

Part I

Artificial Intelligence for Medical Imaging: A Brief Review of Clinical Evidence

Sergio Uribe, DDS, MSc, PhD.

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Aim

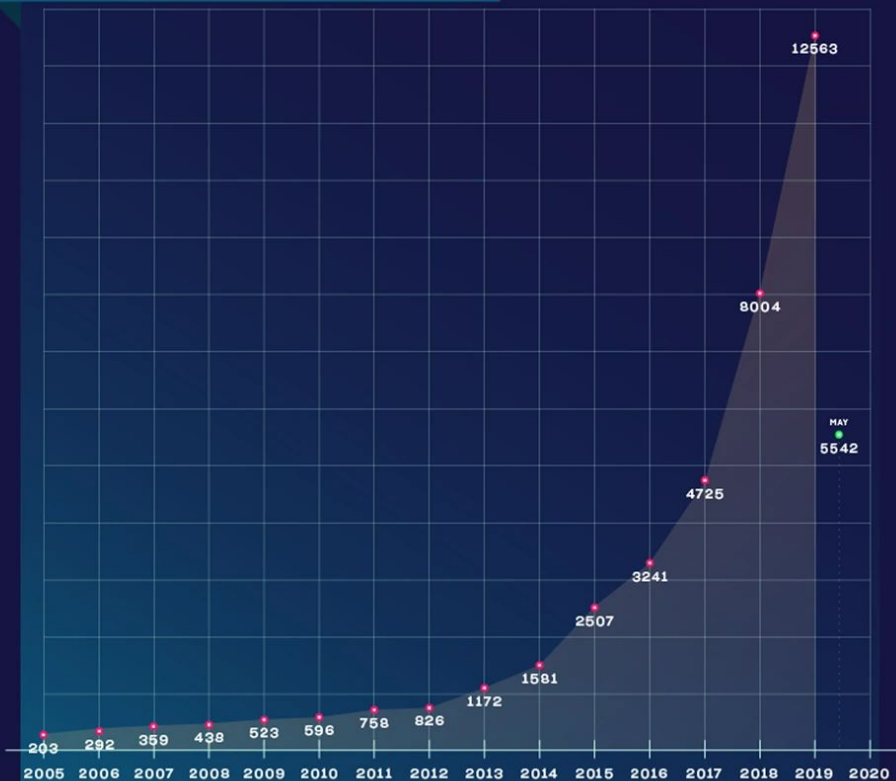
Brief introduction of the key terms of IA in medical imaging
Evidence of its clinical effectiveness
Limitations and future perspectives

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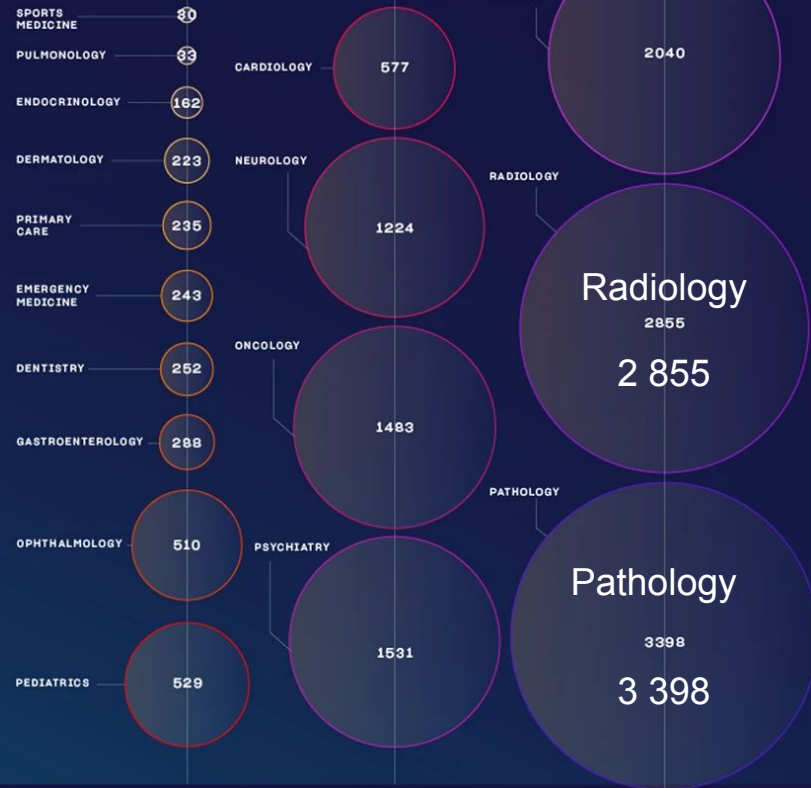
MACHINE AND DEEP LEARNING STUDIES ON PUBMED.COM

TOTAL NUMBER OF STUDIES



b

STUDIES PER SPECIALTY



“There is no function the computer cannot do in radiology”



Gwilym S. Lodwick, MD

VOL. 81 NO. 2

Radiology

AUGUST 1963

a monthly journal devoted to clinical radiology and allied sciences
PUBLISHED BY THE RADIOLOGICAL SOCIETY OF NORTH AMERICA, INC.

