Deep Learning Opportunities in Cancer Imaging

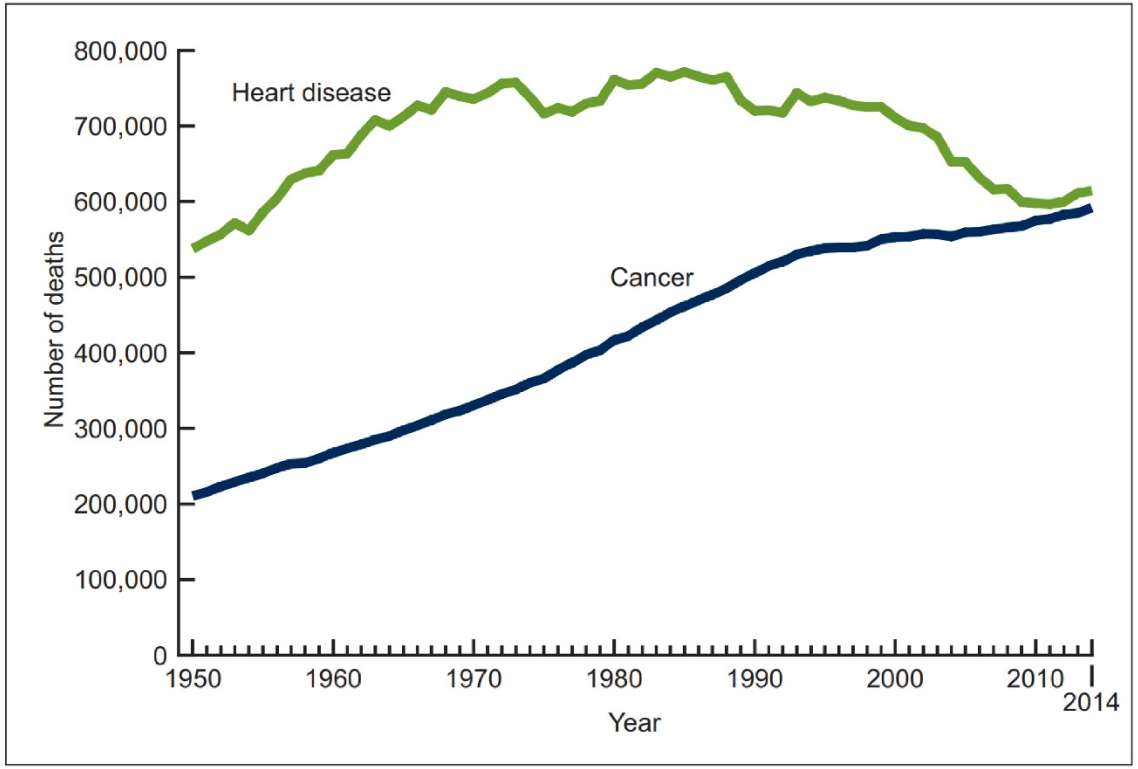
Ahmed Hosny

HARVARD MEDICAL SCHOOL | BRIGHAM AND WOMEN'S HOSPITAL | DANA-FARBER CANCER INSTITUTE

RE•WORK Deep Learning in Healthcare Summit
Boston, May 2018

Cancer is a Big Deal

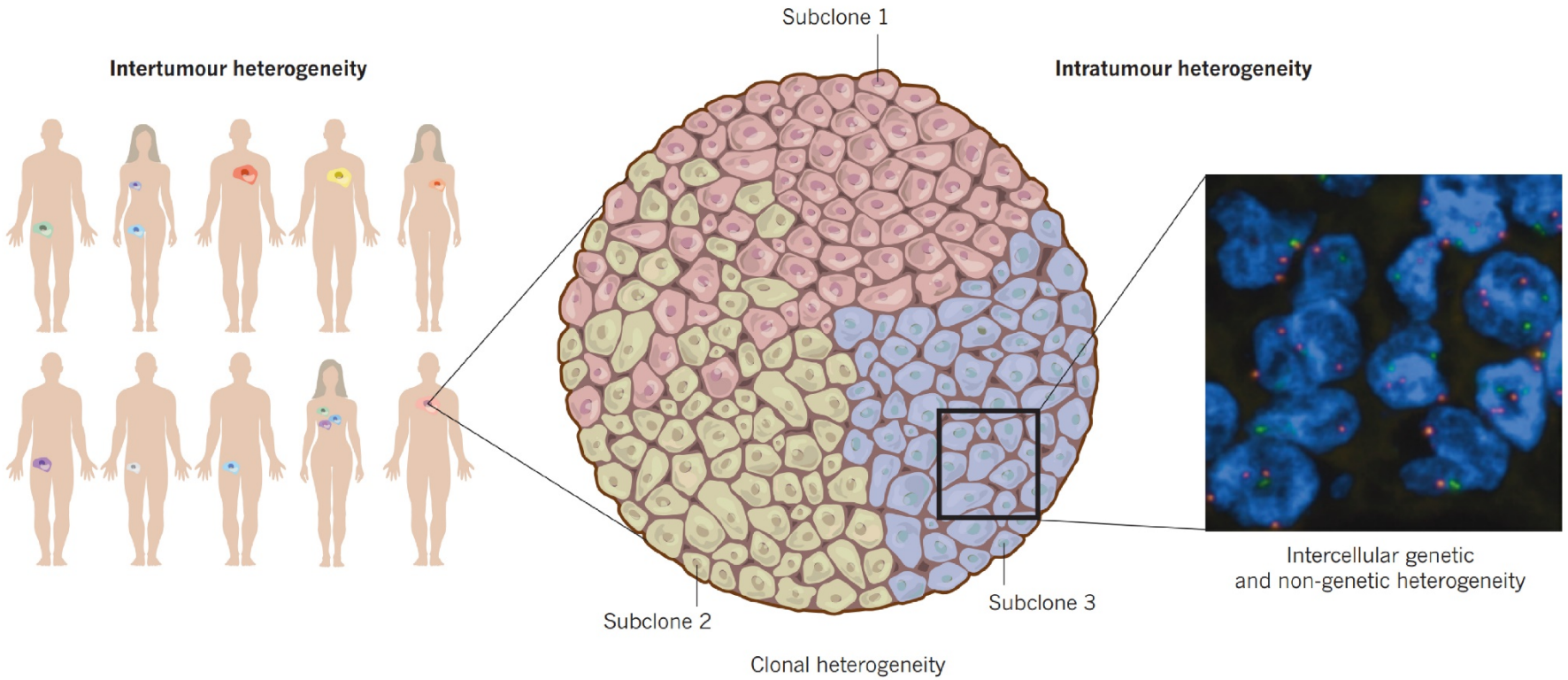
Figure 1. Number of deaths due to heart disease and cancer: United States, 1950–2014



Centers for Disease Control and Prevention

Changes in the Leading Cause of Death: Recent Patterns in Heart Disease and Cancer Mortality
https://www.cdc.gov/nchs/data/databriefs/db254.pdf

Intra-tumor Heterogeneity



Rebecca A Burrell, Nicholas McGranahan, Jiri Bartek, and Charles Swanton

The Causes and Consequences of Genetic Heterogeneity in Cancer Evolution

Nature - 2013

Early Logic and Statistical Pattern Recognition in Medicine

3 July 1959, Volume 130, Number 3366 SCIENCE

Reasoning Foundations of Medical Diagnosis

Symbolic logic, probability, and value theory aid our understanding of how physicians reason.

Robert S. Ledley and Lee B. Lusted

The purpose of this article is to analyze the complicated reasoning processes inherent in medical diagnosis. The importance of this problem has received recent emphasis by the increasing interest in the use of electronic computers as an aid to medical diagnostic processes (*1*, *2*). Before computers can be used effectively for such purposes, however, we need to know more about how the physician makes a medical diagnosis.

If a physician is asked, "How do you make a medical diagnosis?" his answer tion of the process m "First, I obtain the patient's history, ph and laboratory tests. the relative importan signs and symptoms. may be of first-orde other data of less im make a differential the diseases which th reasonably resemble. disease after another from the list until it becomes apparent that the case can be fitted into a definite disease category, or that it may be one of several possible diseases, or else that its exact nature cannot be determined." This, obviously, is a greatly simplified explanation of the process of diagnosis, for the physician might also comment that after seeing a patient he often has a "feeling about the case." This "feeling," although hard to explain, may be a summation of his impressions concerning the way the data seem to fit together, the patient's reliabi general appearance, facial expres be integrated by the physician with a large store of possible diseases. It is widely believed that errors in differential diagnosis result more frequently from errors of omission than from other sources. For instance, concerning such errors of omission, Clendening and Hashinger (*3*) say: "How to guard against incompleteness I do not know. But I do know that, in my judgment, the most brilliant diagnosticians of my acquaintance are the ones who do remember and consider the most possibilities."

Computers are especially suited to help the physician collect and process clinical information and remind him of diagnoses which he may have overlooked. In many cases computers may be as simple as a set of hand-sorted cards, whereas in other cases the use of a large-scale digital electronic computer may be indicated. There are other ways in which computers may serve the physician, and some of these are suggested in this paper. For example, medical students might find the computer an important aid in learning the methods of differential diagnosis. But to use the computer thus we must understand how the physician makes a medical diagnosis. This, then, brings us to the subject of our investigation: the reasoning foundations of medical diagnosis and treatment.

Medical diagnosis involves processes that can be systematically analyzed, as well as those characterized as "intangible." For instance, the reasoning foundations of medical diagnostic procedures are precisely analyzable and can be separated from certain considered intangible judgments and value decisions. Such a separation has several important advantages. First, systematization of the reasoning process enables the physician to can be developed. However, a consideration of foundations is always essential as the first step in the development of practical applications.

The reasoning foundations of medical diagnosis and treatment can be most precisely investigated and described in terms of certain mathematical techniques. Before material to illustrate these techniques was selected, many of the *New England Journal of Medicine*

Dr. Ledley is a part-time member of the staff of the National Academy of Sciences-National Research Council, Washington, D.C., where he is principal investigator of the Survey and Monograph on Electronic Computers in Biology and Medicine. He is on the faculty of the electrical engineering department of George Washington University and mathematician at the Data Processing Systems Division of the National Bureau of Standards. Dr. Lusted is radiologist and associate professor at the University of Rochester School of Medicine, Rochester, N.Y.

