Artificial Intelligence in Healthcare: Promises and Pitfalls

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UNIVERSITY OF WATERLOO

Neural Rehab Engineering Lab

Today's lecture

- About me
- Artificial Intelligence (AI) as a 'tool' for Healthcare
  - Supervised learning
  - Why is data so important?
  - Strengths and limitations
- Physician perspective
- Optimistic future

About me

Acquired brain injury and mobility

Fulai

Me

Dave

KellyLee Evans – Juno award winner (R&B)

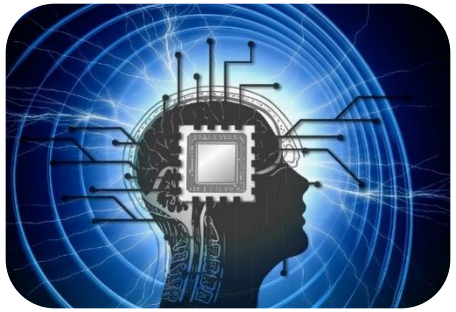
UNIVERSITY OF WATERLOO

Neural Rehab Engineering Lab

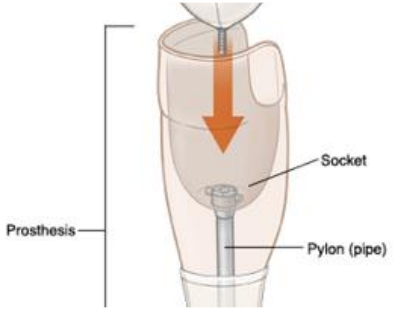
Mission: Advance mobility assistive technology for those with mobility disabilities

Robotic Rollator

Wearables for Parkinson's Disease



Brain-Computer Interface (BCI)



Dynamic Sockets for Prosthetics

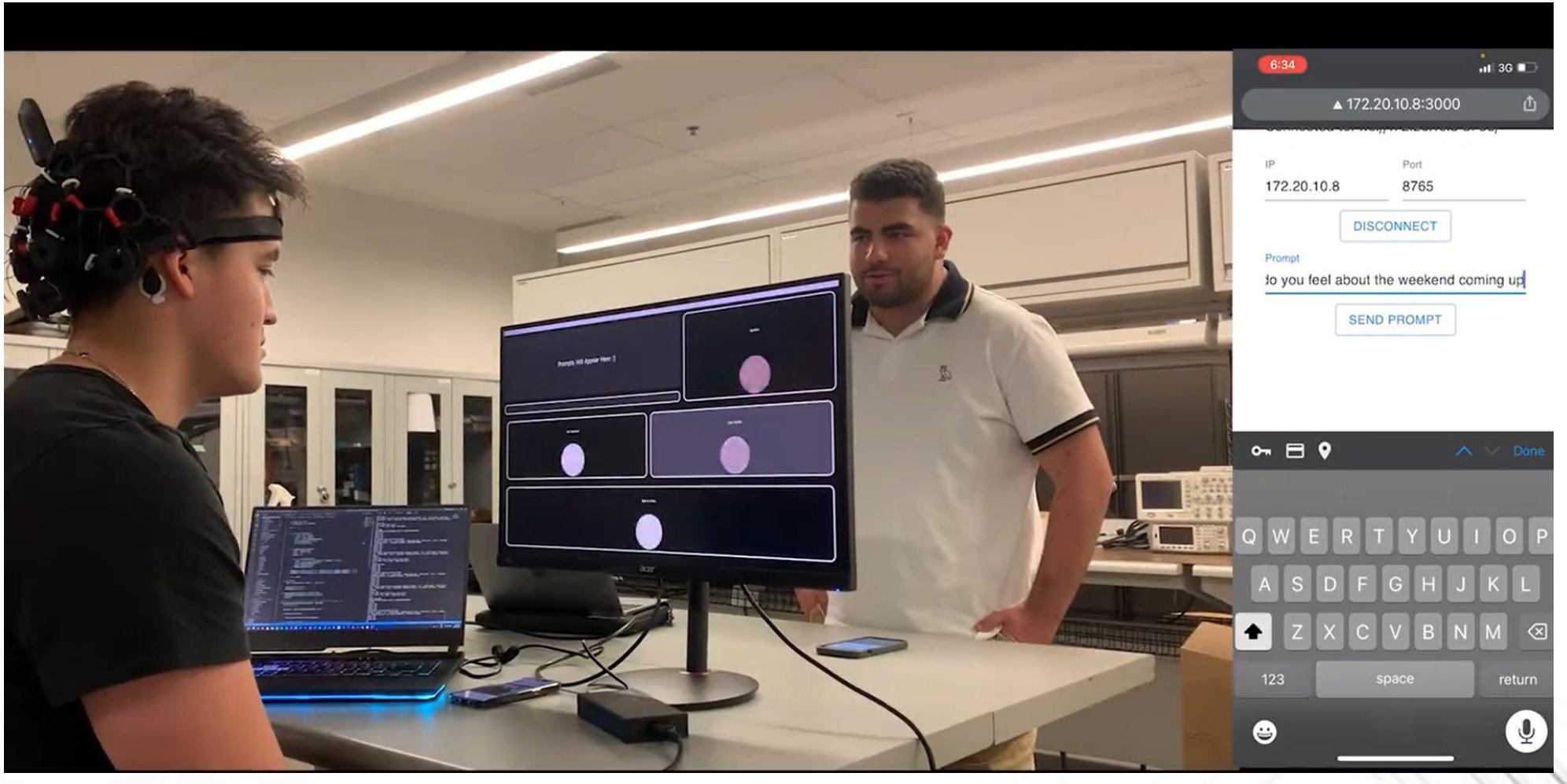
Exoskeleton-user interfaces

Wearable fall risk assessment

Lower limb exoskeletons

Neural Rehab Engineering Lab

Brain-computer interfaces



Artificial Intelligence in Healthcare

What is Artificial Intelligence (AI)?