The Coding of Roentgen Images for Computer Analysis as Applied to Lung Cancer¹

GWILYM S. LODWICK, M.D., THEODORE E. KEATS, M.D., and JOHN P. DORST, M.D.

THIS PAPER WILL DESCRIBE a concept of converting the visual images on roentgenograms into numerical sequences that can be manipulated and evaluated by the digital computer and will report the results of employing this system to

cause, against a background of air density, the intimate details of the relationship between tumor and host may be faithfully reproduced roentgenographically. Parenthetically, it may be stated that similar density ranges exist in the relationships

Computers for image classification

IMAGENET

14,197,122 images, 21841 synsets indexed

SEARCH

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Jan-2019: ImageNet server is under maintenance. Synsets outside ILSVRC are temporarily unavailable. Oct-2019: Due to scheduled maintenance, ILSVRC downloads are temporarily unavailable.

Domestic cat, house cat, Felis domesticus, Felis catus

Any domesticated member of the genus Felis

1831
pictures

66.18%
Popularity
Percentile

Wordnet
IDs

- natural object (1112)
- sport, athletics (176)
- artifact, artefact (10504)
- fungus (308)
- person, individual, someone, some
- animal, animate being, beast, brute
- invertebrate (766)
- homeotherm, homoiotherm, hon
- work animal (4)
- darter (0)
- survivor (0)
- range animal (0)
- creepy-crawly (0)
- domestic animal, domesticated i
- domestic cat, house cat, Feli
- Egyptian cat (0)
- Persian cat (0)
- kitty, kitty-cat, puss, puss
- tiger cat (0)
- Angora, Angora cat (0)
- tom, tomcat (1)
- Siamese cat, Siamese (1
- Manx, Manx cat (0)
- Maltese, Maltese cat (0)