3 JULY 1959

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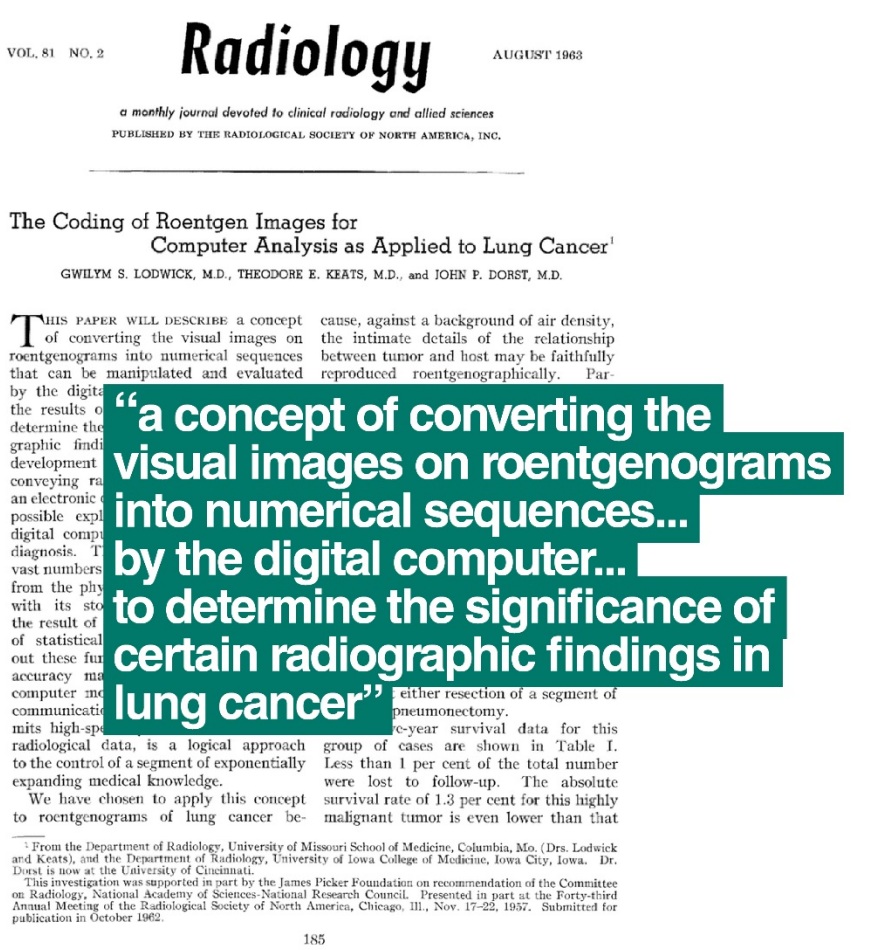
"increasing interest in the use of electronic computers as aid to medical diagnostic processes"

Robert S Ledley and Lee B Lusted

Reasoning Foundations of Medical Diagnosis

Science - 1959



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 Cancer[1]

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 digita the results o determine the graphic findi development conveying ra an electronic possible expl digital compu diagnosis. T vast numbers from the phy with its sto the result of of statistical out these fu accuracy ma computer me communicati mits high-sp radiological data, is a logical approach to the control of a segment of exponentially expanding medical knowledge.

We have chosen to apply this concept to roentgenograms of lung cancer because, against a background of air density, the intimate details of the relationship between tumor and host may be faithfully reproduced roentgenographically. Par- either resection of a segment of pneumonectomy. re-year survival data for this group of cases are shown in Table I. Less than 1 per cent of the total number were lost to follow-up. The absolute survival rate of 1.3 per cent for this highly malignant tumor is even lower than that

[1] From the Department of Radiology, University of Missouri School of Medicine, Columbia, Mo. (Drs. Lodwick and Keats), and the Department of Radiology, University of Iowa College of Medicine, Iowa City, Iowa. Dr. Dorst is now at the University of Cincinnati.

This investigation was supported in part by the James Picker Foundation on recommendation of the Committee on Radiology, National Academy of Sciences-National Research Council. Presented in part at the Forty-third Annual Meeting of the Radiological Society of North America, Chicago, Ill., Nov. 17–22, 1957. Submitted for publication in October 1962.

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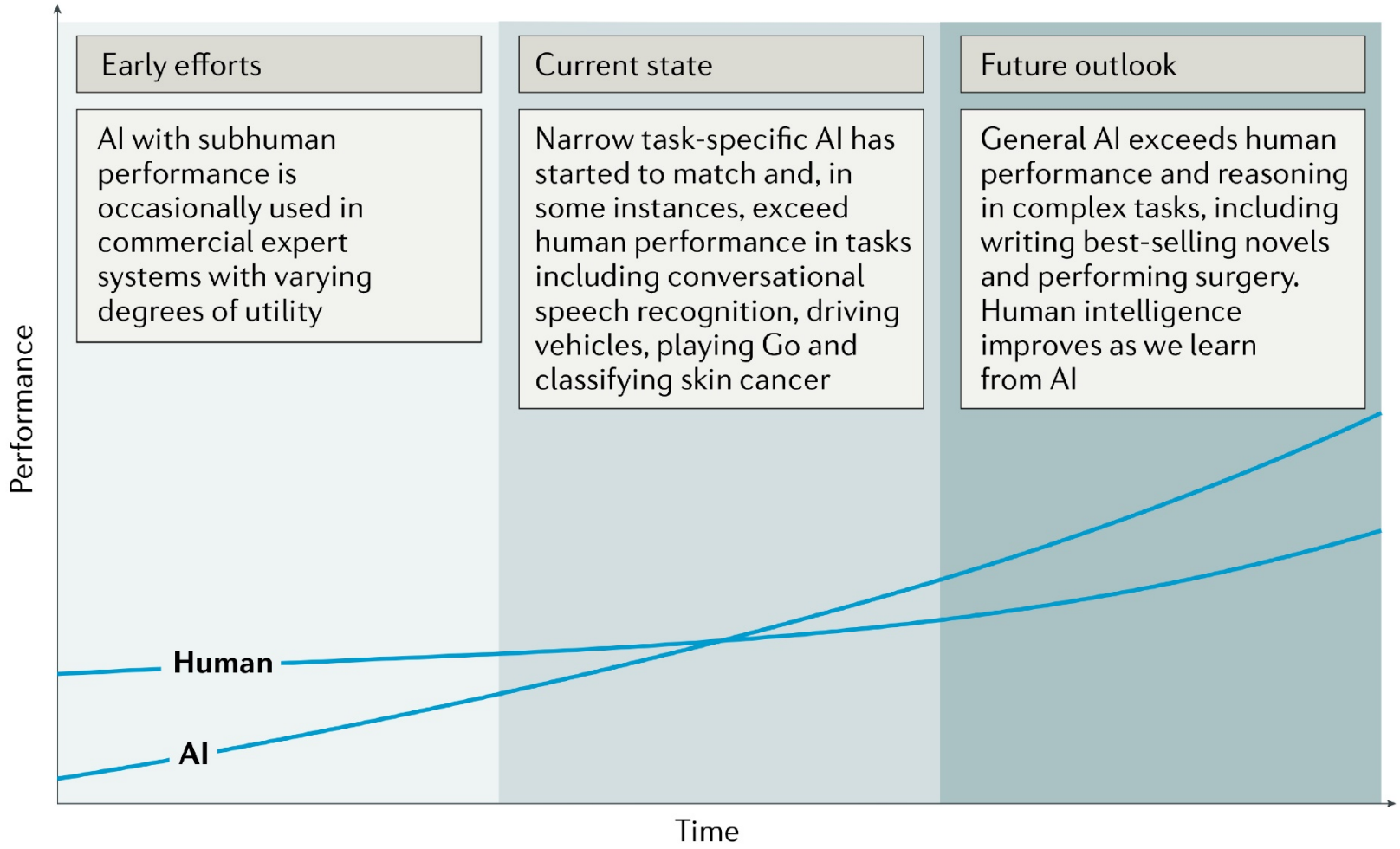
"a concept of converting the visual images on roentgenograms into numerical sequences... by the digital computer... to determine the significance of certain radiographic findings in lung cancer"

Gwilym S Lodwick, Theodore E Keats and John P Dorst

The Coding of Roentgen images for computer analysis as applied to lung cancer

Radiology - 1963

Artificial vs. Human Intelligence



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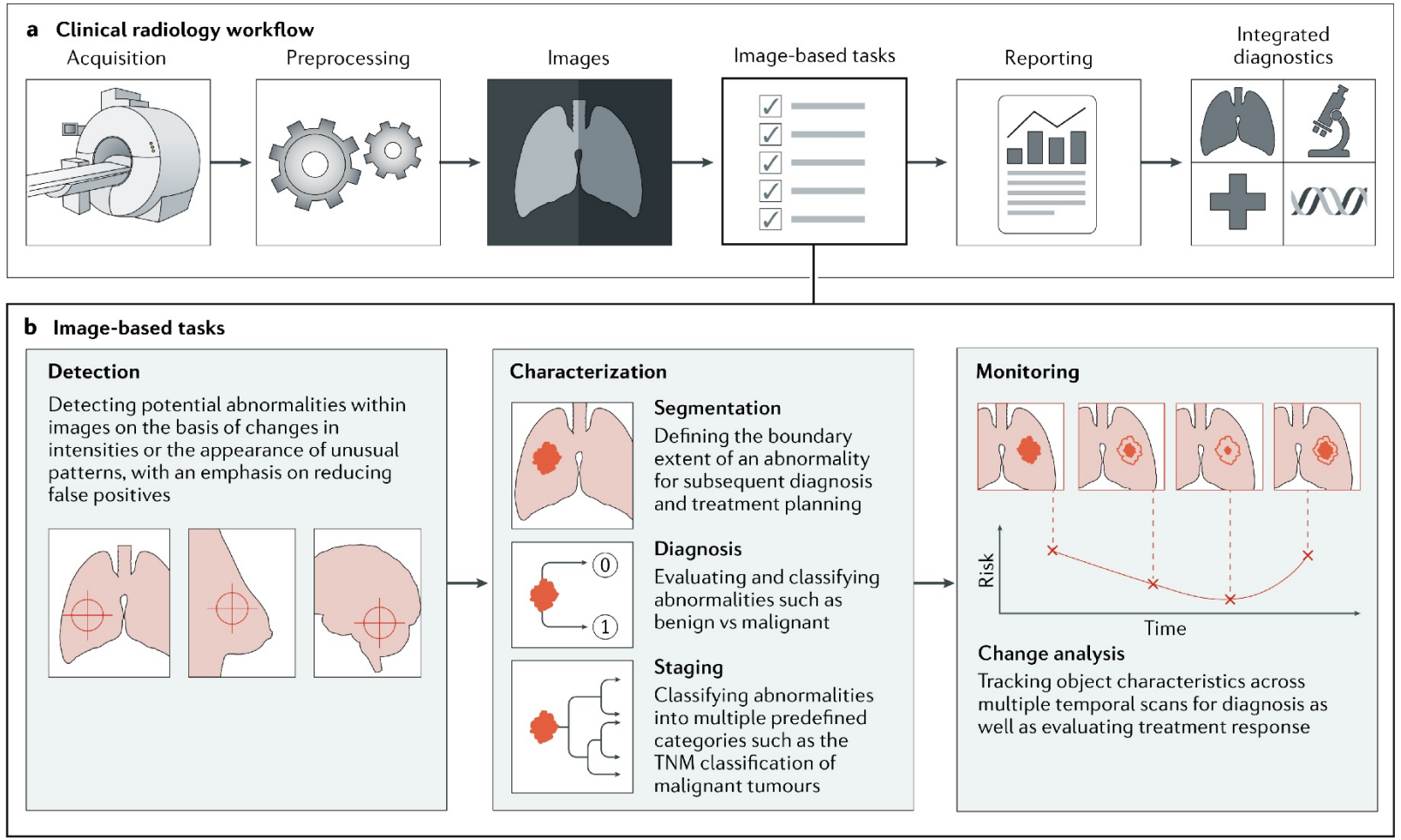
Artificial Intelligence in Radiology

Nature Reviews Cancer - 2018

Artificial Intelligence Impact Areas within Oncology Imaging



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Prognosis

Because statistics are based on large groups of people, they cannot be used to predict exactly what will happen to you. **Everyone is different. Treatments and how people respond to treatment can differ greatly.** Also, it takes years to see the benefit of new treatments and ways of finding cancer. So, the statistics your doctor uses to make a prognosis may not be based on treatments being used today.

