, web, household, rehabilitation, and robotics technologies

Our North Star: Medicine is About People Taking Care of People

How is your arm feeling today?

Successful Technology Enhances Care

Medical Images
Lab tests
Patient Vitals

I just got your **images** back
and I saw that .....

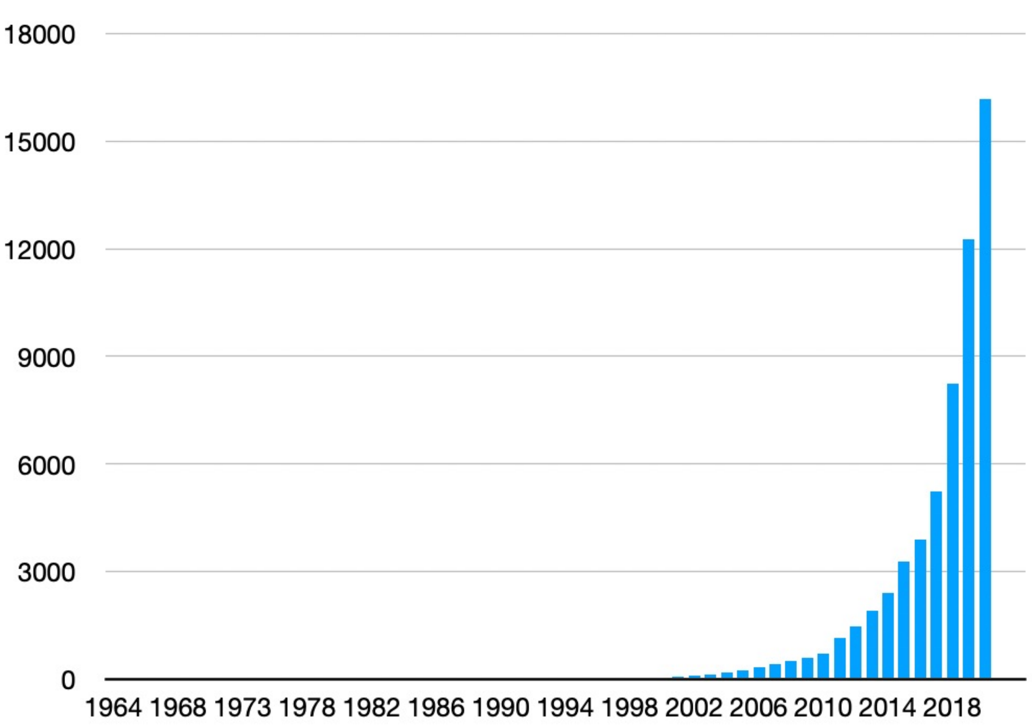
Successful Technology Enhances Care

Medical Images
Lab tests
Patient Vitals
AI

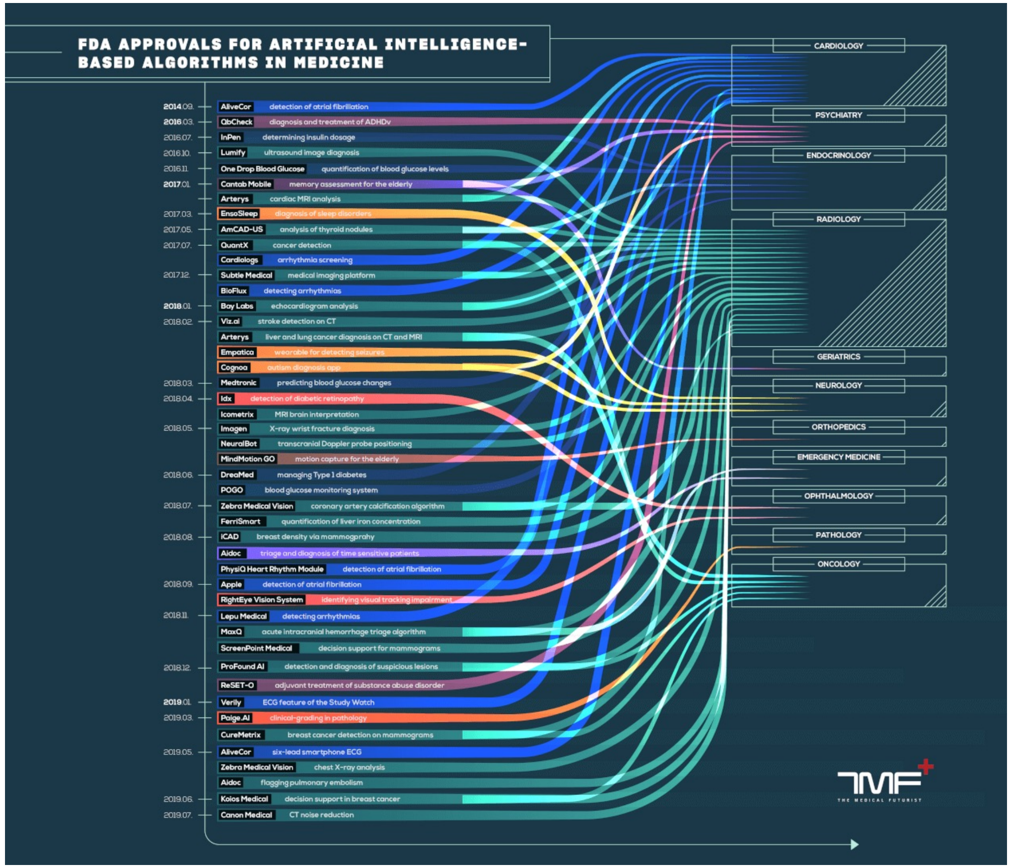
My **Analytics** tell me ....??

Dear Medicine: Welcome to Life In an Exponential World

PubMed Articles with Keyword Machine Learning



https://pubmed.ncbi.nlm.nih.gov/?term=Machine+Learning



https://medicalfuturist.com/fda-approvals-for-algorithms-in-medicine/

Opportunities Abound – Not All Created Equal

Learning-based algorithms had been shown to accurately

forecast the onset of septic shock,[1]

classify skin lesions with dermatologist-level accuracy,[2]

identify diabetic retinopathy during routine primary care visits,[3]

screen for breast cancer better than human radiologists by a fairly large margin,[4]

differentiate the emergency severity index,[5]

simplify interventional workflows,[6]

enable redesign of infusion centers[7] .... and much much more ....