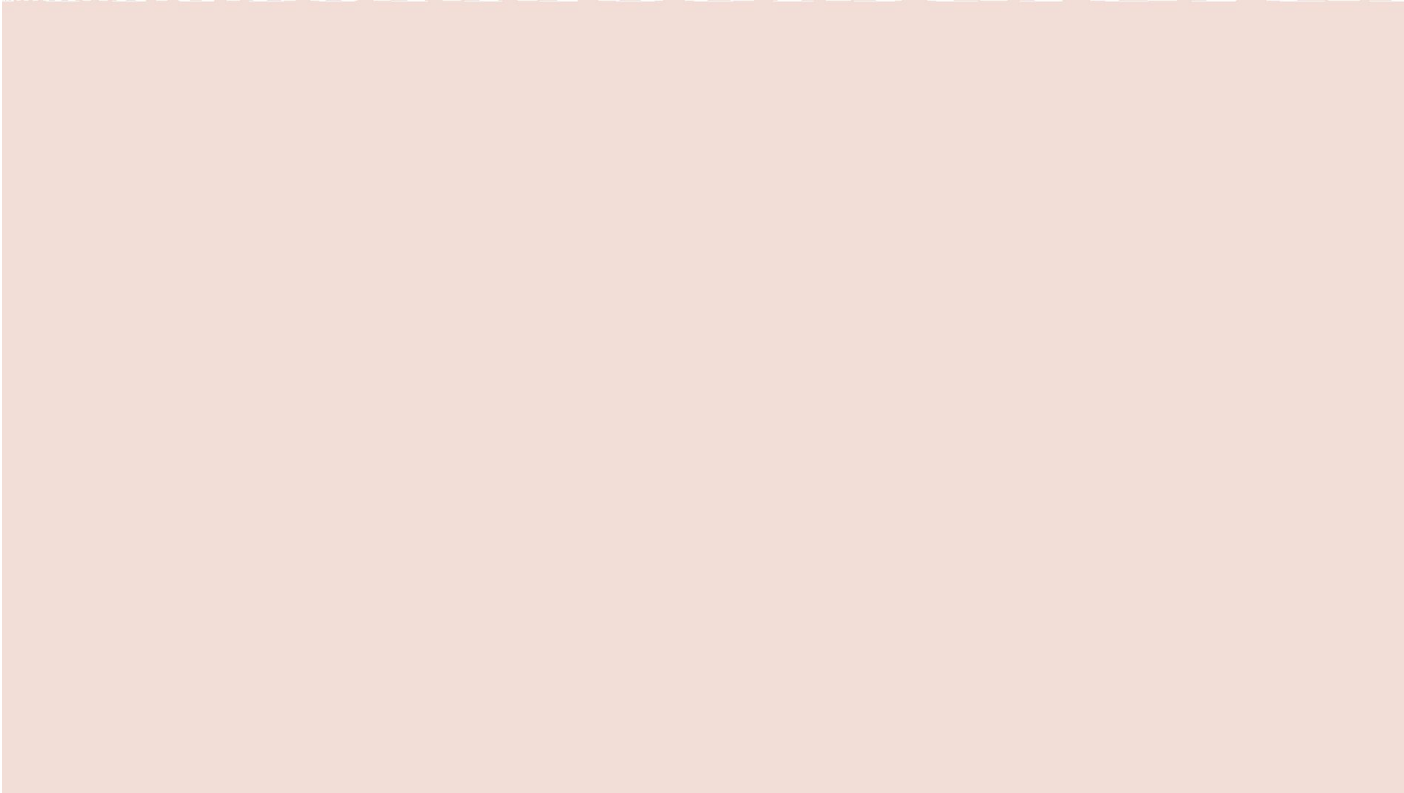
Treemap Visualization

Images of the Synset

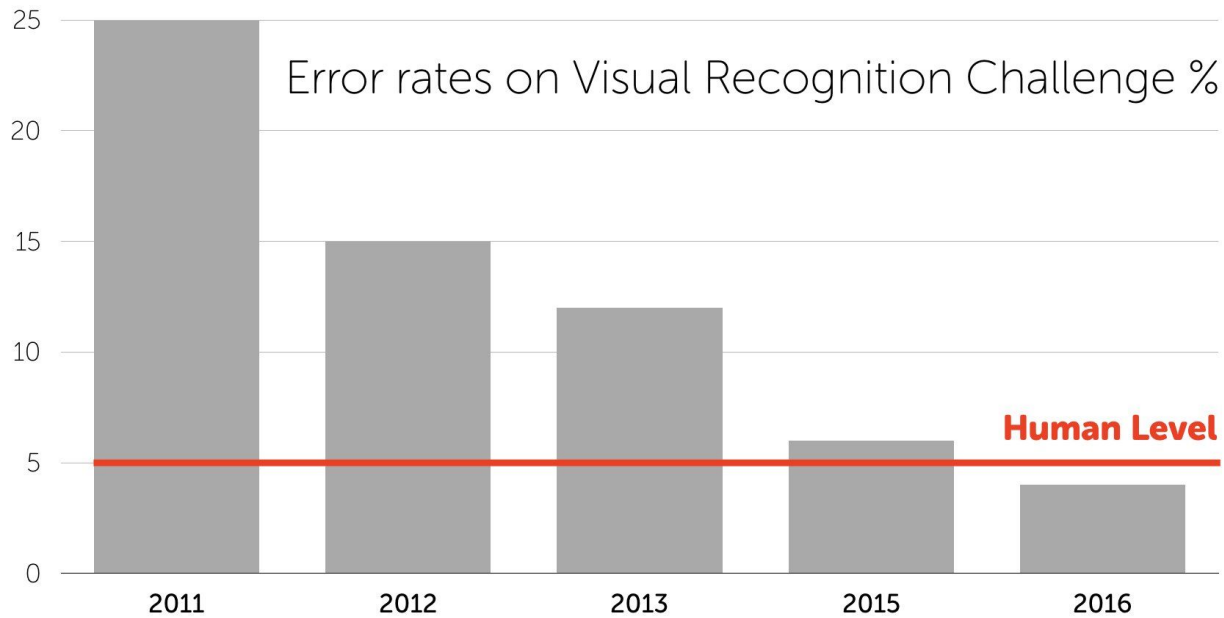
Downloads



Computers for image classification



BRISQ



DESDR

Why AI for radiology?

Diagnostic errors play a role in **up to 10%** of patients deaths
Reporting error rate up to 20-30% more complex studies such as computed tomography (CT) and magnetic resonance imaging (MRI)
> 101 050 radiology reports contain clinically significant errors

~

Committee on Diagnostic Error in Health Care. 2016 National Academies Press (US), Washington (DC).
[Insights Imaging](#). 2017 Feb; 8(1): 171–182.

Why AI for radiology?

Q Popular Latest

The Atlantic

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HEALTH

Most of the World Doesn't Have Access to X-Rays

One hospital in Boston has 126 radiologists. Liberia has two.