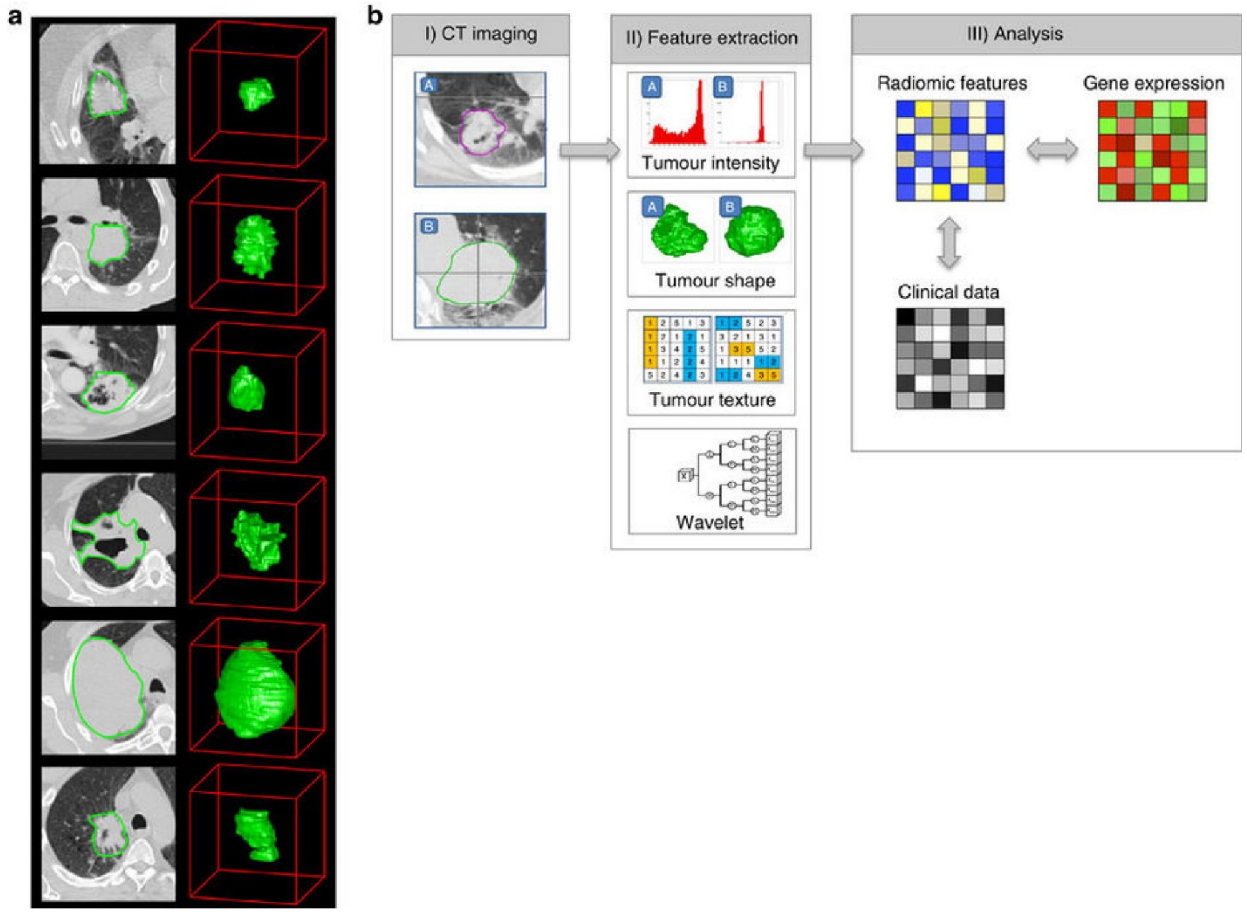
Still, your doctor may tell you that you have a good prognosis if statistics suggest that your cancer is likely to respond well to treatment. Or, he may tell you that you have a poor prognosis if the cancer is harder to control. **Whatever your doctor tells you, keep in mind that a prognosis is an educated guess.** Your doctor cannot be certain how it will go for you.

National Institutes of Health - National Cancer Institute

Understanding Cancer Prognosis

https://www.cancer.gov/about-cancer/diagnosis-staging/prognosis

Tumor Phenotyping in 2014



Hugo JWL Aerts, Emmanuel R Velazquez, Ralph TH Leijenaar, et al.

Decoding Tumour Phenotype by Noninvasive Imaging using a Quantitative Radiomics Approach

Nature Communications - 2014

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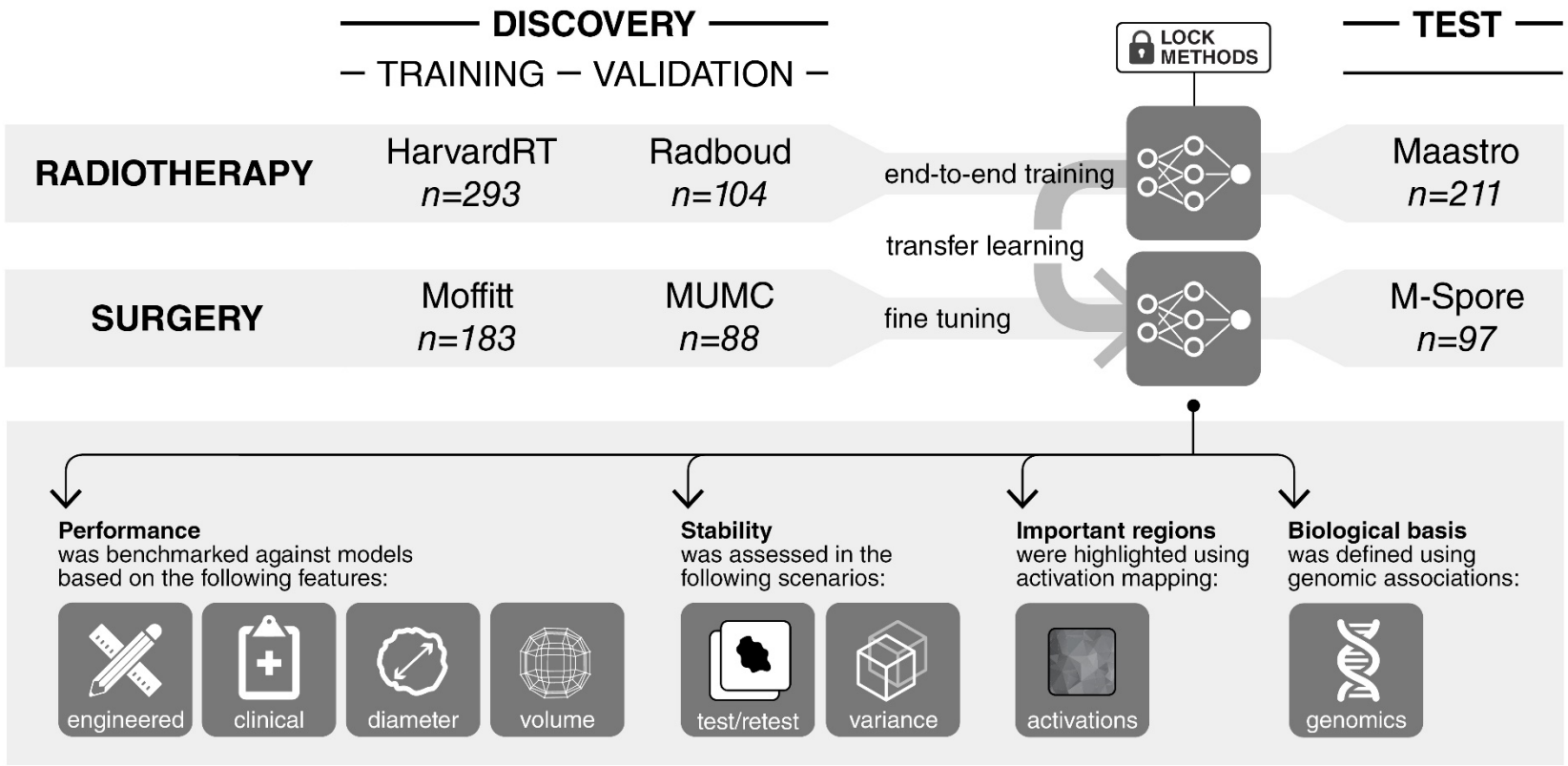
Deep Learning for Automated Quantification of Radiographic Tumor Phenotypes