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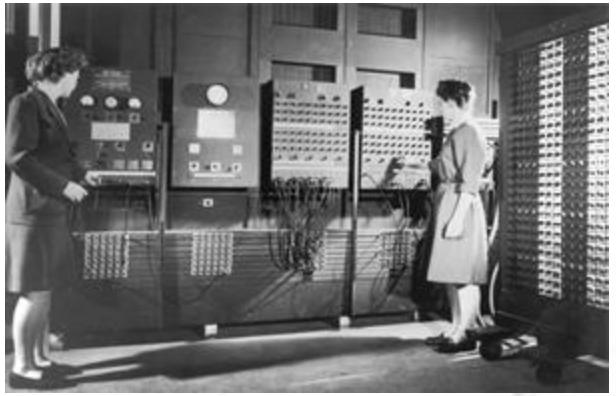
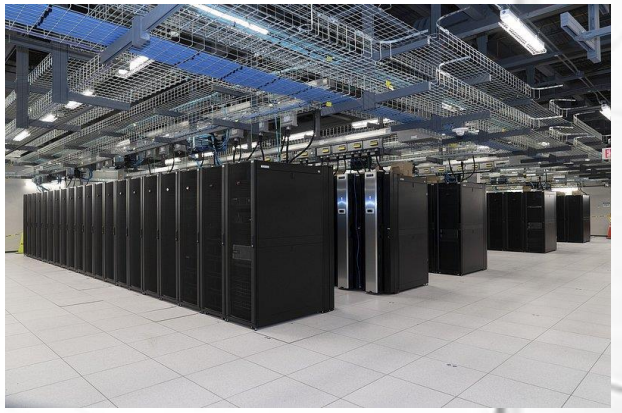
- 1950s: the science and engineering of making intelligent machines

- Today: mostly directed at getting computers to make inferences and decisions that have traditionally required human insight





Artificial Intelligence

Artificial Intelligence (AI) systems can be broadly classified into systems that learn and systems that do not learn.

AI System That Do Not Learn

AI Systems That Learn

Some AI systems do not learn. Examples include expert systems and classical planning systems

Artificial Intelligence

Artificial Intelligence (AI) systems can be broadly classified into systems that learn and systems that do not learn.

AI System That Do Not Learn	**AI Systems That Learn**

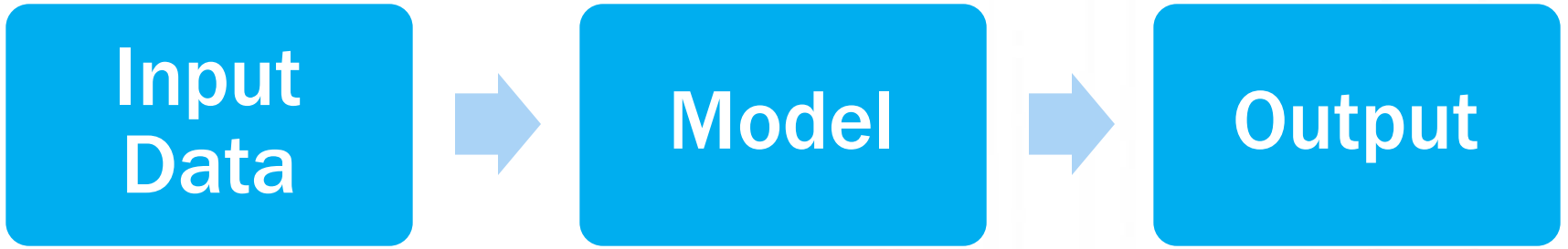
Modern AI focuses on systems that learn, which improves its performance as it integrates new information. These and related approaches are collectively called **machine learning**, or ML.

Machine learning also has a more practical connotation than the term “AI” in that the emphasis of ML is on solving narrower, practical problems rather than trying to create intelligence.

Supervised Learning

Machine Learning in Healthcare

- Mostly using a type of ML called supervised learning



- Building models that can predict, infer, or make decision from given input data

Machine Learning in Healthcare

- Mostly using a type of ML called supervised learning

Dataset

- Uses examples with input data and known outputs (or labels)

