Distributed and Federated Learning

Federated learning for healthcare data

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Us

This material is presented by:

- Theoretical lecture: **Yuri Gordienko**
- Exercise session: **Ivan Zhuk** and **Yuriy Kochura**

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Yuriy Kochura

Ivan Zhuk

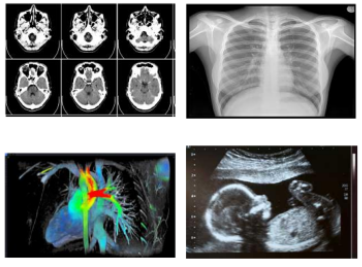
Yuri Gordienko

Agenda

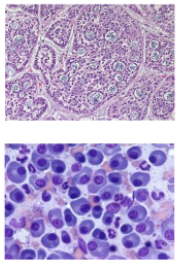
- AI in Healthcare
- Market Size & Trends
- Federated Learning (FL) in Healthcare
- Why we need FL?
- How does FL work?
- Data harmonization challenges for FL
- Large-scale standardized dataset (MedMNIST)
- Future directions for FL in Healthcare

AI in Healthcare

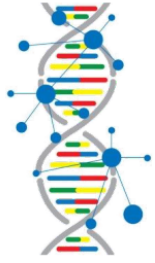
AI in medicine



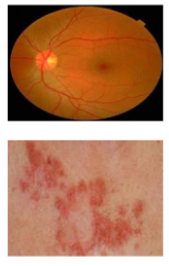
RADIOLOGY
CT, MR, US, X-RAY



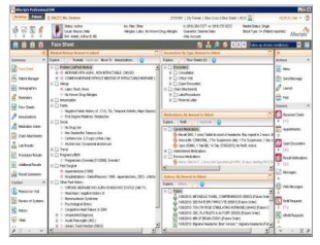
PATHOLOGY
TISSUE & CELL



GENETICS



DERMATOLOGY
OPHTHALMOLOGY



ELECTRONIC HEALTH
RECORDS

Year	FDA-Approved AI Tools	Global Investment (USD)
2021	~128	~$7B
2024	~169	~$26.57B

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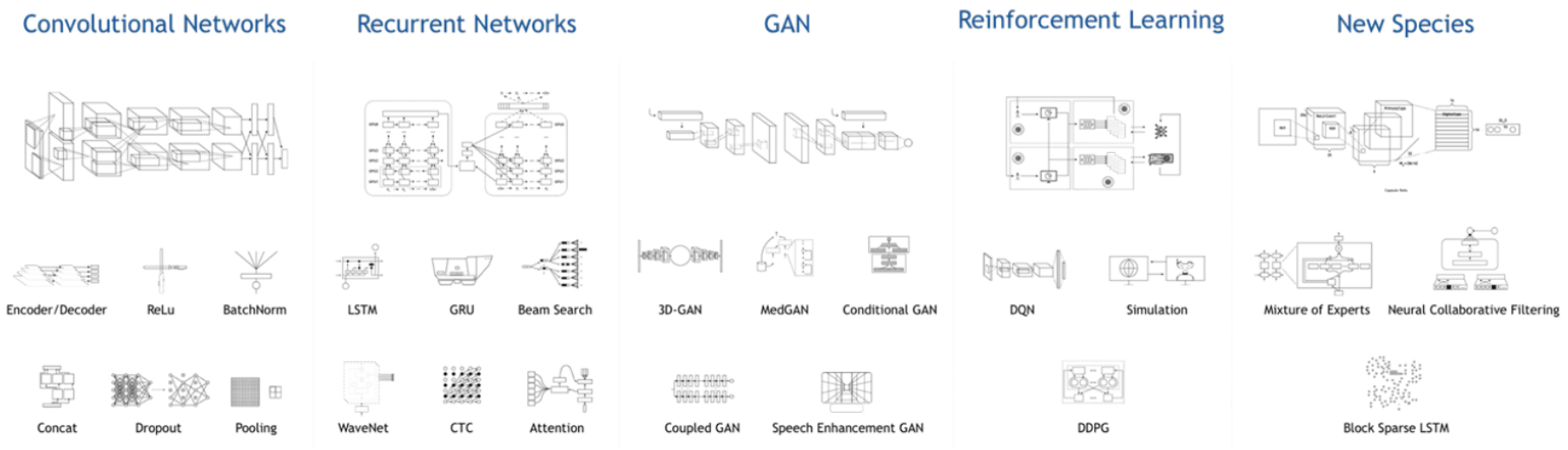
Credit: Artificial Intelligence and Machine Learning (AI/ML)-Enabled Medical Devices. Nicola Rieke and Yuhong Wen - FEDERATED LEARNING FOR MEDICAL IMAGING.

From research ...

Improving state of the art performance in controlled settings



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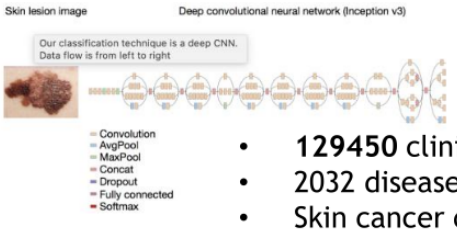
Credit: Nicola Rieke and Yuhong Wen - FEDERATED LEARNING FOR MEDICAL IMAGING.