Under Review

Analytical Setup



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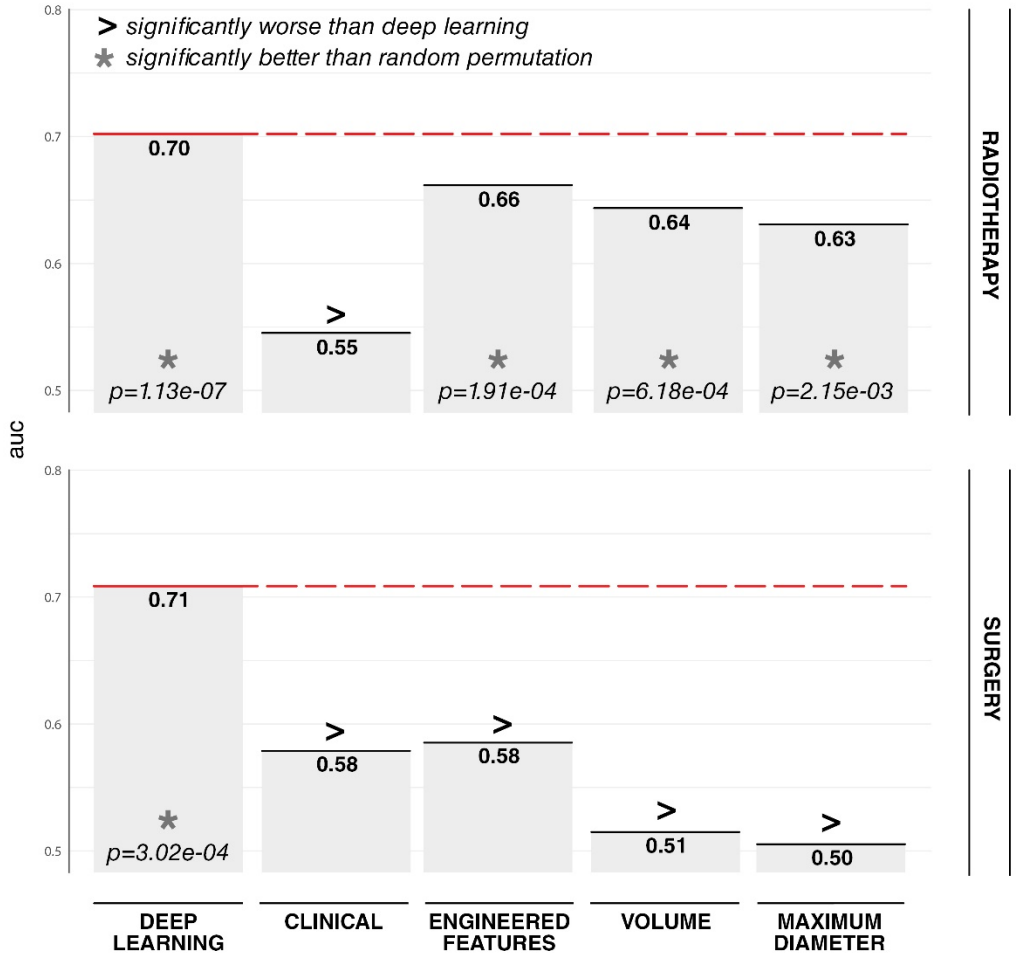
Under Review

Benchmarking



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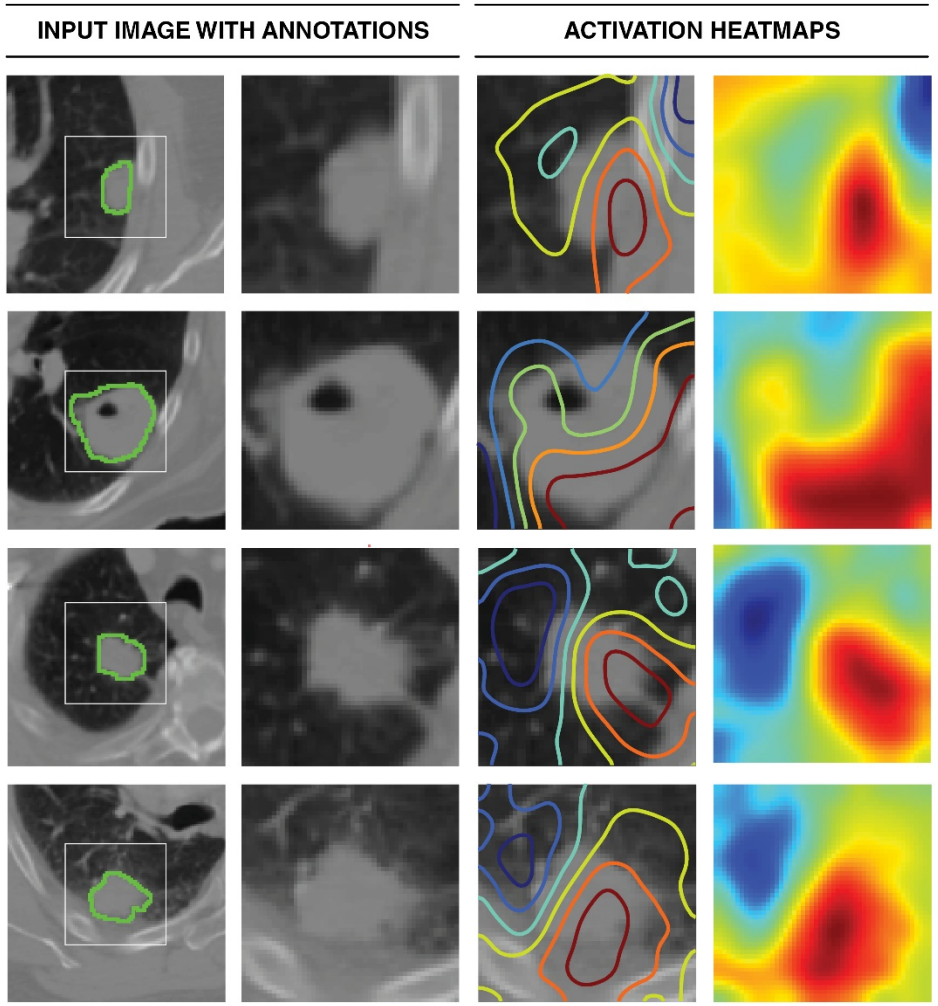
Activation Mapping



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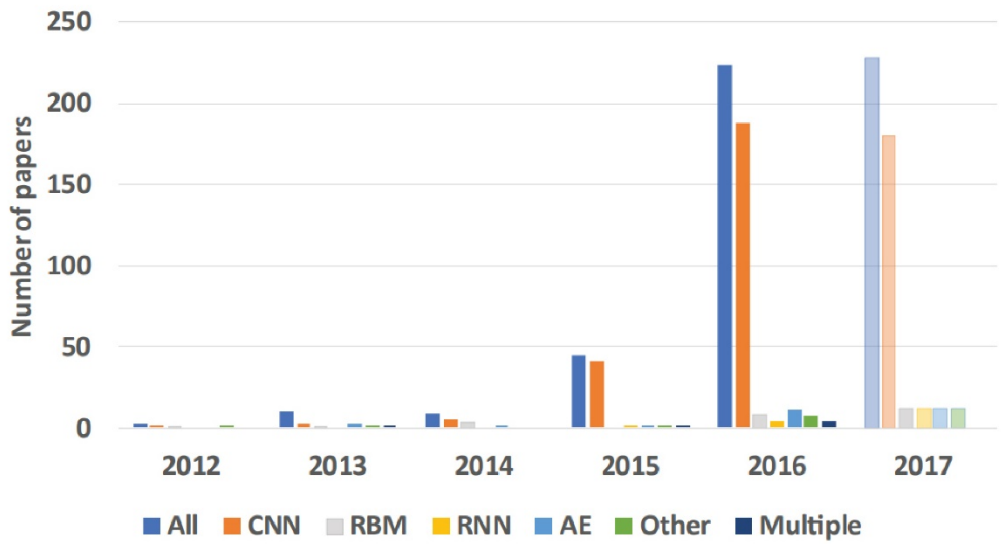
State of the Art



Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, et al.

A Survey on Deep Learning in Medical Image Analysis

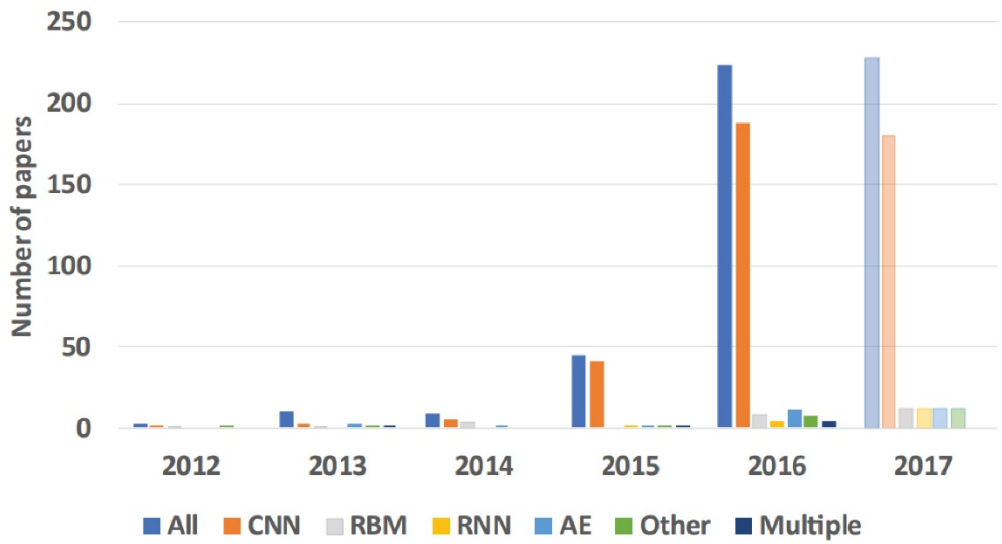
Medical Image Analysis - 2017

Misc.