JASON SILVERSTEIN SEPTEMBER 27, 2016



MORE STORIES

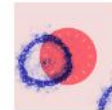
Trump's Pathology Is Now Clear

JAMES HAMBLIN



The Simple Rule That Could Keep COVID-19 Deaths Down

SARAH ZHANG



DRS

Some definitions

Artificial intelligence



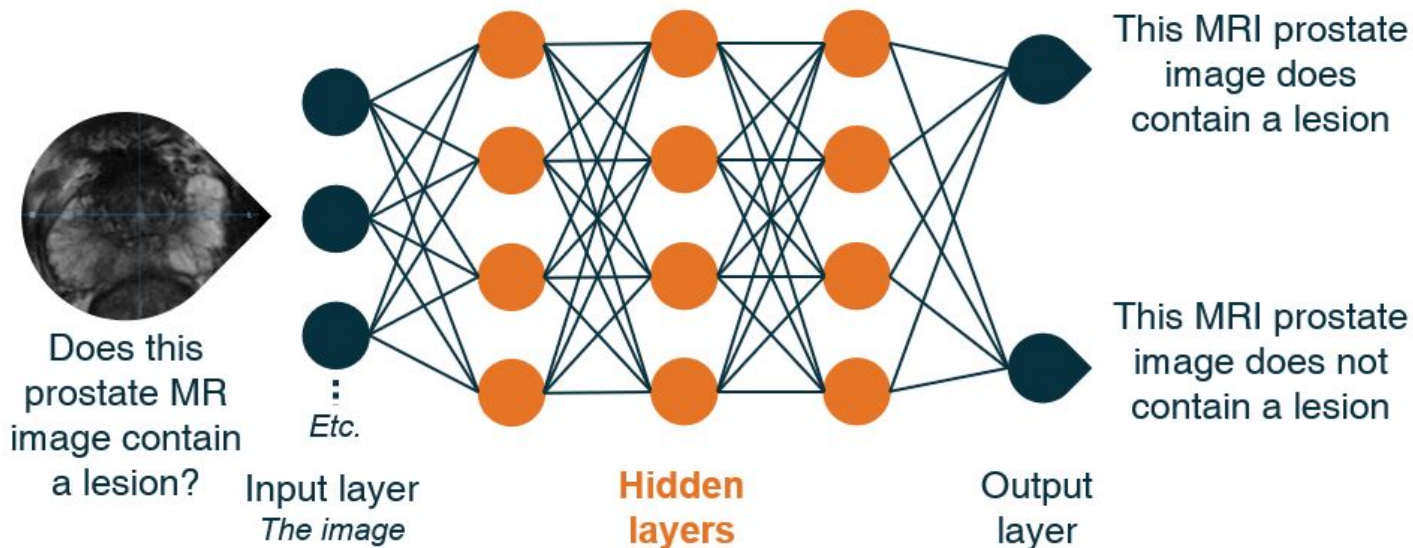
Machine learning

Deep learning

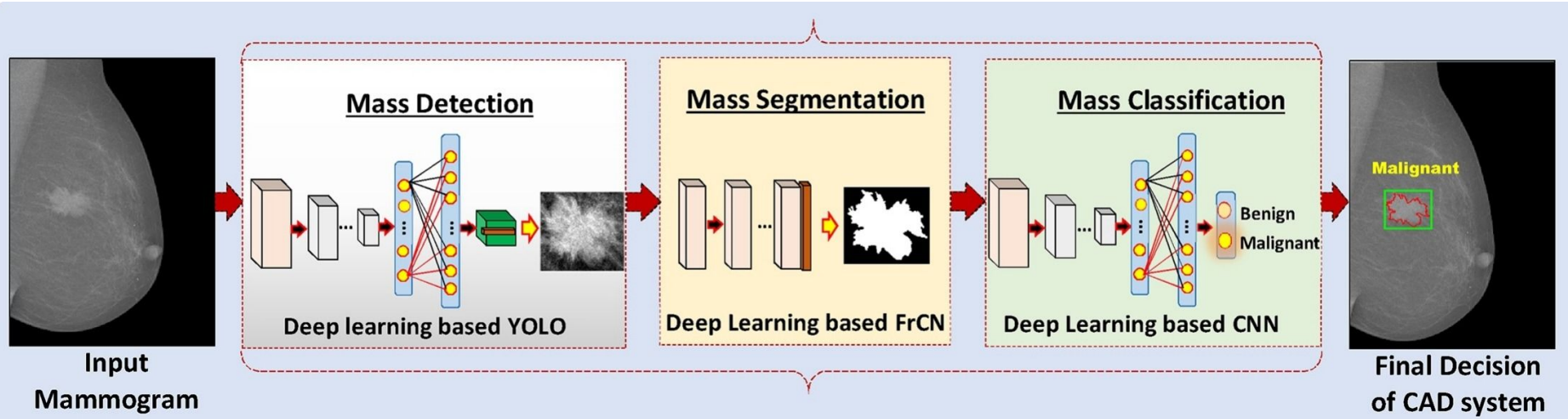
CNN

Convolutional Neural Networks (CNN)