1 K. E. Henry, D. N. Hager, P. J. Pronovost, S. Saria, *Sci. Trans. Med.* 2015, **7**.

2 A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, S. Thrun, *Nature* 2017, **542.**

3 M. D. Abràmoff, P. T. Lavin, M. Birch, N. Shah, J. C. Folk, *NPJ Digital Med.* 2018, **1**,

4 S. M. McKinney, et al. *Nature* 2020,.

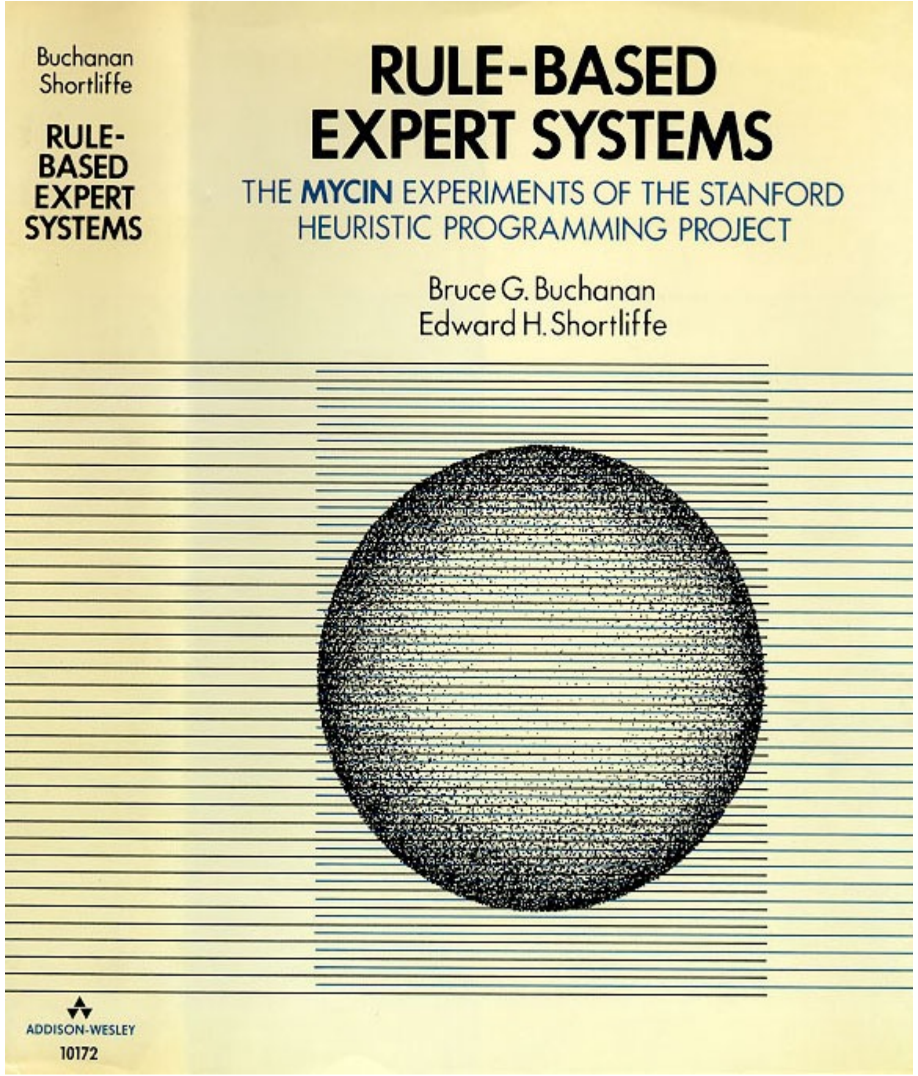