Open-Source Deep Learning Tools

github.com

State of the Art



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Flying Blind

Resources to facilitate an informed conversation about AI

Understand the larger context of our efforts

Effectively measure and communicate progress

Ahmed Hosny and Hugo JWL Aerts

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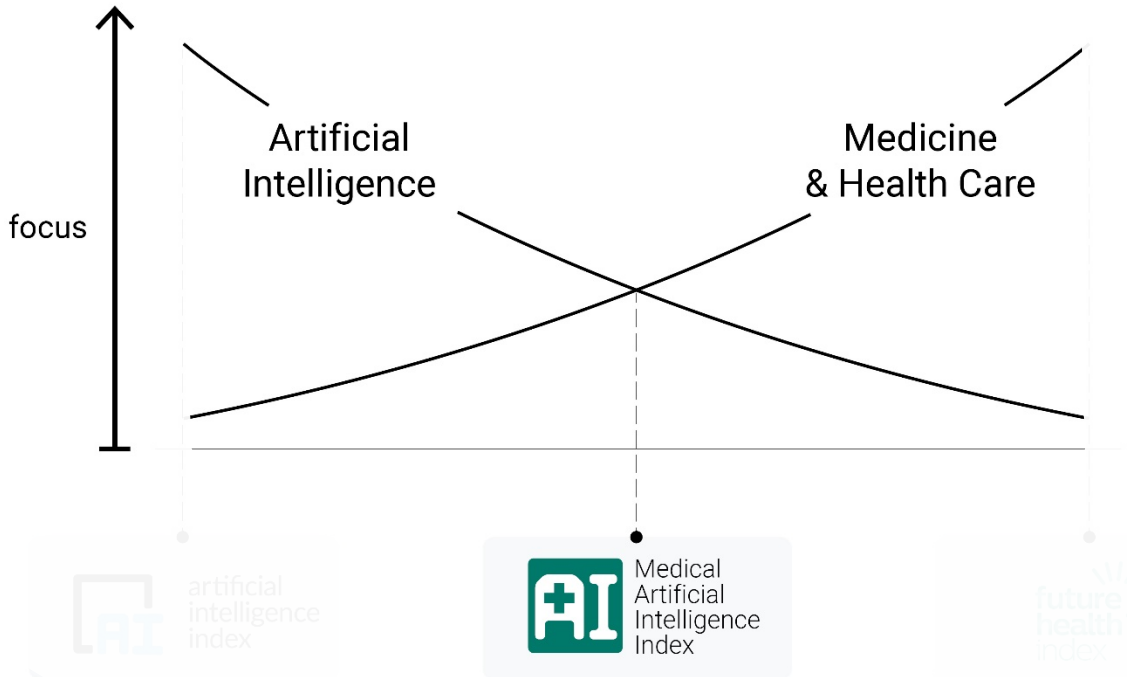

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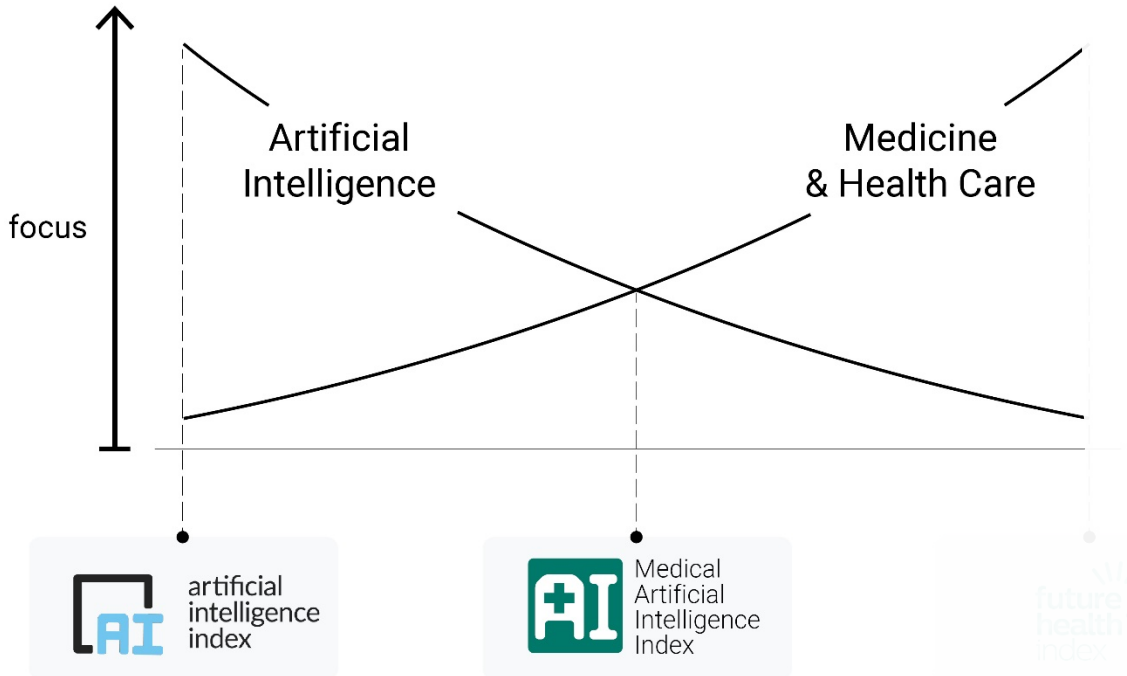

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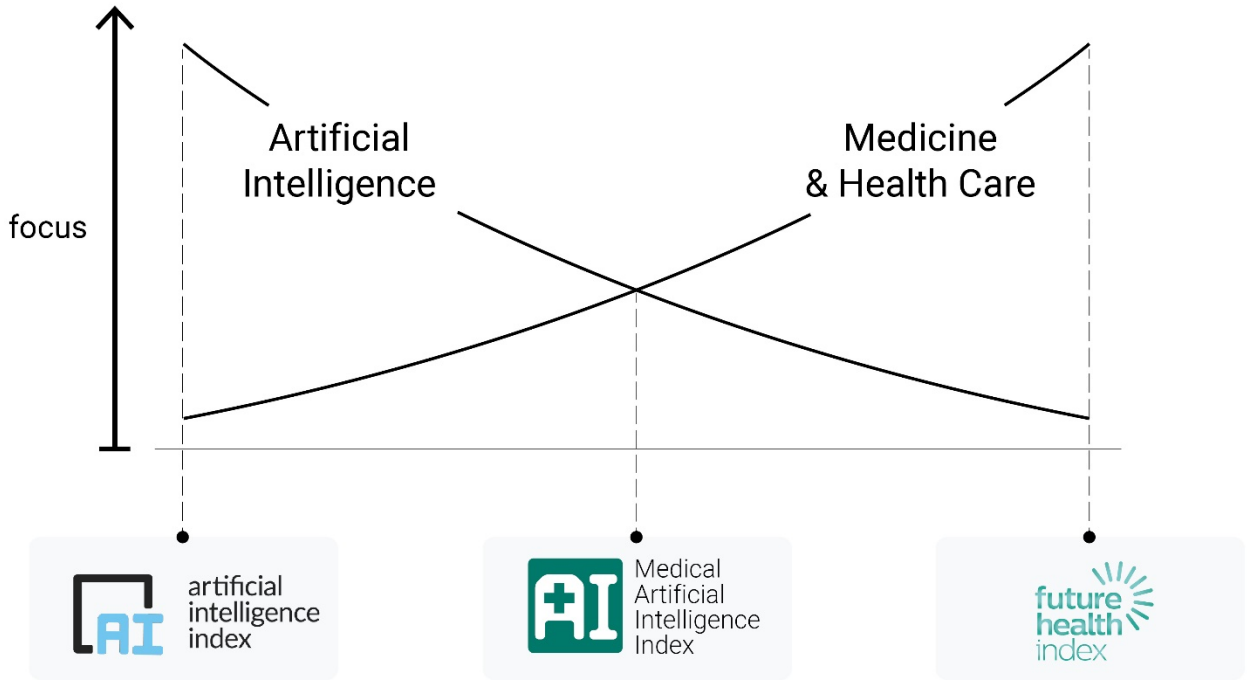

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Audience


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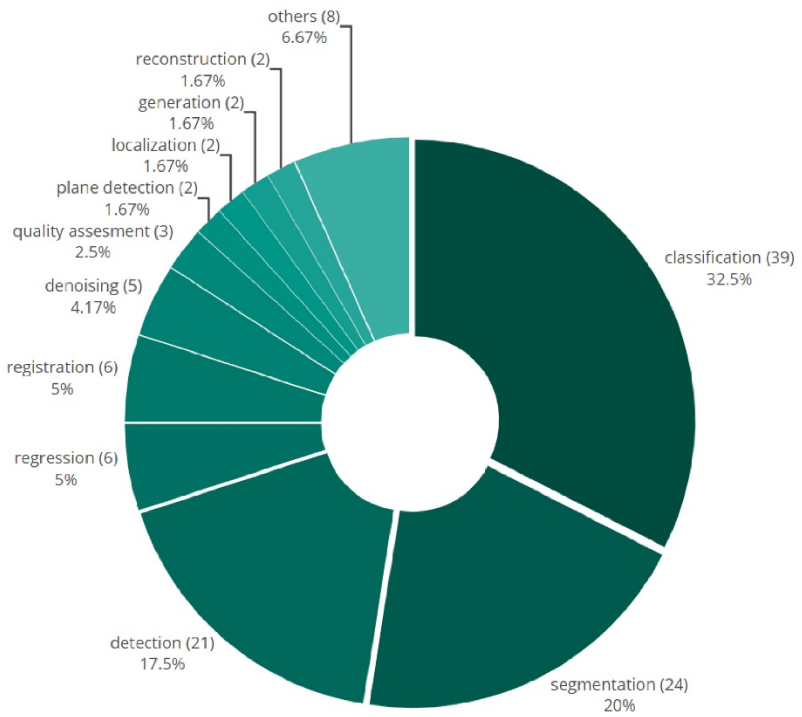
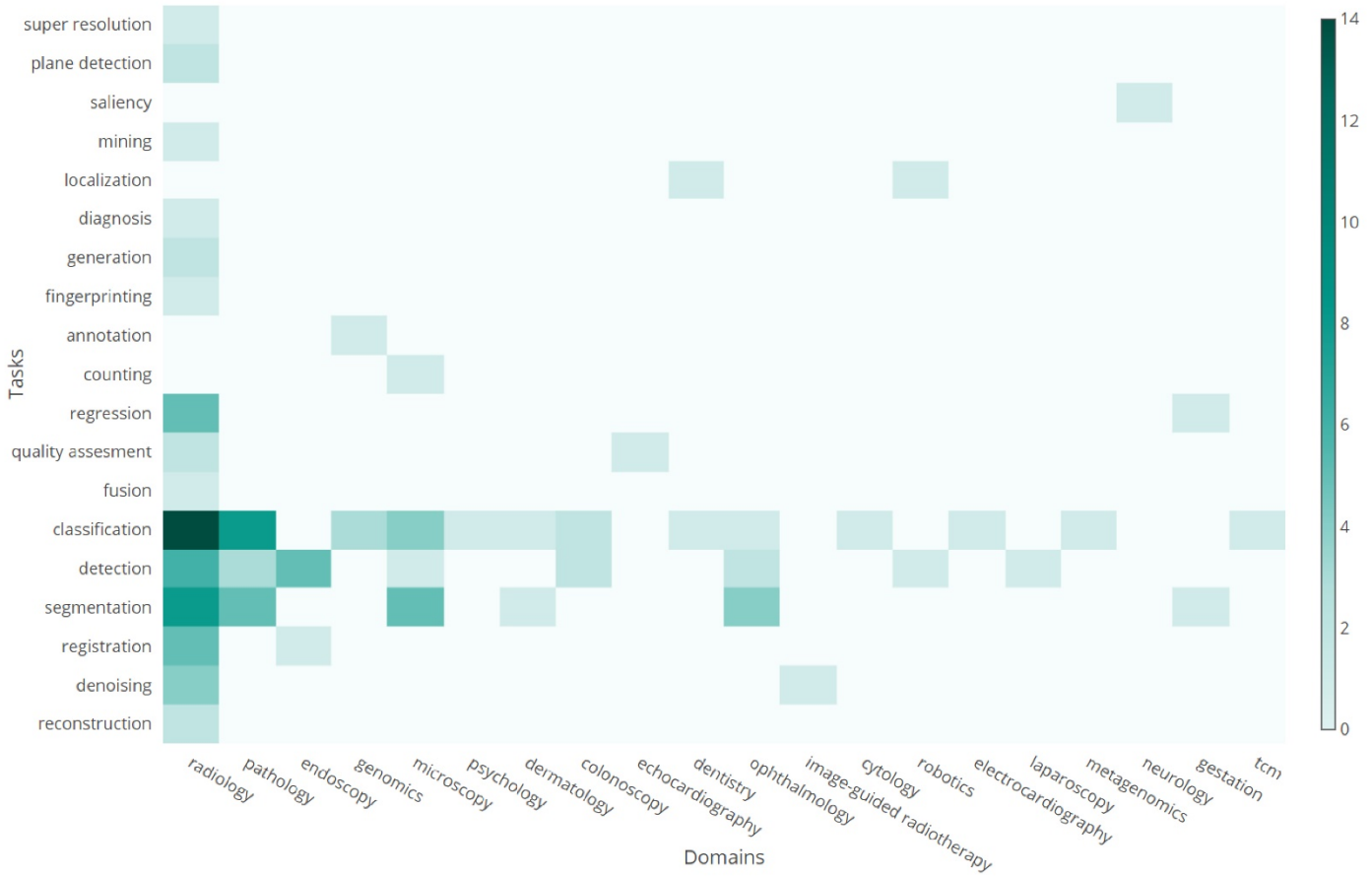
regulatory agencies
AI
Medical Artificial Intelligence Index
researchers
journalists