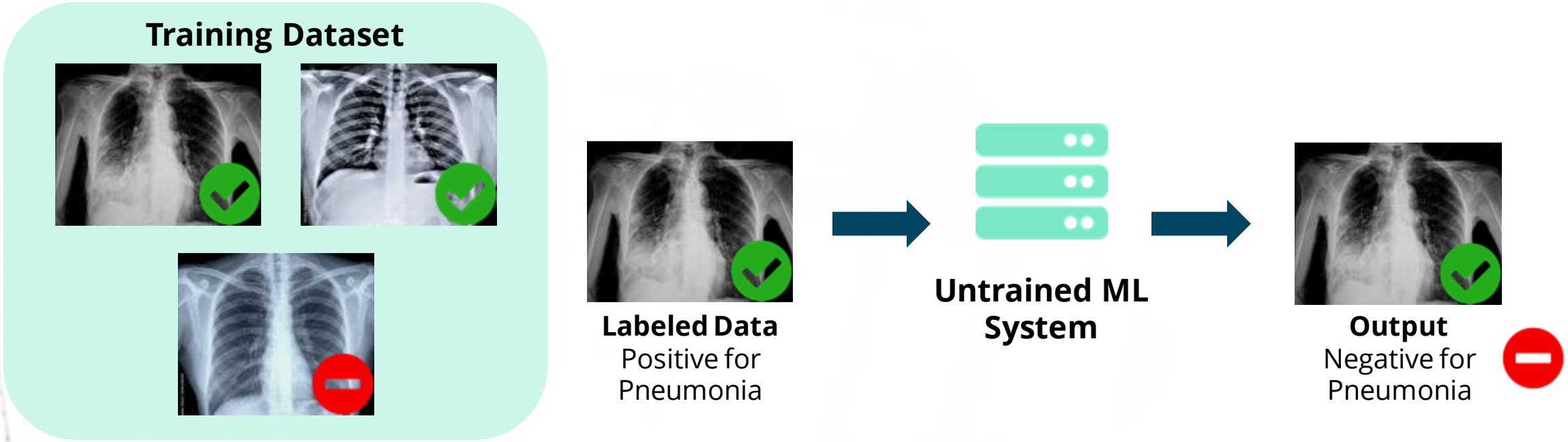
Learning or Training

- Conducts trial-and-error to change parameters
- Repeated millions of times

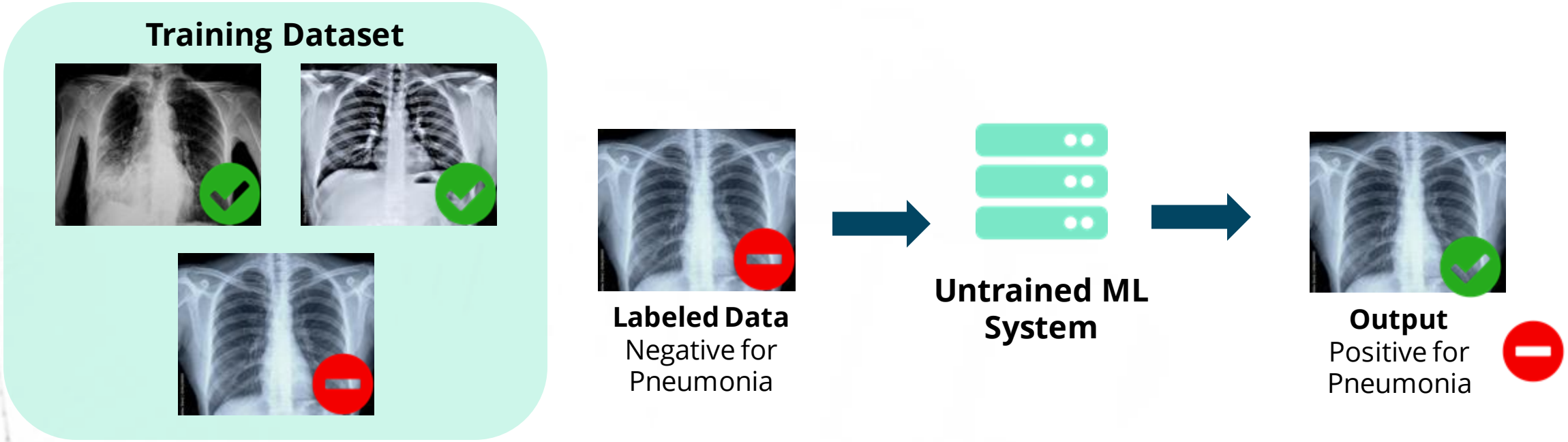
Final model

- Trained model that emulates a result from a given input

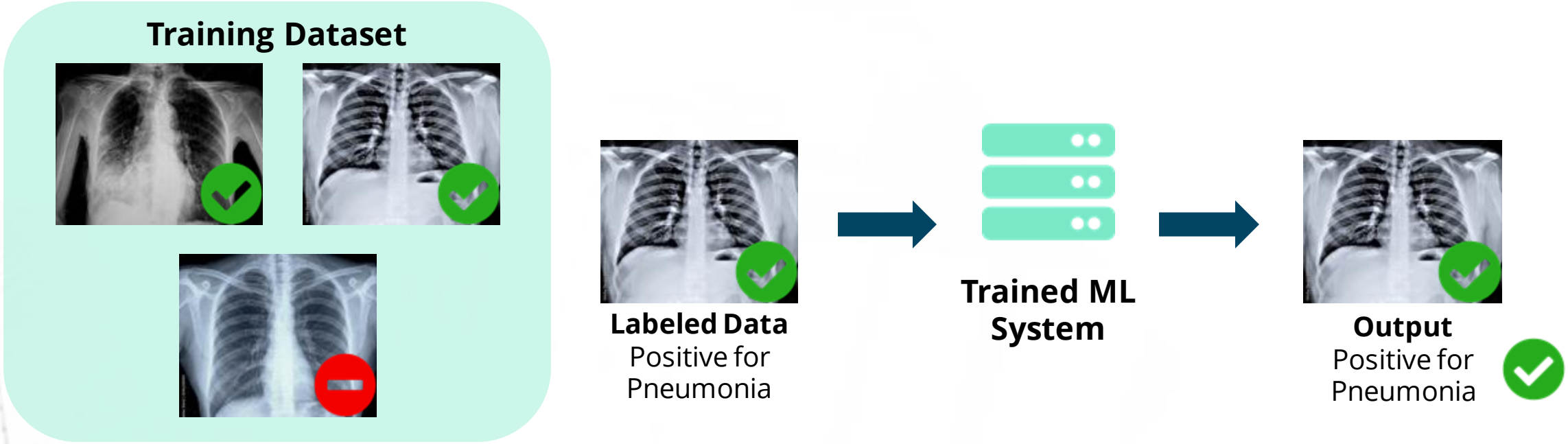
Supervised Learning Process



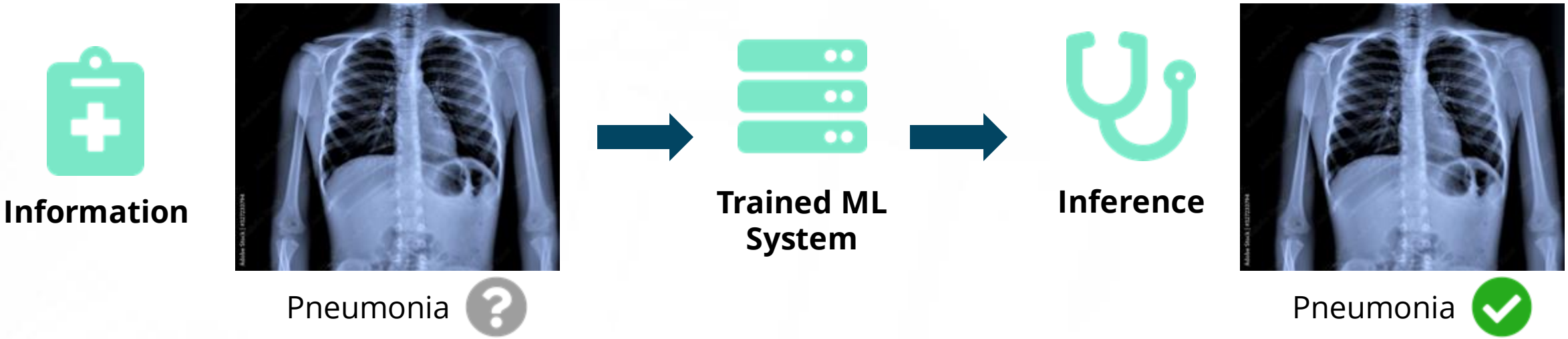
Supervised Learning Process



Supervised Learning Process



Supervised Learning Process



Clinical Applications of Computer Vision

Computer vision can identify patterns in imaging data in the **detection of early symptoms**, providing early treatment options.

- Especially for radiology and pathology applications, such as classifying lung nodules as benign or malignant

- Some studies reporting accuracy in narrow tasks on par with specialists

Chest x-ray output from a computer vision algorithm. Airspace opacity (associated with pneumonia) was highlighted by the algorithm.