5 S. Levin, M. Toerper, E. Hamrock, J. S. Hinson, S. Barnes, H. Gardner, A. Dugas, B. Linton, T. Kirsch, G. Kelen, *Ann. Emergency Med.* 2018.

6 T. Vercauteren, M. Unberath, N. Padoy, N. Navab, *Proc. IEEE* 2019.

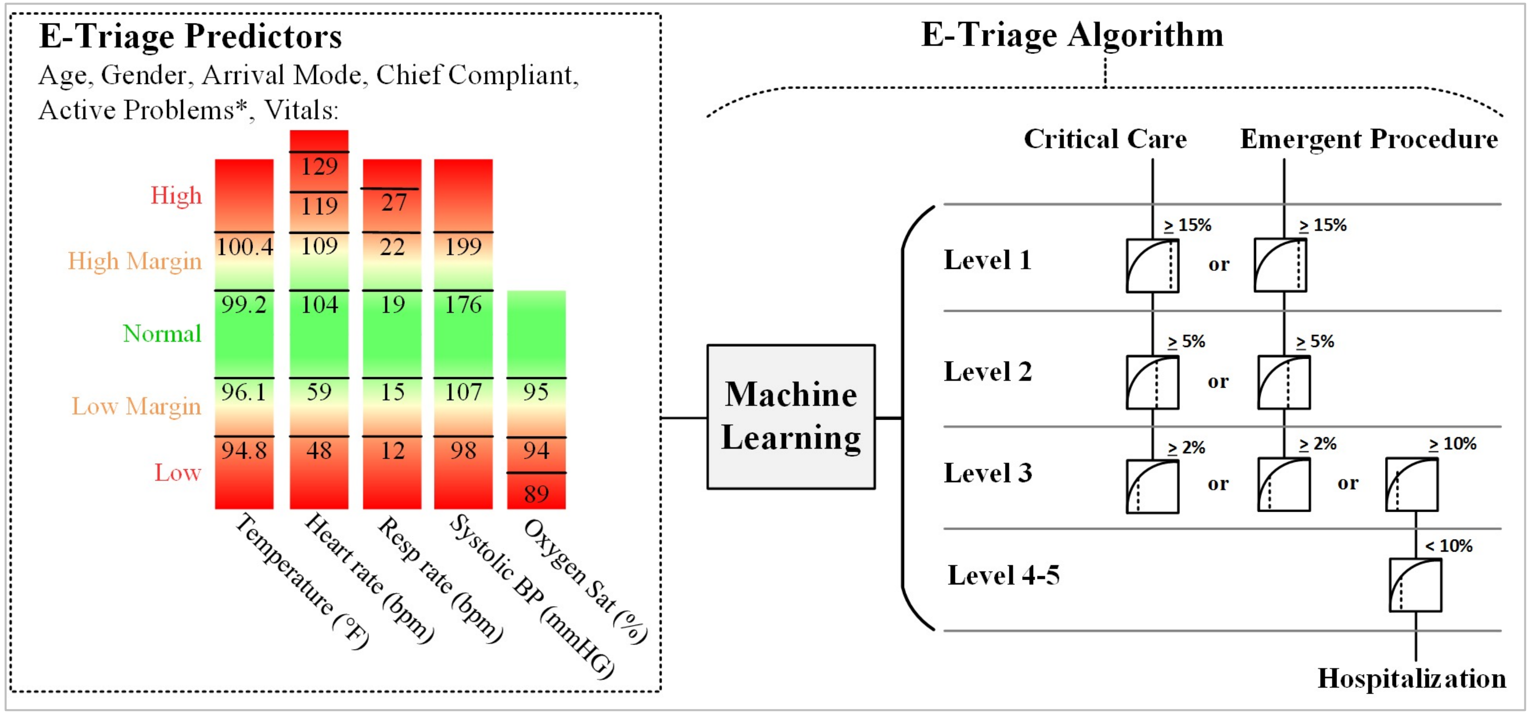
7 K. Ghobadi, A. C. Zenteno, A. R. Marshall, P. F. Dunn, R. Levi, J. H. Stone, *NEJM Catalyst* 2017.