A DEEP NEURAL NETWORK FOR LESION DETECTION

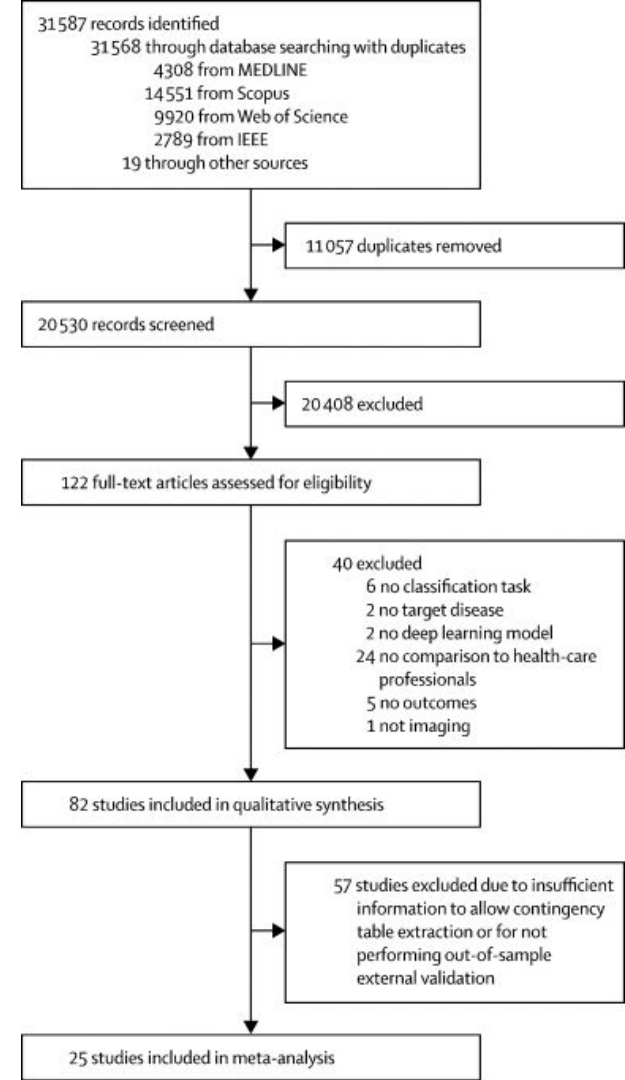


Example



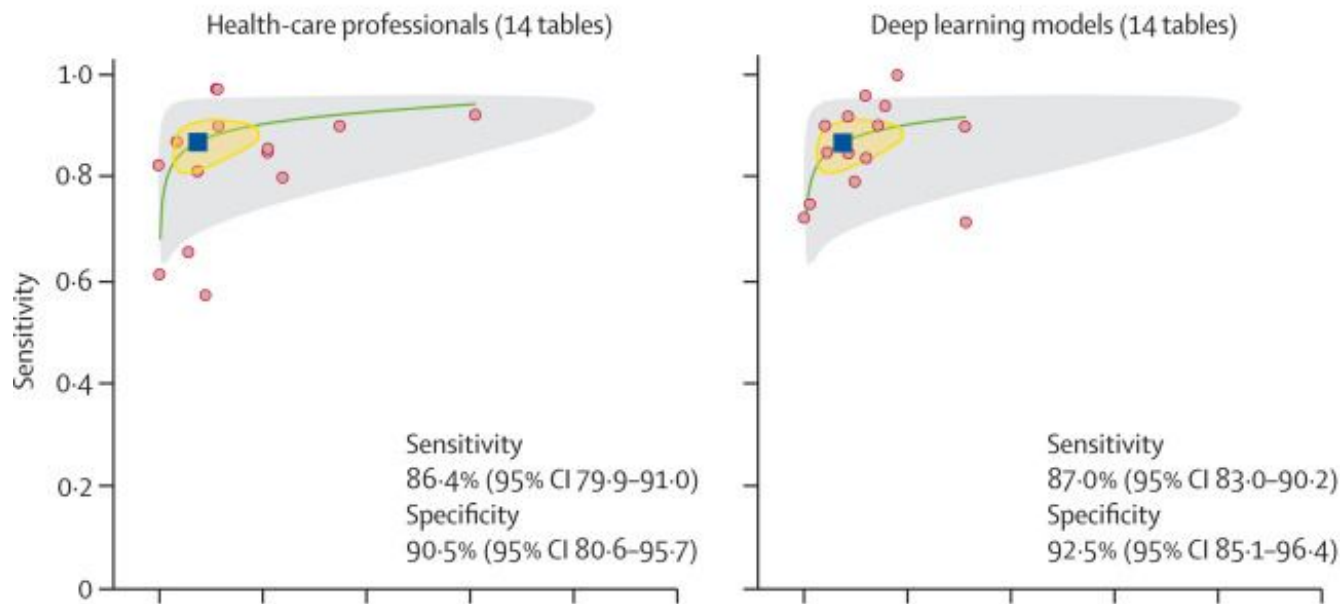
Diagnostic performance of AI vs health care professionals

Liu et al. 2019. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. *The Lancet Digital Health* 1, e271–e297.



Diagnostic performance of AI vs health care professionals

A Same out-of-sample validation sample



Major challenges ahead

1. Explainability
2. Augmented intelligence
3. Quality and quantity of data
4. Privacy issues
5. Legal issues and liability
6. Biased A.I.

DSR

Learn more

Liu et al. 2019. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. *The Lancet Digital Health* 1, e271–e297.

Haibe-Kains et al. Transparency and reproducibility in artificial intelligence. *Nature* 586, E14–E16.

Meskó, B., Görög, M., 2020. A short guide for medical professionals in the era of artificial intelligence. *npj Digital Medicine* 3, 1–8.

European Society of Radiology (ESR), 2019. What the radiologist should know about artificial intelligence - an ESR white paper. *Insights Imaging* 10, 44.

Part II AI Workflow for Medical Imaging Diagnosis: Critical steps from acquisition to prediction

Sergio Uribe, PhD, MSc, DDS

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RSD

Aim

To identify key stages from image acquisition and imaging protocols that allow the processing, annotation and use of images for the use of artificial intelligence algorithms

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Critical steps

Aim: Proof of concept? Diagnostic accuracy? Patient outcomes?