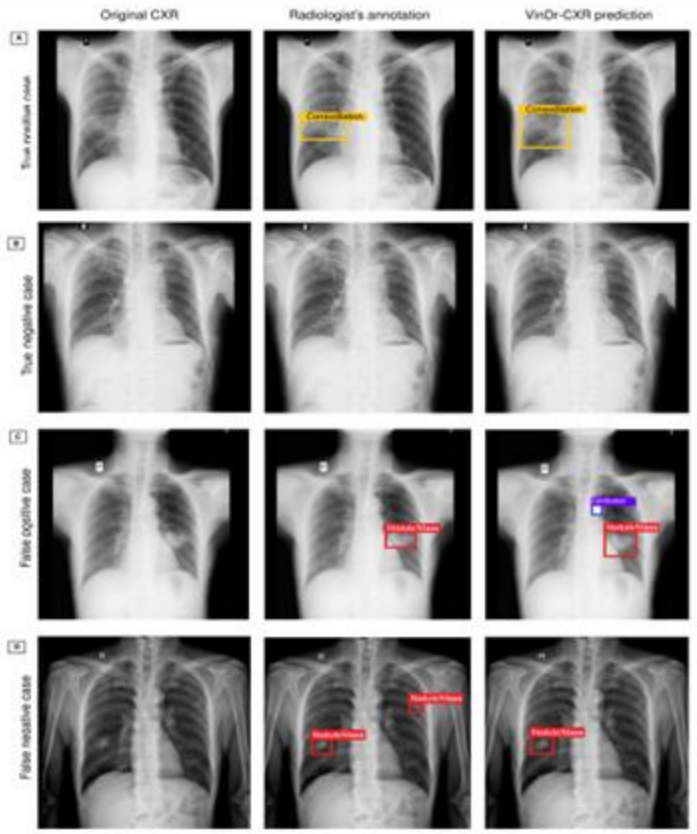
Why is data so important?

Datasets in AI

A **dataset** is a compilation of data that is stored in a digital format readable by a computer.

Datasets can consist of images, text notes, audio, videos, numerical values, or codes, used for solving various AI challenges.

Image-Based Dataset	Numerical Dataset



Dataset of chest radiographs. In digital form, images consist of lists of numbers that represent the brightness of each pixel.

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Image-Based Dataset	Numerical Dataset

	Years of Education	Age	Postal Code	Condition
1	Secondary	60	A1B 2C3	Parkinson's Disease
2	Secondary	73	B2C 3D4	Parkinson's Disease
3	Post-Secondary	68	C3D 4E5	Alzheimer's Disease
4	Graduate/Professional	84	D4E 5F6	Alzheimer's Disease
5	Secondary	71	E5F 6G7	Stroke
6	Post-Secondary	63	F6G 7H8	Parkinson's Disease
7	Graduate/Professional	85	G7H 8I9	Alzheimer's Disease
8	Secondary	77	H8I 9J0	Alzheimer's Disease
9	Graduate/Professional	69	I9J 0K1	Stroke
10	Graduate/Professional	76	J0K 1L2	Stroke
11	Post-Secondary	74	K1L 2M3	Multiple Sclerosis
12	Secondary	82	L2M 3N4	Multiple Sclerosis

Tabular dataset containing parameters such as years of education, age, postal code, and condition.

	Years of Education	Age	Postal Code	Condition
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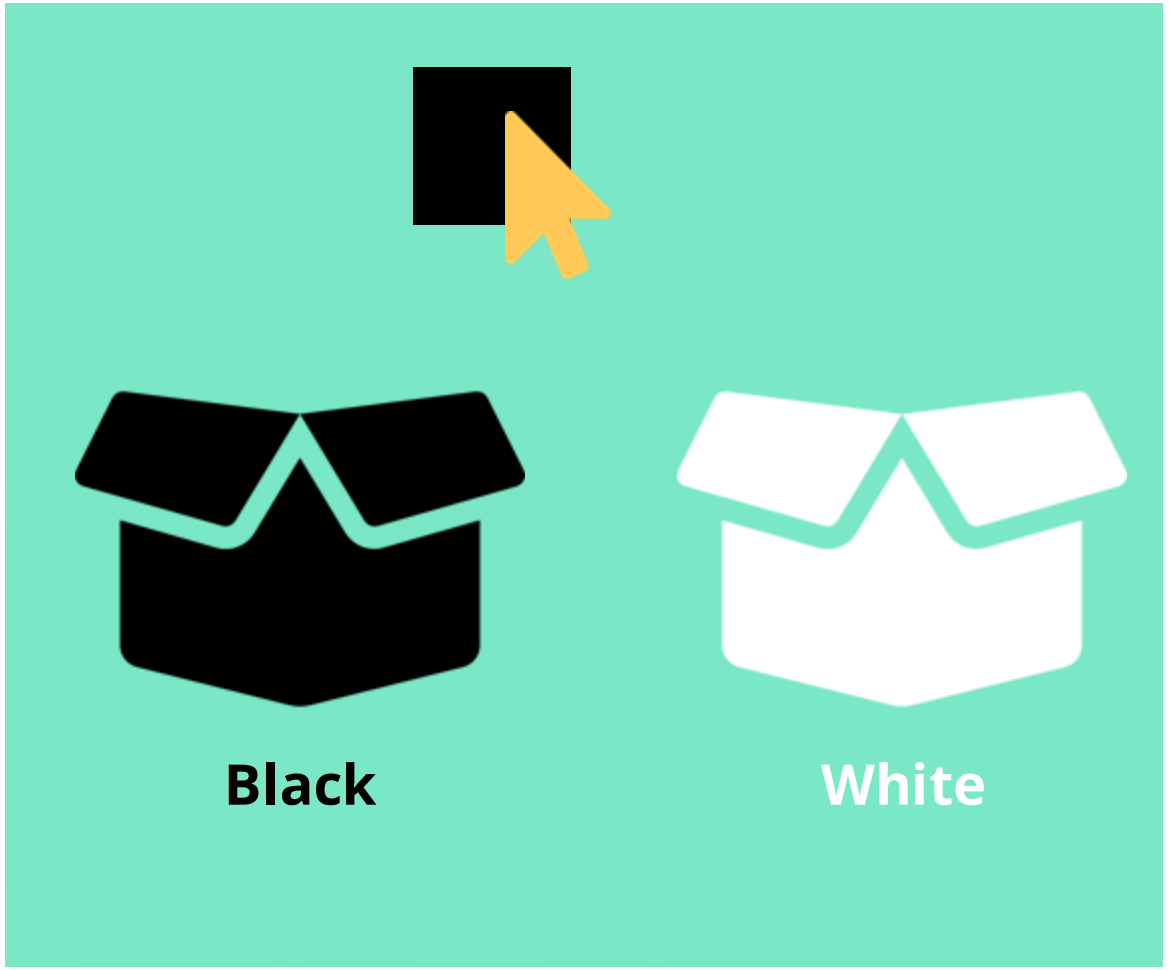
Choice of Datasets

The choice of dataset is critical to produce a good ML system.