Peril #1: Let Us Not Forget History

- Expert Systems: Mycin, Dendral
- Use expert knowledge to establish a logical (later probabilistic) chain of reasoning from inputs to outputs
- Viewed as a physician's assistant (augmenting, not replacing)
- Ulitimately hit a wall
  - Not scalable
  - Too many corner cases
  - Hard to engineer
  - Got the easy stuff right, but it was easy …
- Early results inspire, but it takes effort to find the real **value proposition** amid the hype



Finding a Value Proposition: Reducing ED Crowding



Machine Learning to triage patients significantly reduced time in ER by reducing uncertainty to admit, treat, or send home

Levin et al., Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared With the Emergency Severity Index, Annals of Emergency Medicine, 2018

Finding a Value Proposition: Reducing ED Crowding

ED Objective

58 – 82 min decrease ↓ in time to critically ill

Time to ICU transfer

Time to emergent surgery

20 – 30 min decrease ↓ door-to-disposition*

Site 1: ~29 min for admits | ~3 min discharges

Site 2: ~10 min for admits | ~11 min discharges

8,000 – 11,000 bed-hours gained

$520k - $730k in cost-savings[ⱡ]

Improving Triage

Increased ↑ early identification of critical care

15% ↑ (e.g., 67% to 80%) identification as high-acuity and expedited

No real change in low-acuity hospital admits

Despite increases in low-acuity designations

Nurse Agreement with TriageGO

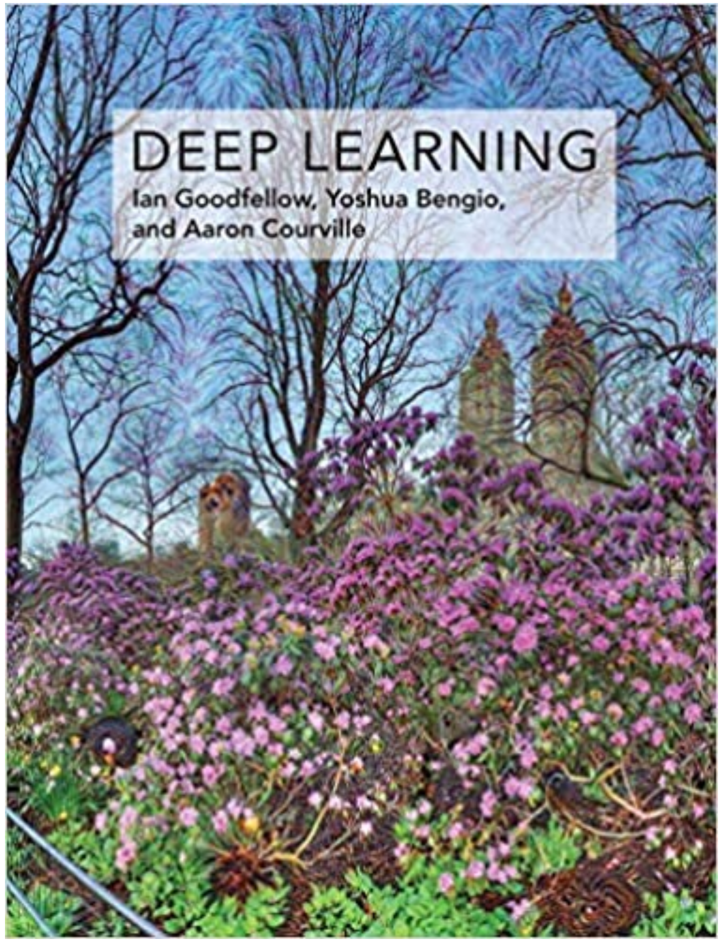
45-55% prior to implementation

65-70% early implementation

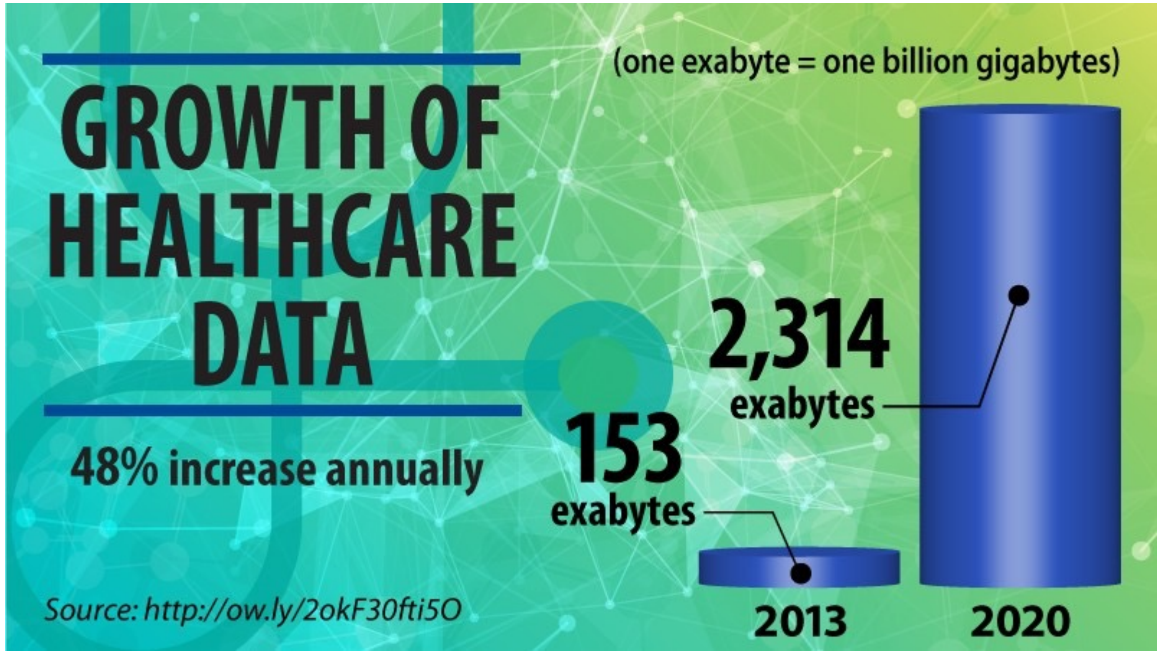
80-90% in steady-state

Machine Learning to triage patients significantly reduced time in ER by reducing uncertainty to admit, treat, or send home