Prospective or retrospective

Data de-identification

Data collection and curation

DDSDR



Resources

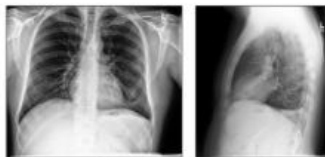
Shared Datasets

[CheXpert: Chest Xray's](#)[EchoNet-Dynamic
Cardiac Ultrasound](#)[LERA- Lower Extremity
RAdiographs](#)[MURA: MSK Xrays](#)[MRNet: Knee MRI's](#)[RSNA: Bone Age](#)[RSNA: CT Brain](#)[RSNA: Chest Xray's](#)

Software Tools

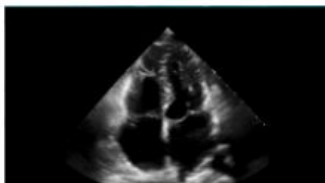
[COVID-19](#)

Shared Datasets



CheXpert: Chest X-rays

CheXpert is a dataset consisting of 224,316 chest radiographs of 65,240 patients who underwent a radiographic examination from Stanford University Medical Center between October 2002 and July 2017, in both inpatient and outpatient centers. Included are their associated radiology reports.



EchoNet-Dynamic Cardiac Ultrasound

EchoNet-Dynamic is a dataset of over 10k echocardiogram, or cardiac ultrasound, videos from unique patients at Stanford University Medical Center. Each apical-4-chamber video is accompanied by an estimated ejection fraction, end-systolic volume, end-diastolic volume, and position of the left ventricle performed from end-diastolic cardiac

Dataverse (RSU)

 Metrics

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Critical steps

Aim: Proof of concept? Diagnostic accuracy? Patient outcomes?

Prospective or retrospective

Data de-identification

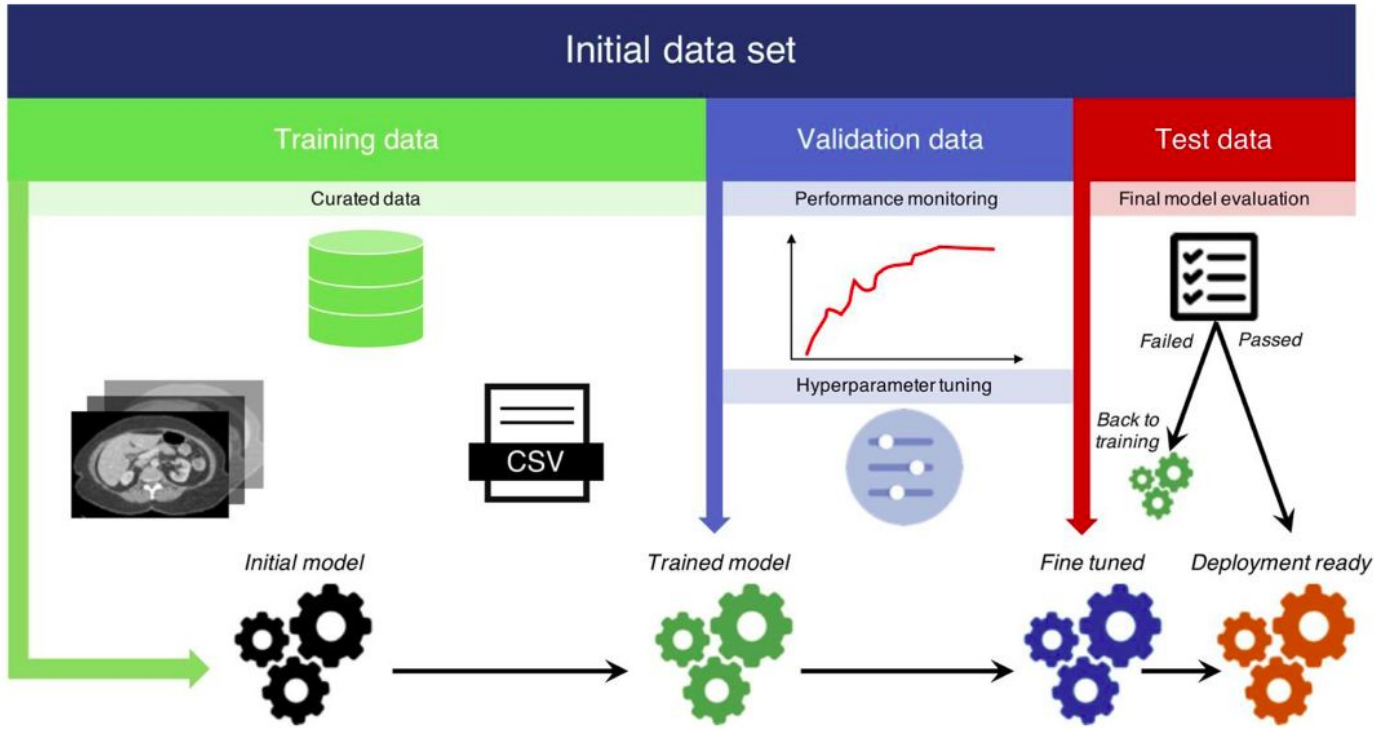
Data collection and curation

Reference standard

Dataset sampling strategies

DATA
DR

Types of datasets



DS
RS

Critical steps

Aim: Proof of concept? Diagnostic accuracy? Patient outcomes?