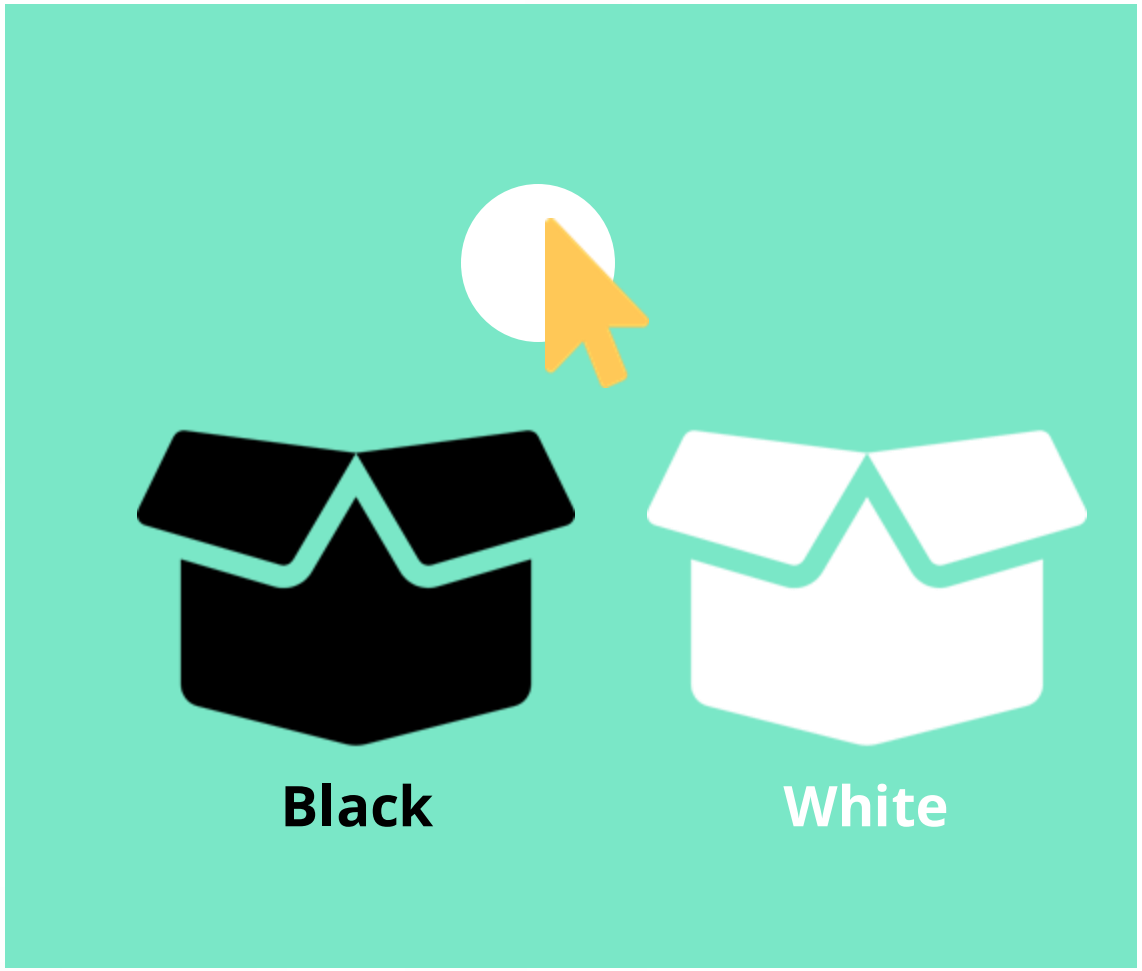
It is important for datasets to:

- use datasets with **high quality labels** for supervised learning
  - e.g., cancer diagnosis by team of expert clinicians
- contain a realistically **wide variety** of examples
  - e.g., including both men and women

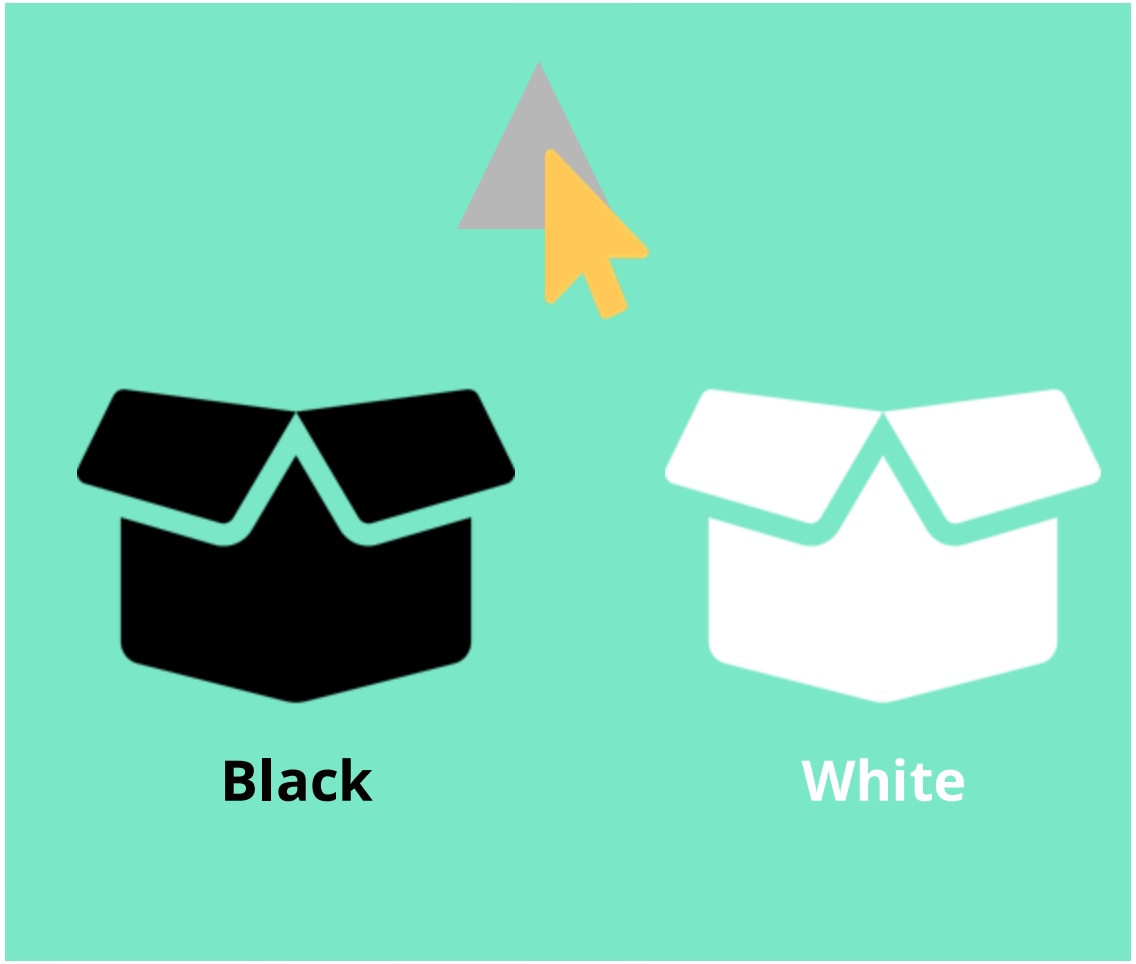
Labels



Labels



Labels may have interpretations



The Variety of Inputs and Outputs in a Dataset

Dataset has enough records across the desired **range of inputs and outputs**.