Findings - Statistics





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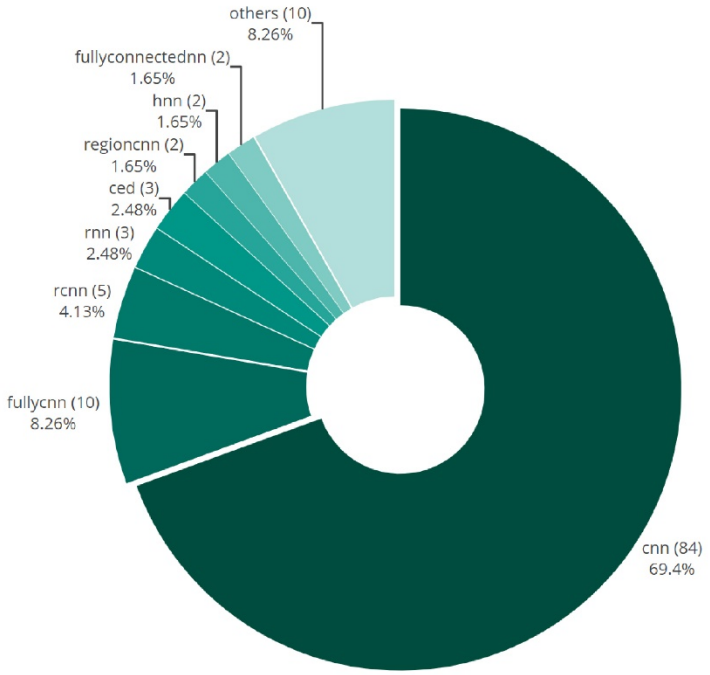
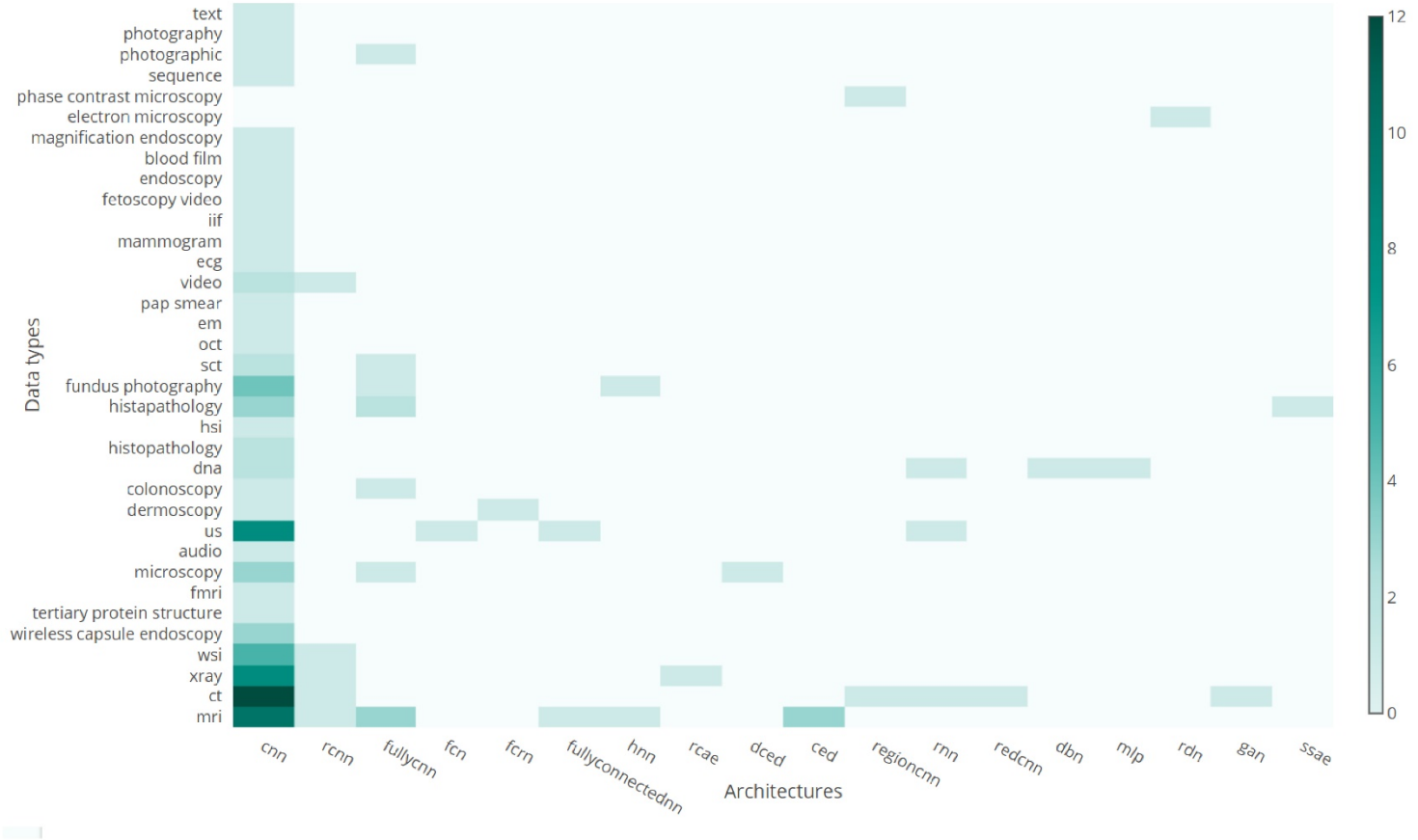
Findings - Statistics





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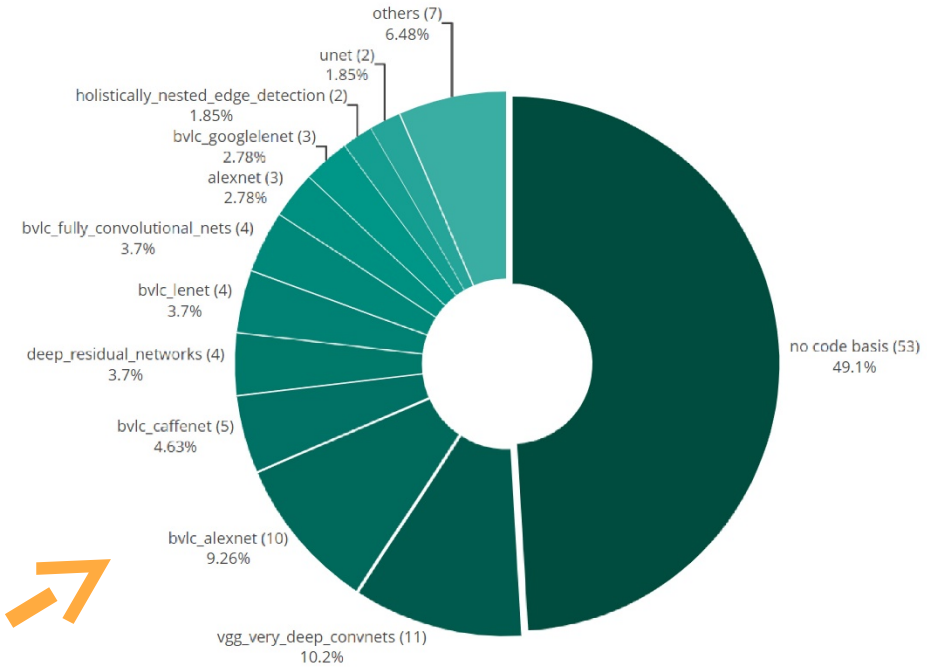
Findings - Reproducibility



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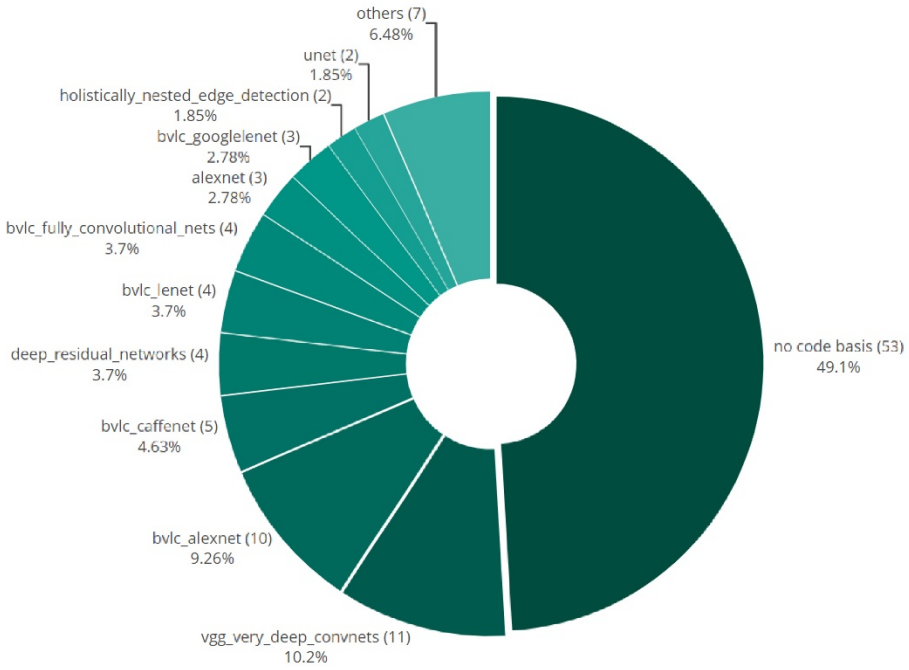