Prospective or retrospective

Data de-identification

Data collection and curation

Reference standard

Dataset sampling strategies

Deep learning libraries and architectures

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R

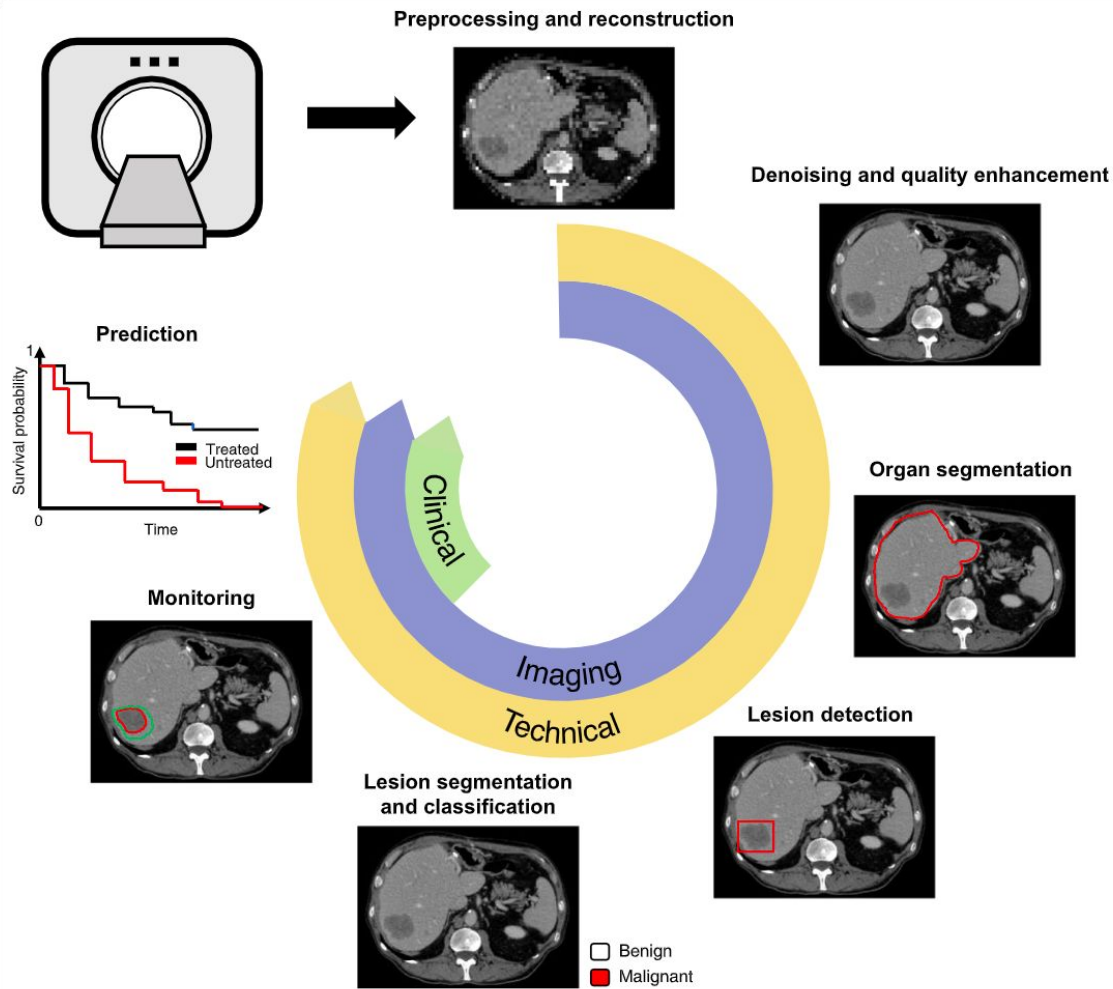
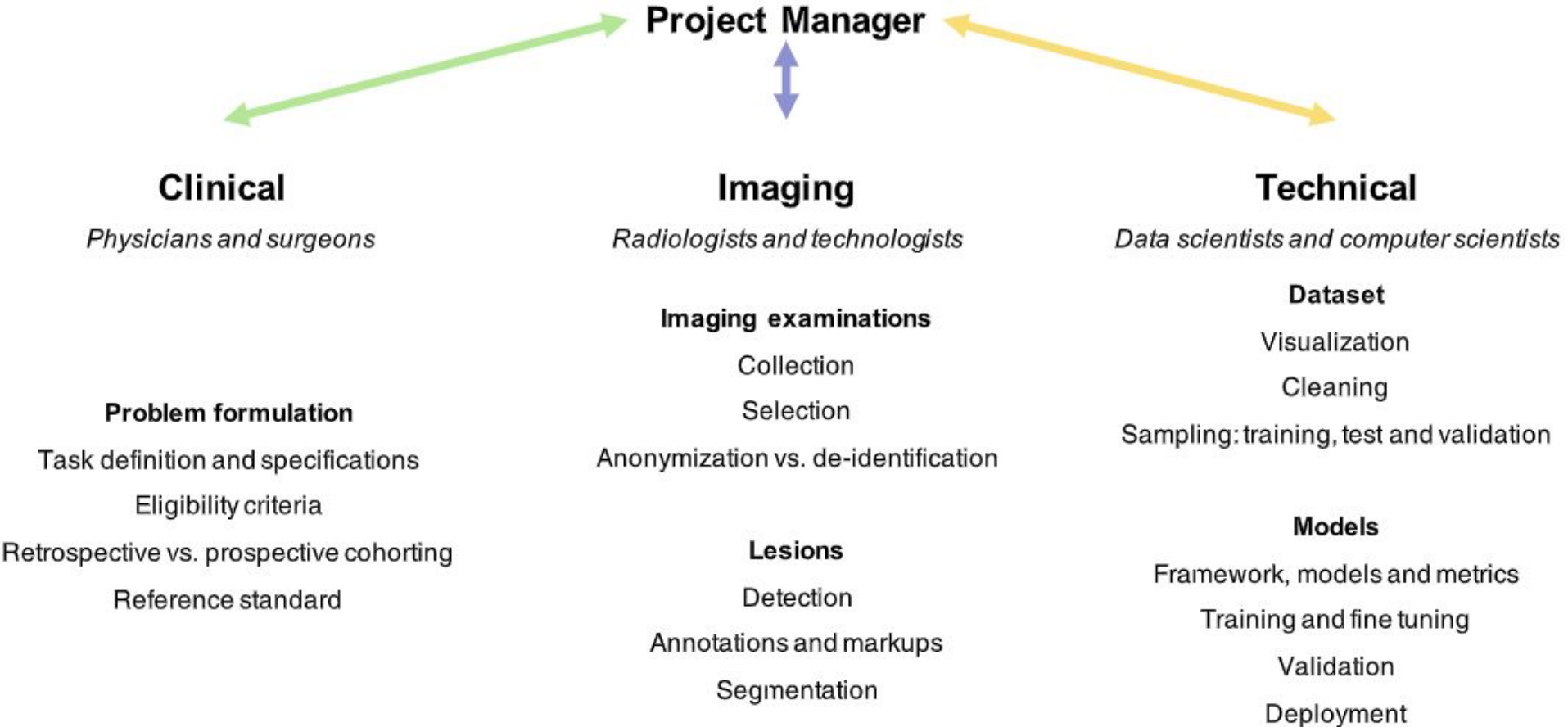