- e.g., example skin neoplasms

Should also contain realistic **variety**

- e.g., brown spots, small lesions with irregular borders, skin tones

Strengths and Limitations

Strengths of AI

Major strengths of AI in the healthcare context include processing speed and cost, ability to learn from large volumes of data, and accuracy.

Processing Speed

Learning from Large Datasets

Accuracy

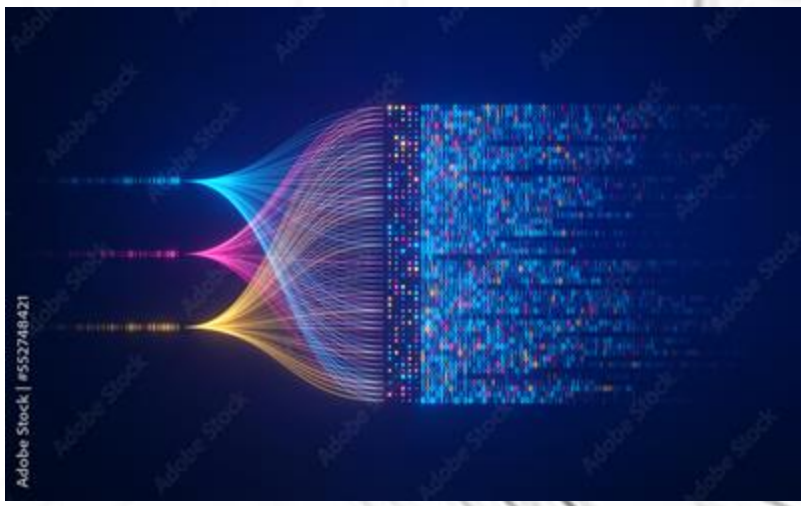
An advantage of AI systems is the ability to process data very rapidly. For example, an AI system can process and make inferences on thousands of images per minute.

Strengths of AI

Major strengths of AI in the healthcare context include processing speed and cost, ability to learn from large volumes of data, and accuracy.

Processing Speed and Cost	**Learning from Large Datasets**	Accuracy

Since AI systems are able to process large volumes of data quickly, these systems can be exposed to and learn from millions of examples.



Strengths of AI

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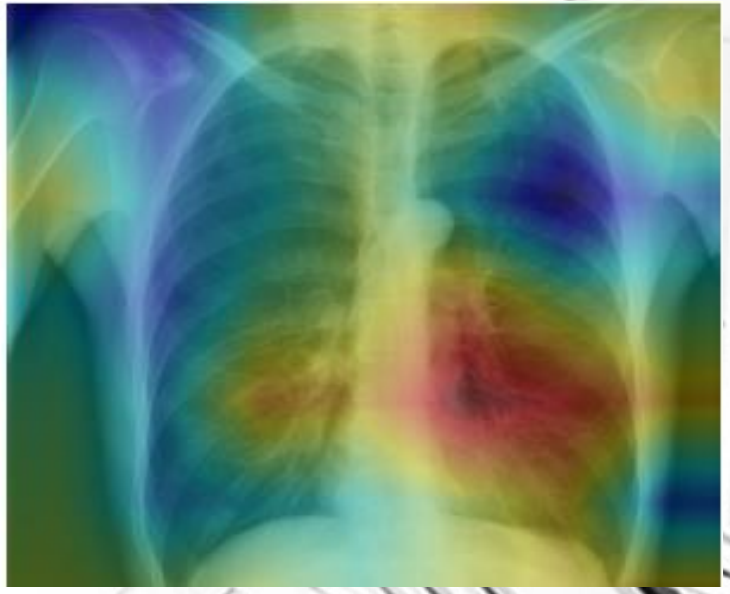
Processing Speed and Cost

Learning from Large Datasets

Accuracy

With the ability to learn from large datasets, the accuracy of AI systems can rival top-performing doctors in narrowly defined tasks.



Pneumonia positive chest x-ray.

Limitations of AI

AI creates possibilities that did not exist even a few years ago. However, these systems have a number of weaknesses and limitations.

Quality of Evidence	Pattern Extrapolation	Brittleness	Black Boxes

While impressive AI performance is often reported, these findings are usually based on fixed retrospective datasets. The evidence, especially high-quality evidence, to support AI adoption remains relatively sparse.

Limitations of AI

AI creates possibilities that did not exist even a few years ago. However, these systems have a number of weaknesses and limitations.

Quality of Evidence	Pattern Extrapolation	Brittleness	Black Boxes

AI is a sophisticated tool designed to find patterns based on past experience (i.e., the data it is given). However, these models only learn and know what to do based on what is provided (fed) to them as training data.

Limitations of AI

AI creates possibilities that did not exist even a few years ago. However, these systems have a number of weaknesses and limitations.

Quality of Evidence	Pattern Extrapolation	Brittleness	Black Boxes

AI platforms are often brittle, meaning they can be fooled or broken by small distractions that seem irrelevant to humans.

For example, an AI system for melanoma recognition was found to use the presence of surgical skin markings as a clue about whether skin neoplasms were malignant.

Limitations of AI

AI creates possibilities that did not exist even a few years ago. However, these systems have a number of weaknesses and limitations..