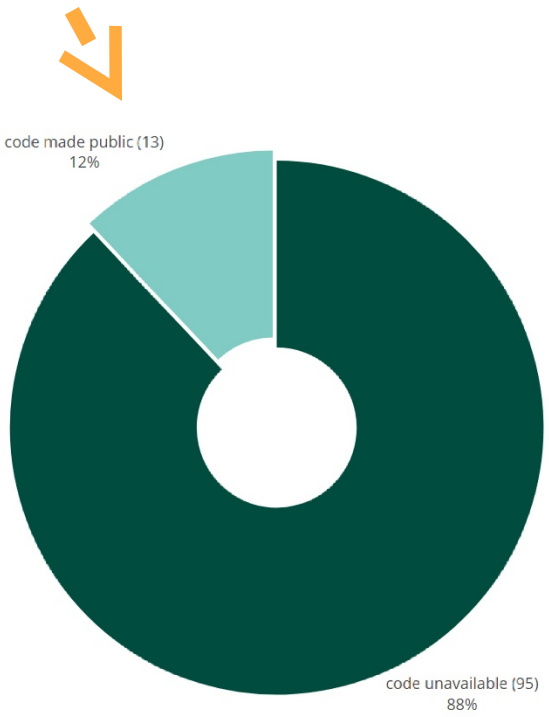

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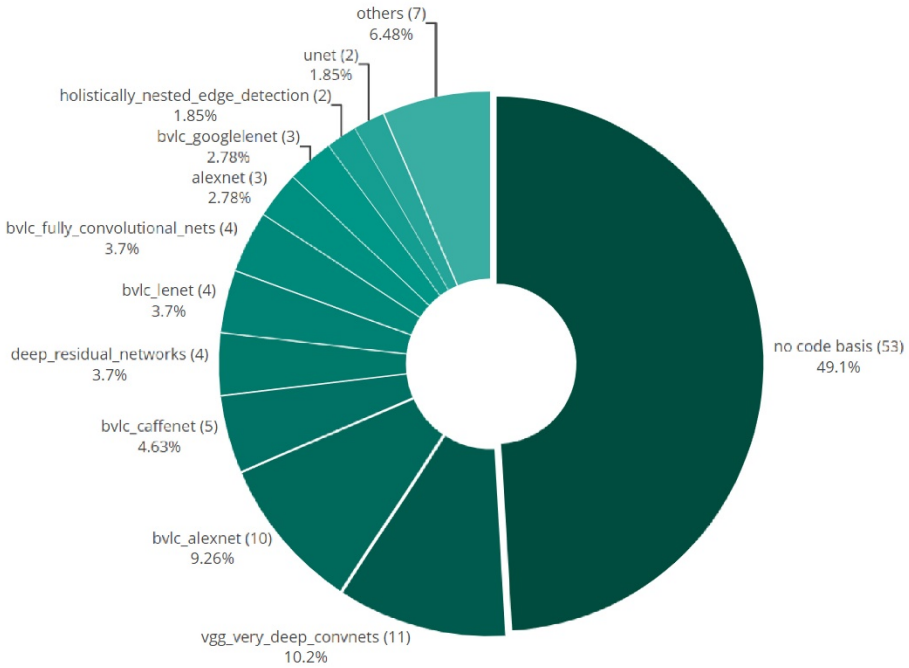

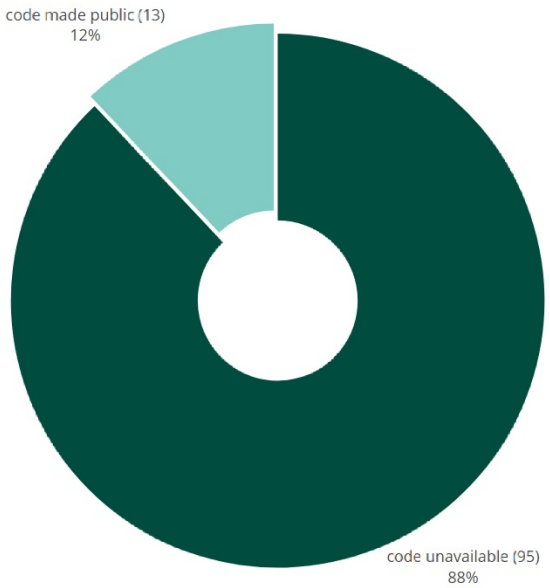

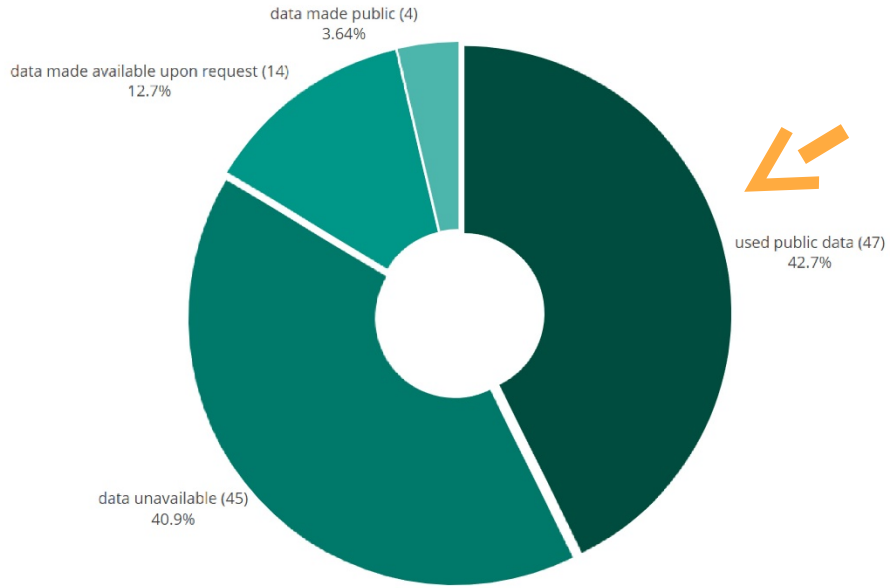

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Existing Solutions

houseroad Rename ZFNet to ZFNet-512 (#36) — Latest commit 3be4824 11 hours ago

bvlc_alexnet	Update bvlc_alexnet model	4 months ago
bvlc_googlenet	Add the value_info.json for the remaining of the models except style ...	3 months ago
bvlc_reference_caffenet	Add the value_info.json for the remaining of the models except style ...	3 months ago
bvlc_reference_rcnn_ilsvrc13	Add the value_info.json for the remaining of the models except style ...	3 months ago
densenet121	Add DenseNet-121 model	4 months ago
detectron	Add Detectron e2e_faster_rcnn_R-50-C4_2x model	3 months ago
inception_v1	Add Inception models	4 months ago
inception_v2	Add Inception models	4 months ago
resnet50	Add ResNet-50 model	4 months ago
scripts	Add Detectron e2e_faster_rcnn_R-50-C4_2x model	3 months ago
squeezenet	Correct SqueezeNet value_info to 227x227	3 months ago
style_transfer	Add other style transfer models	4 months ago
vgg19	Add VGG models	4 months ago
zfnet512	Rename ZFNet to ZFNet-512 (#36)	11 hours ago
.gitattributes	Remove squeezenet-specific lines from .gitattributes.	4 months ago
LICENSE	Add Apache 2.0 license	4 months ago
README.md	Update README to describe subdirectory access	3 months ago

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Caffe: Convolutional Architecture for Fast Feature Embedding

arxiv.org/abs/1408.5093

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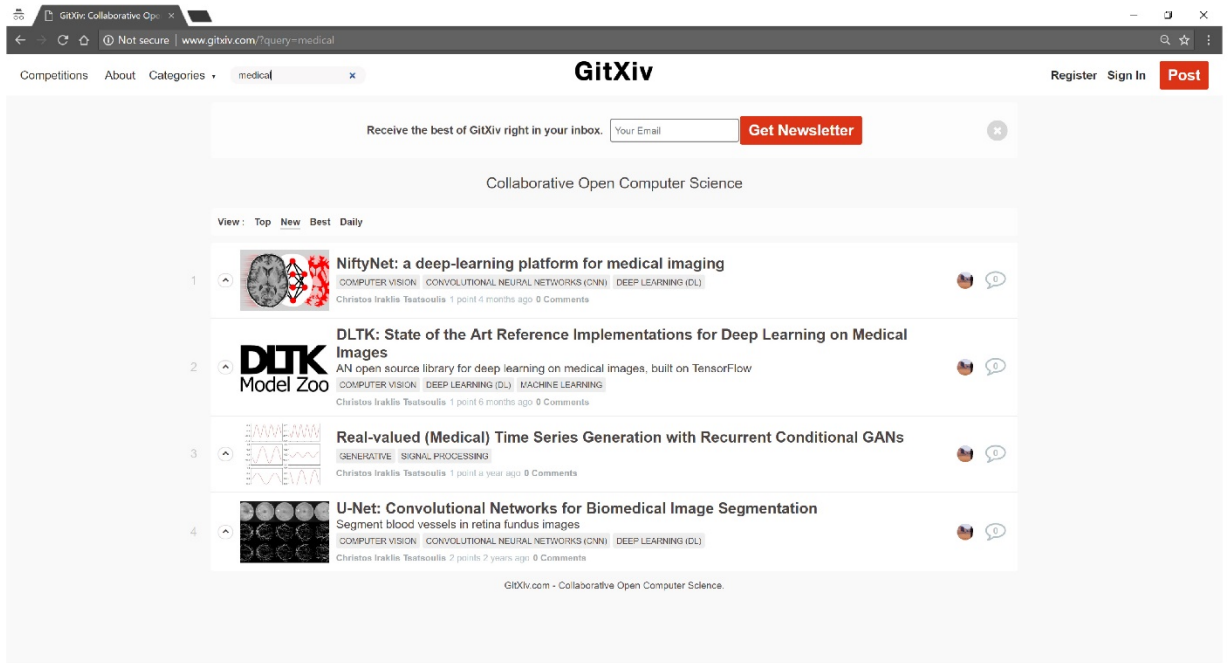