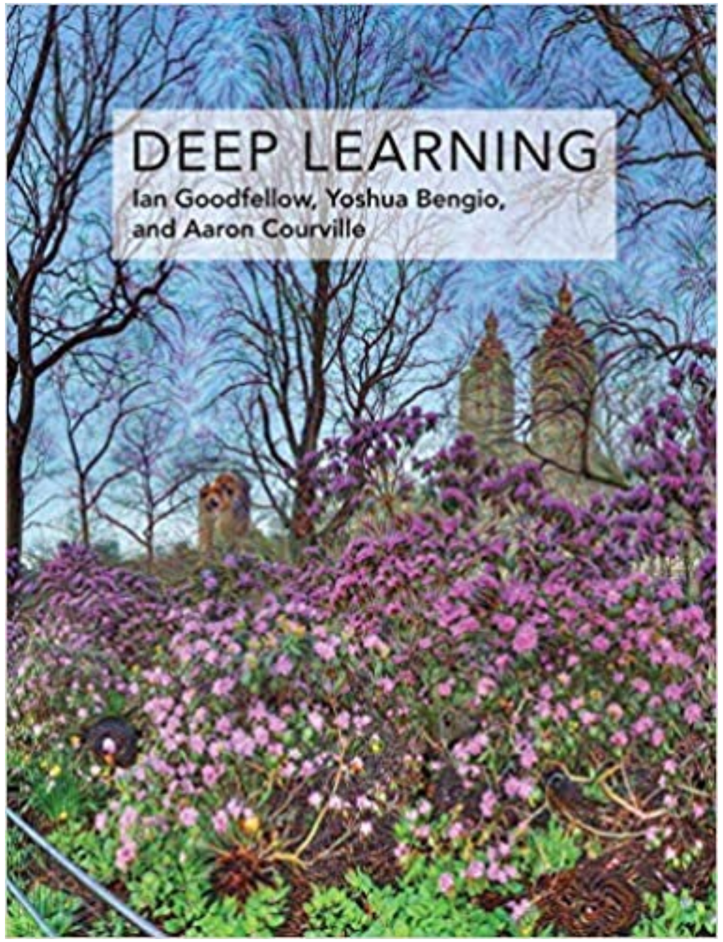
Peril #2: Correlation is Not Causality



- Machine learning is solving a **regression problem**
- Exponential data growth + exponential model size + exponential experiments = **exponential chance for irreproducible results**



Peril #2: Correlation is Not Causality



For COVID 19

33 diagnostic models were identified for detecting covid-19,

75 other diagnostic models based on medical images,

10 diagnostic models for severity classification,

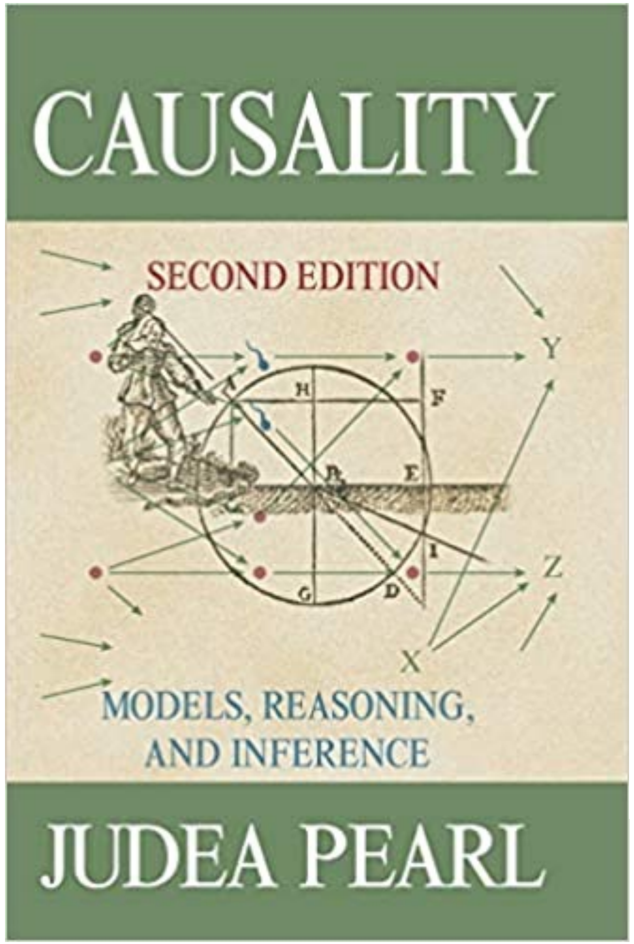
107 prognostic models for predicting progression