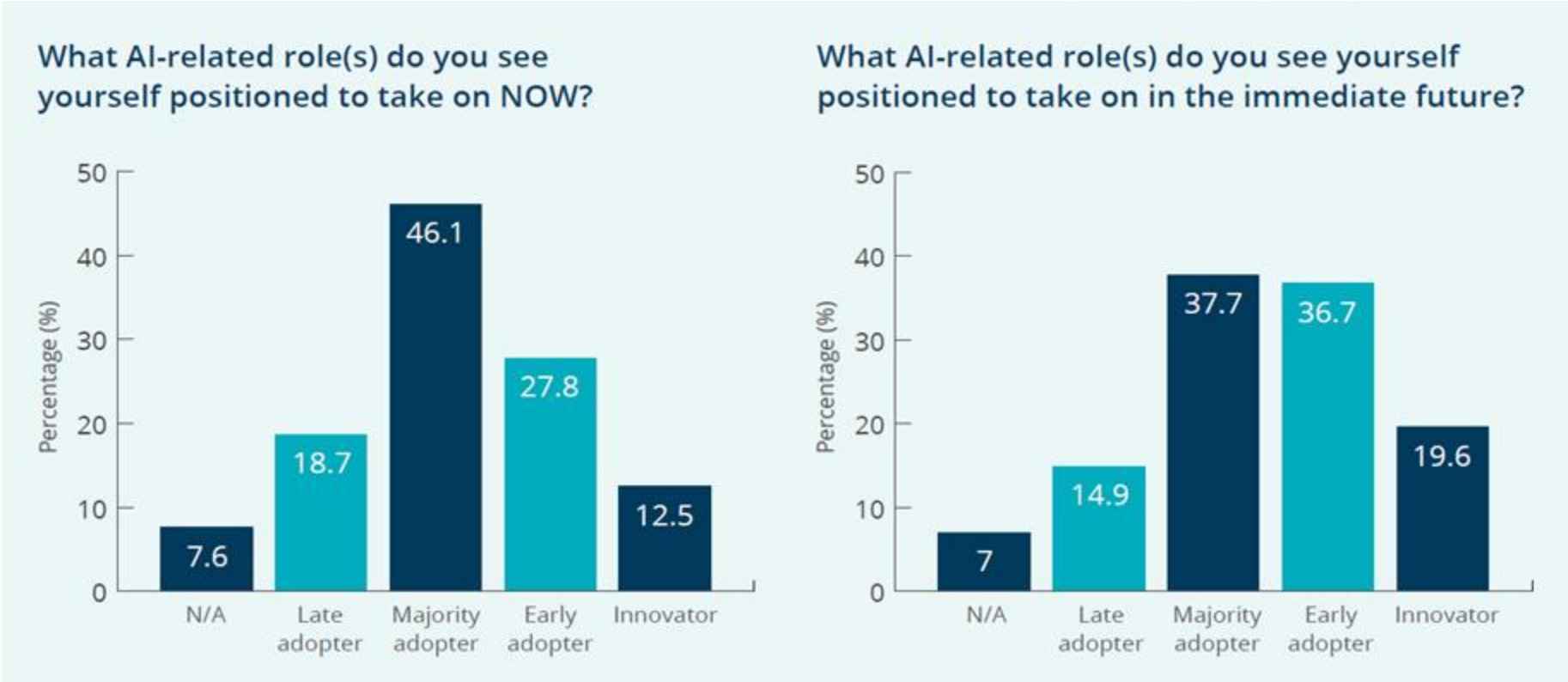
Quality of Evidence	Pattern Extrapolation	Brittleness	Black Boxes

AI systems that operate on complex data (such as images or text) are considered “black boxes” because it is difficult to explain how they arrived at a given decision. This is a concern in healthcare, because the provider is ultimately responsible for decisions.

Physician’s perspective

Physicians and AI Adoption

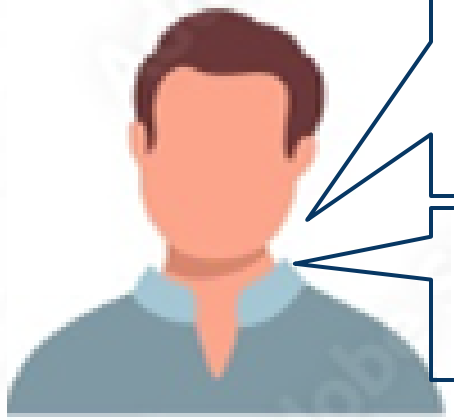
In a survey conducted by the Royal College of Physicians and Surgeons for their 2020 *Task Force Report on Artificial Intelligence and Emerging Digital Technologies*, the majority of physicians who responded indicated they were currently positioned to adopt AI tools within their practice.



Canadian College of Physicians and Surgeons survey responses to current and anticipated future roles with respect to AI adoption.

Antonio Di Leva's Perspective: Projected Impact of AI on Medical Practice

As Antonio Di Leva, Associate Professor of Neuroanatomy and Neurosurgery at Macquarie University (Sydney, Australia) states in the Royal College Task Force Report on AI and Emerging Digital Technology:



"While it is very unlikely that AI will replace doctors anytime soon (or ever), it is more likely that doctors who know how to thoughtfully and carefully incorporate the benefits that AI promises, while avoiding the pitfalls, will be better positioned than those doctors who do not."

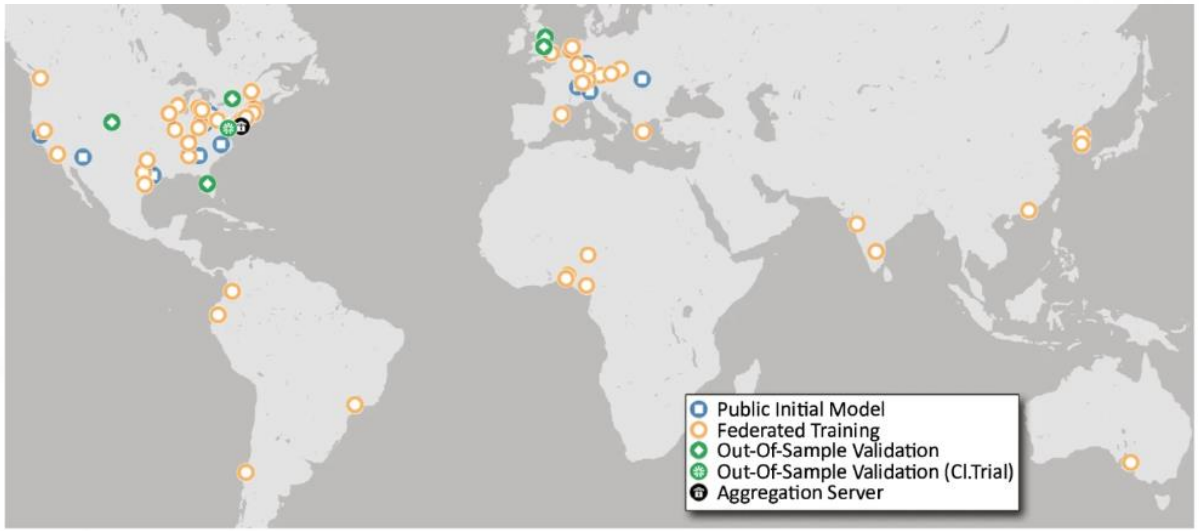
"**Machines will not replace physicians, but physicians using AI will soon replace those not using it**."

