



- Anesthesia
- Bioengineering
- Biomedical Data Science
- Cardiothoracic Surgery
- Computer Science
- Dermatology
- Emergency Medicine
- Genetics
- Medicine
- Neurology & Neurological Sciences
- Neurosurgery
- Ophthalmology
- Pathology
- Pediatrics
- Psychiatry & Behavioral Sciences
- Psychology
- Radiation Oncology
- Radiology
- Surgery
- Urology



Center for Artificial Intelligence in Medicine and Imaging







Key Computer Science Faculty Collaborators



Fei Fei Li, PhD Creator of ImageNet



Chris Manning, PhD Stanford Al Lab Director



Andrew Ng, PhD
Deep Learning Pioneer



Chris Re', PhD Founder, Snorkel Al

Radiology

A Roadmap for Foundational Research on Artificial **Intelligence in Medical Imaging:** From the 2018 NIH/RSNA/ACR/The Academy Workshop

Curtis P. Langlotz, MD, PhD • Bibb Allen, MD • Bradley J. Erickson, MD, PhD • Jayashree Kalpathy-Cramer, PhD • Keith Bigelow, BA • Tessa S. Cook, MD, PhD • Adam E. Flanders, MD • Matthew P. Lungren, MD, MPH • David S. Mendelson, MD • Jeffrey D. Rudie, MD, PhD • Ge Wang, PhD • Krishna Kandarpa, MD, PhD

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Conflicts of interest are listed at the end of this article.

Radiology 2019; 00:1-11 • https://doi.org/10.1148/radiol.2019190613 • Content code: IN

ORIGINAL ARTICLE

Current State Area Software use Al algorithms are being created cases for Al based on use cases developed at single institutions working with single developers, limiting diversity and generalizability to widespread clinical practice.

https://doi.org/10.1016/j.jacr.2019.04.014

A Road Map for Translational Research on Artificial Intelligence in Medical Imaging: From the 2018 National Institutes of Health/RSNA/ACR/The Academy Workshop

Bibb Allen Jr, MD^d, Steven E. Seltzer, MD^{b,c}, Curtis P. Langlotz, MD, PhD^d, Keith P. Dreyer, DO, PhD^e, Ronald M. Summers, MD, PhD^f, Nicholas Petrick, PhD^g, Danica Marinac-Dabic, MD, PhD, MMSC^f, Marisa Cruz, MD¹, Tarik K. Alkasab, MD, PhD², Robert J. Hanisch, PhD³, Wendy J. Nilsen, PhD^k, Judy Burleson, BSW, MHSA^l, Kevin Lyman, BS^m, Krishna Kandarpa, MD, PhDⁿ

Area

Current State of the Art

Data needs for machine learning research

Few public image data sets are available. mostly small in size and lacking real-world variation.

Radiology

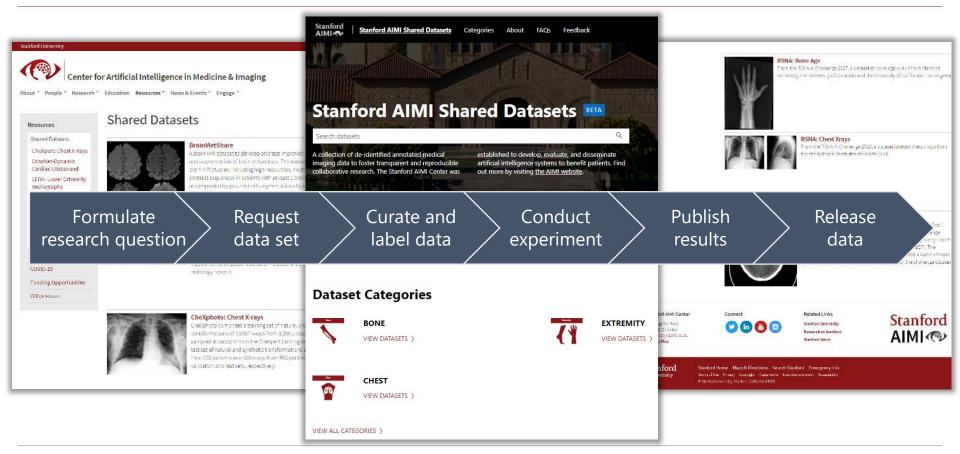
Ethics of Using and Sharing Clinical Imaging Data for Artificial Intelligence: A Proposed Framework

David B. Larson, MD, MBA • David C. Magnus, PhD • Matthew P. Lungren, MD, MPH • Nigam H. Shah, MBBS, PhD • Curtis P. Langlotz, MD, PhD

"After clinical data are used to provide care, the primary purpose for acquiring the data is fulfilled. At that point, clinical data should be treated as a form of public good, to be used for the benefit of future patients."