Proposed models are poorly reported and at high risk of bias … their **predictions could be unreliable when applied in daily practice**

Two prediction models …were identified **as being of higher quality**

(Wynats et al., BMJ, 2020)

We Will Learn to Transcend the Limitations of Data



Biostatistics (2020) **21**, 2, *pp.* 345–352
doi:10.1093/biostatistics/kxz041
Advance Access publication on November 19, 2019

From development to deployment: dataset shift, causality, and shift-stable models in health AI

ADARSH SUBBASWAMY

Department of Computer Science, Johns Hopkins University, 160 Malone Hall, 3400 N. Charles Street, Baltimore, MD, USA

SUCHI SARIA*

Department of Computer Science; Department of Applied Math & Statistics, and Department of Health Policy & Management, Johns Hopkins University, 160 Malone Hall, 3400 N. Charles Street, Baltimore, MD, USA

ssaria@cs.jhu.edu

"In domains like healthcare and education where safety is crucial, building models that don't fail in unanticipated ways due to small shifts in underlying datasets is critical."

Peril #3: Forgetting Medicine is About People Taking Care of People

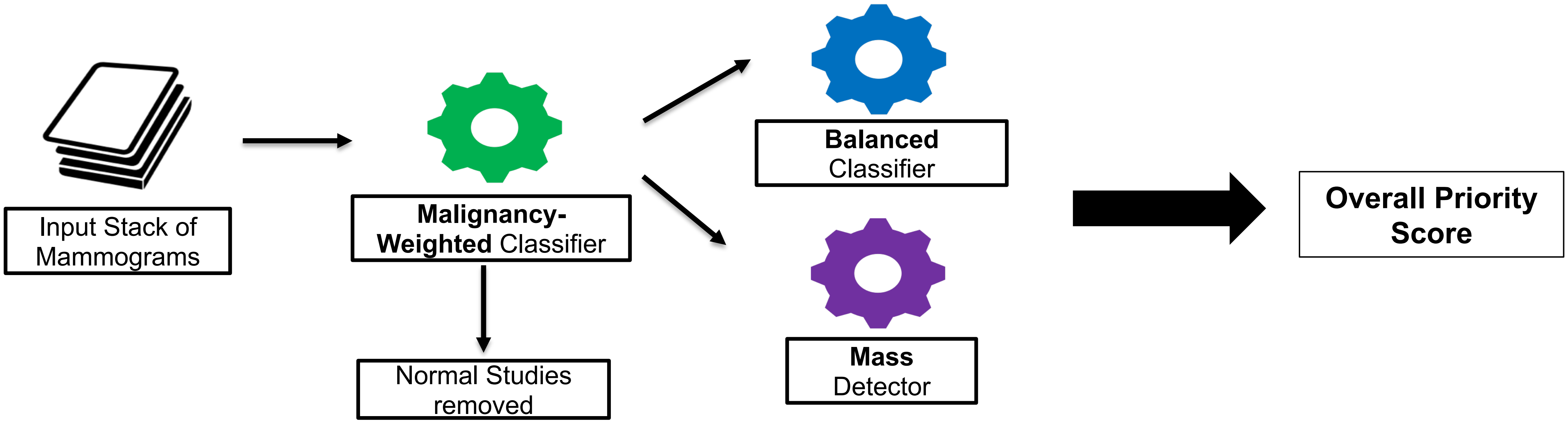
INNOVATION

AI Will Change Radiology, but It Won’t Replace Radiologists

by Thomas H. Davenport and Keith J. Dreyer, DO

MARCH 27, 2018 Harvard Business Review

DeepCAT: Deep Computer-Aided Triage of Mammograms to Enhance Efficiency



Of 595 testing images, DeepCAT would theoretically discard 315 images (53%) as normal!

None contained a malignant mass.

Yi et al., *Journal of Digital Imaging*, 2021

AI Will Change Medicine: But not by replacing doctors or nurses

… but by changing the way they do their job!

Less effort on needless work
Better decisions informed by analytics
More time for what matters: taking care of patients