Fig. 1 Potential clinical uses of deep learning techniques. Tasks such as monitoring of treatment response or prediction of survival, can be derived from lesion detection, classification, and longitudinal follow-up

BRISQ

Metrics

	Detection	Segmentation	Classification	Prediction
Features	-Bounding boxes -Masks	-Lesion patch -Full image at max diameter -Radiomics features -Masks	-Lesion patch -Radiomic features	-Lesion patch -Time to recurrence -Survival time -TRG
Model architectures	-CNN	-U-Net	-Fully connected	-CNN
Performance metrics	-Intersection over union (IOU) -Mean average precision (mAP)	-Dice score -IOU	-Receiver operating characteristic (ROC) -Accuracy	-ROC curve -Accuracy - R^2



Report

nature
medicine

CONSENSUS STATEMENT

<https://doi.org/10.1038/s41591-020-1037-7>



OPEN

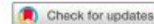
Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension

Samantha Cruz Rivera^{1,2,3}, Xiaoxuan Li^{1,2,3,6,10,11,12},
Melanie J. Calvert^{1,2,3,6,10,11,12}, The SPIRIT-AI
CONSORT-AI Steering Group and SPIRIT-AI

CONSENSUS STATEMENT

<https://doi.org/10.1038/s41591-020-1034-x>

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Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension

Xiaoxuan Liu^{1,2,3,4,5}, Samantha Cruz Rivera^{5,6,7}, David Moher^{8,9}, Melanie J. Calvert^{4,5,6,7,10,11,12},
Alastair K. Denniston^{2,3,4,5,6,13} and The SPIRIT-AI and CONSORT-AI Working Group*

Learn more

Lambin P, Rios-Velazquez E, Leijenaar R et al (2012) Radiomics: extracting more information from medical images using advanced feature analysis. *Eur J Cancer* 48:441–446

Gebu T, Morgenstern J, Vecchione B et al (2018) Datasheets for datasets. Available via <https://arxiv.org/abs/1803.09010>. Accessed 3 Sept 2020

SPIRIT-AI and CONSORT-AI Consensus Group, 2020. Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension. *Nat. Med.* 26, 1351–1363.

SPIRIT-AI and CONSORT-AI Working Group, 2020. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension. *Nat. Med.* 26, 1364–1374.