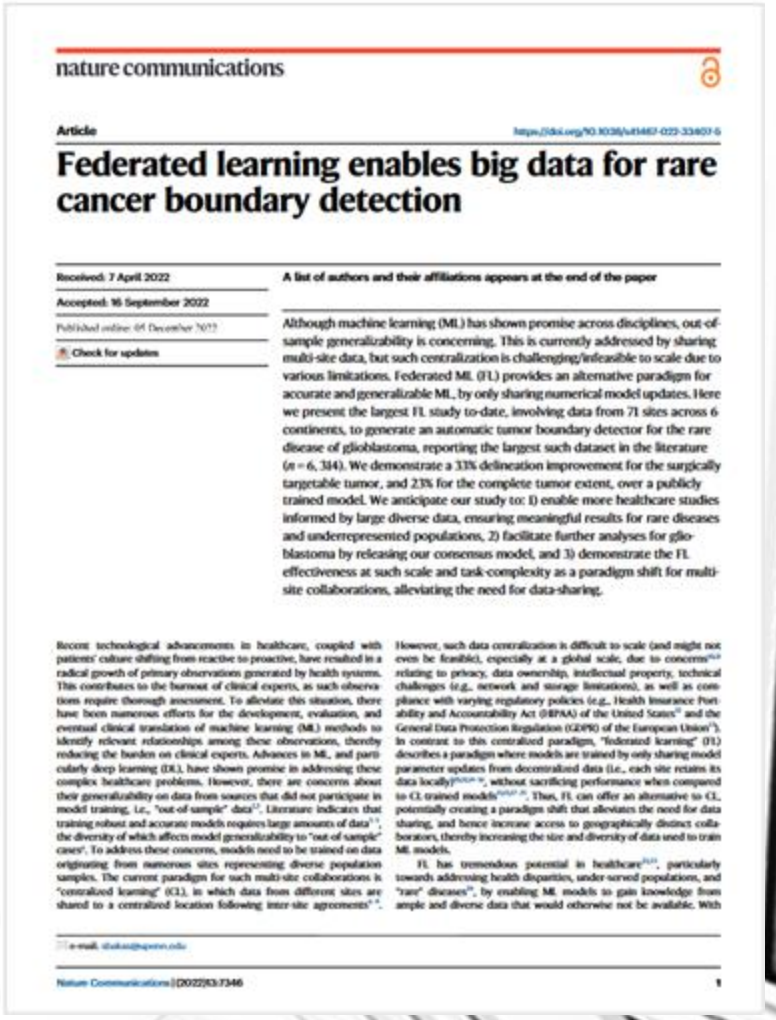
– Antonio Di Leva, Associate Professor of Neuroanatomy and Neurosurgery, Macquarie University

Optimistic future

Collaborating to build datasets

In 2022, Intel and Penn Medicine combined data from 71 medical institutions to build a large brain imaging dataset with 6,314 glioblastoma patients across six continents.





nature communications

Article

Federated learning enables big data for rare cancer boundary detection

Received: 7 April 2022

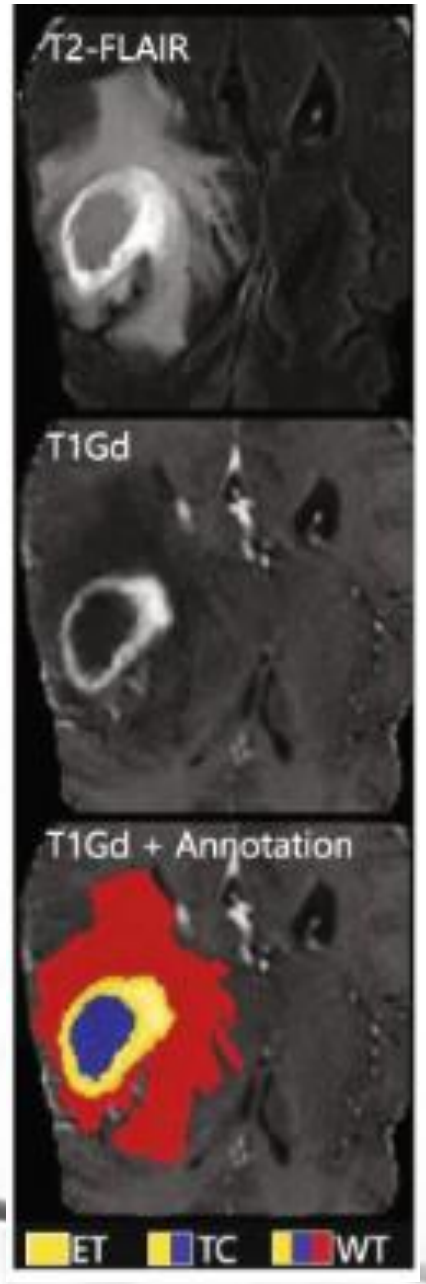
Accepted: 16 September 2022

Check for updates

A list of authors and their affiliations appears at the end of the paper

Although machine learning (ML) has shown promise across disciplines, out-of-sample generalizability is concerning. This is currently addressed by sharing multi-site data, but such centralization is challenging/infeasible to scale due to various limitations. Federated ML (FL) provides an alternative paradigm for accurate and generalizable ML, by only sharing numerical model updates. Here we present the largest FL study to-date, involving data from 71 sites across 6 continents, to generate an automatic tumor boundary detector for the rare disease of glioblastoma, reporting the largest such dataset in the literature (n = 6, 314). We demonstrate a 33% delineation improvement for the surgically targetable tumor, and 23% for the complete tumor extent, over a publicly trained model. We anticipate our study to: 1) enable more healthcare studies informed by large diverse data, ensuring meaningful results for rare diseases and underrepresented populations, 2) facilitate further analyses for glioblastoma by releasing our consensus model, and 3) demonstrate the FL effectiveness at such scale and task-complexity as a paradigm shift for multi-site collaborations, alleviating the need for data-sharing.

https://doi.org/10.1038/s41467-022-33407-5



Collaborating to build datasets

Successful in maintaining patient privacy and data integrity across multiple institutions, the system significantly improved AI-enabled tumour boundary detection for neurosurgical and radiotherapy planning.

https://doi.org/10.1038/s41467-022-33407-5

Optimism


WELCOME
Neural and
Rehabilitation
Engineering Lab Tours
10 a.m. – 2 p.m.
10 people maximum

Optimism

We are seeking older adults for stakeholder advisory, and to participate in research studies. Please contact me for information.

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519-820-0619

Thank you!