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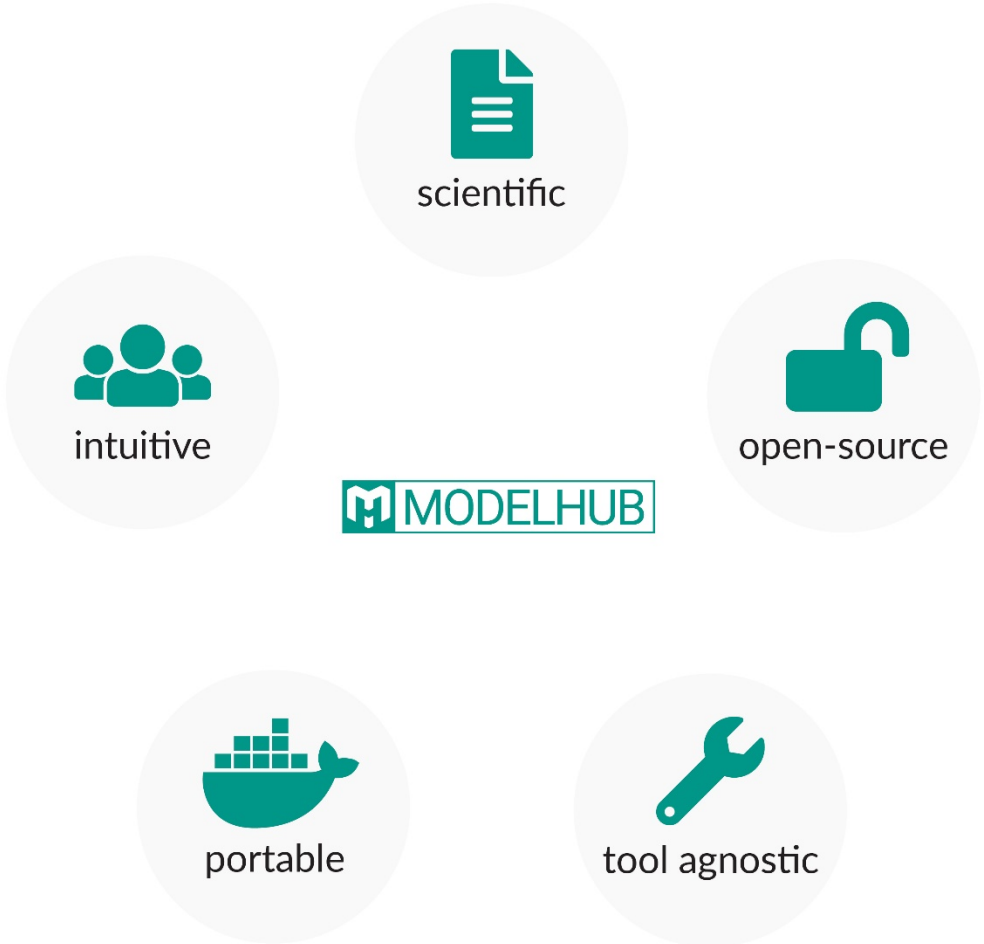
Components



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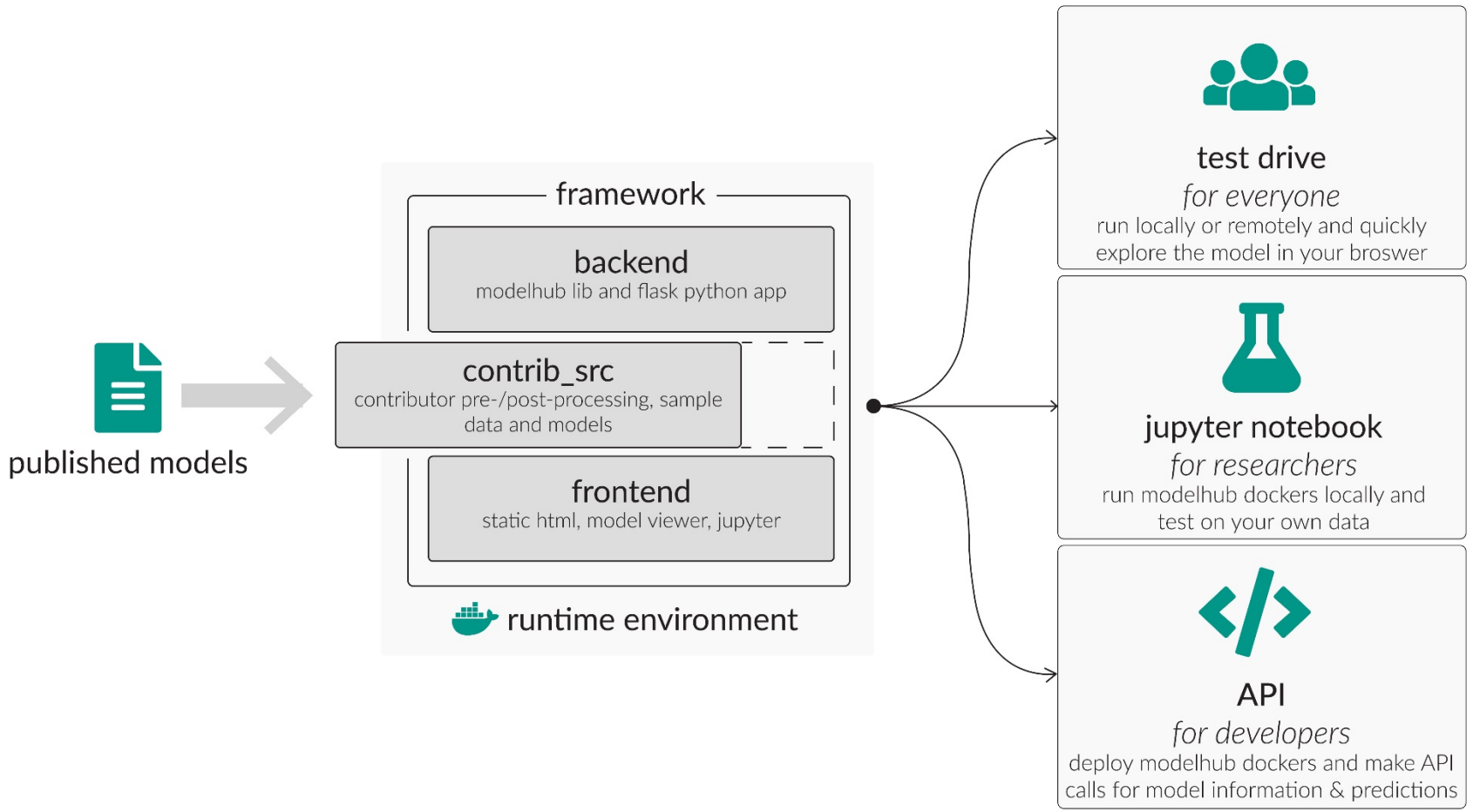
How it Works



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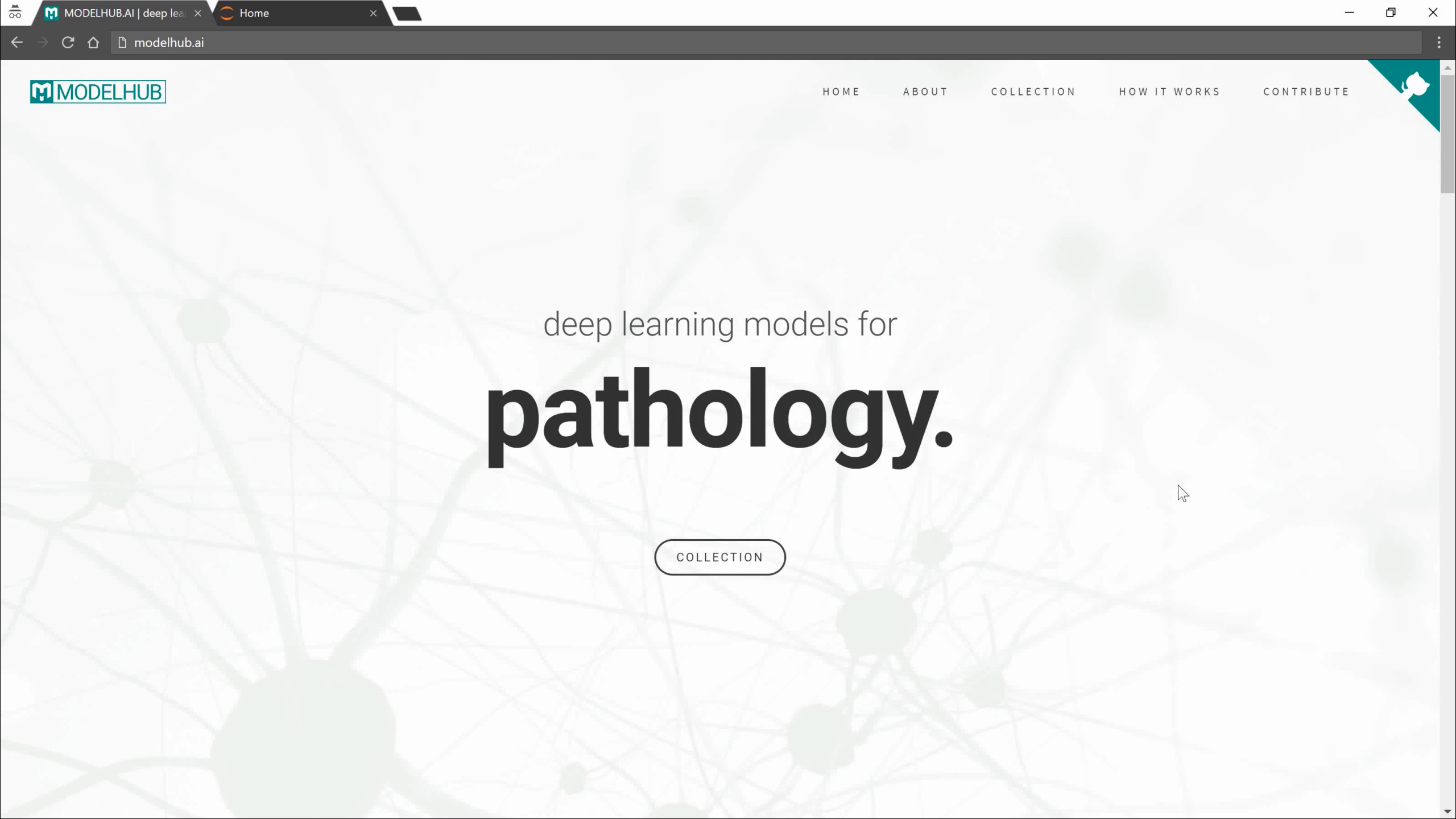
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understand public attitude towards medical AI applications

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Thank you!