Publicly-Released AI-Ready Radiology Datasets





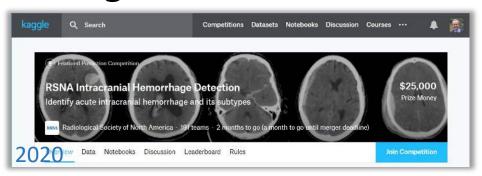


RSNA Data Science Challenges













Overcoming Barriers to Data Sharing



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- Barriers to "Al-readiness" of data
 - Volume, labels, diversity
- Barriers to organizational readiness for data release
 - Organizational capacity
 - Many or no privacy offices, lack of an IRB
 - Risk aversion
 - HIPAA breach, public announcements
 - Legal deliberations
 - Patient consent
 - Data use agreements
 - Commercial use
 - Technical factors
 - De-identification
 - Format harmonization
 - · Data hosting, user tracking
 - Cost

Persistence, enlightened IRB

Mission-related sharing, mandates

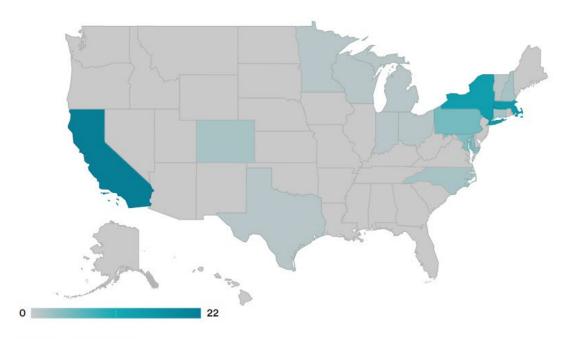
Current language being expanded

Non-commercial only

DICOM Anonymizer, OMOP

Box→Microsoft, RSNA, MIDRC

Geographic Distribution of Cohorts to Train Deep Learning Algorithms



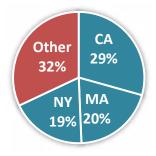
REBECCA ROBBINS/STAT
SOURCE: "GEOGRAPHIC DISTRIBUTION OF US COHORTS USED TO TRAIN DEEP LEARNING ALGORITHMS,"
JAMA 2020.

STAT

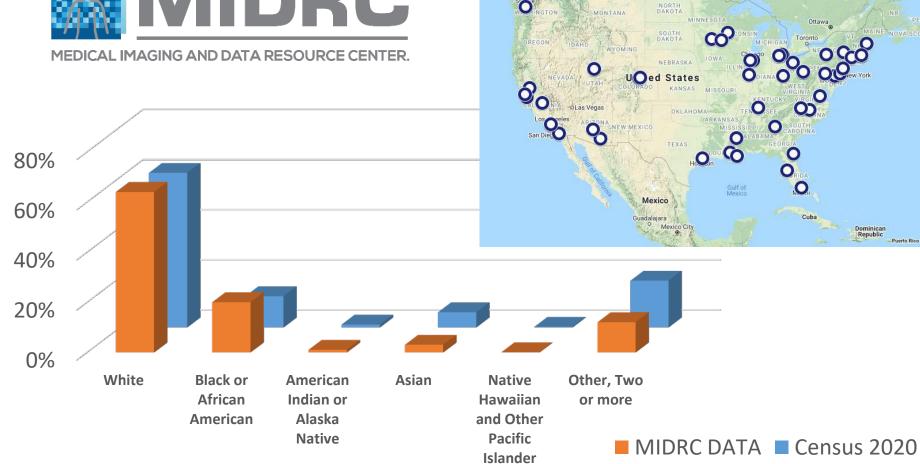
| States | No. of studies |
|----------------|----------------|
| California | 22 |
| Massachusetts | 15 |
| New York | 14 |
| Pennsylvania | 5 |
| Maryland | 4 |
| Colorado | 2 |
| Connecticut | 2 |
| New Hampshire | 2 |
| North Carolina | 2 |
| Indiana | 1 |
| Michigan | 1 |
| Minnesota | 1 |
| Ohio | 1 |
| Texas | 1 |
| Vermont | 1 |
| Wisconsin | 1 |

^a Fifty-six studies used 1 or more geographically identifiable US patient cohort in the training of their clinical machine learning algorithm. Thirty-four states were not represented in geographically identifiable cohorts: Alabama, Alaska, Arizona, Arkansas, Delaware, Florida, Georgia, Hawaii, Idaho, Illinois, Iowa, Kansas, Kentucky, Louisiana, Maine, Mississippi, Missouri, Montana, Nebraska, Nevada, New Jersey, New Mexico, North Dakota, Oklahoma, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Utah, Virginia, Washington, West Virginia, and Wyoming.

JAMA September 22/29, 2020 Volume 324, Number 12







Conclusions

- Lack of data is a key bottleneck.
- Wide public release of data can be accomplished.
- Data readiness and organizational readiness are distinct concepts.
- Recommendations:
 - Large organizations need guidance on best practices.
 - Inexperienced organizations need help from centers of excellence.
 - Sustainable models will require both central and distributed investment.



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