… to applications

Achieving human-level performance on large data and clinical settings

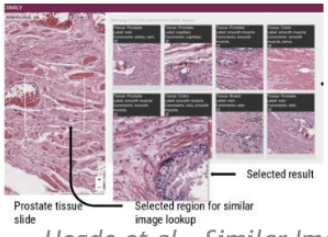


- **129450** clinical images
- 2032 diseases
- Skin cancer detection
- comparable to dermatologists

Esteva et al, Dermatologist-level classification of skin cancer with deep neural networks, Nature 2017

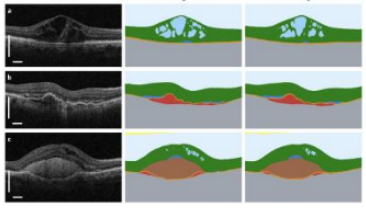
- 6 hospitals in China
- 84424 individuals
- **1036496** endoscopy images
- Gastrointestinal cancer detection
- Perf. similar to the expert endoscopist

Luo et al., Real-time artificial intelligence for detection of upper gastrointestinal cancer by endoscopy: a multicentre, case-control, diagnostic study, Lancet Oncology 2019



- **127000** image patches
- 128,000,000 8 × 8 µm regions
- Histopathology image search

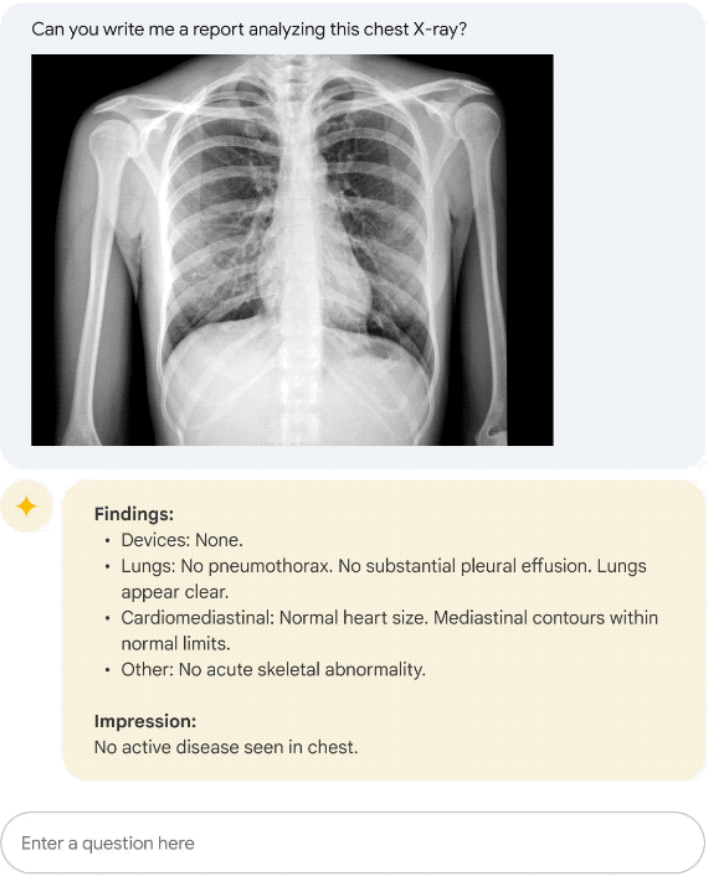
Hegde et al., Similar Image Search for Histopathology: SMILY, Nature digital medicine 2019



- "Only" **14884** OCT 3D scans
- Resolution ~ 5 µm
- Volumetric multi-region segmentation
- Performance comparable to humans

De Fauw et al., Clinically applicable deep learning for diagnosis and referral in retinal disease, Nature Medicine 2018

How AI is advancing medicine (Google, 2018)



Med-PaLM 2 (Google) is a large language model tuned for the medical domain. It reaches 85%+ accuracy on the MedQA medical exam benchmark in research.

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Credit: Google Research, Med-PaLM, 2022.

AlphaFold: From a sequence of amino acids to a 3D structure

nature

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Article | Open access | Published: 15 July 2021

Highly accurate protein structure prediction with AlphaFold

John Jumper ✉, Richard Evans, Alexander Pritzel, Tim Green, Michael Figurnov, Olaf Ronneberger, Kathryn Tunyasuvunakool, Russ Bates, Augustin Žídek, Anna Potapenko, Alex Bridgland, Clemens Meyer, Simon A. A. Kohl, Andrew J. Ballard, Andrew Cowie, Bernardino Romera-Paredes, Stanislav Nikolov, Rishub Jain, Jonas Adler, Trevor Back, Stig Petersen, David Reiman, Ellen Clancy, Michal Zielinski, … Demis Hassabis ✉

+ Show authors

Nature **596**, 583–589 (2021) | Cite this article

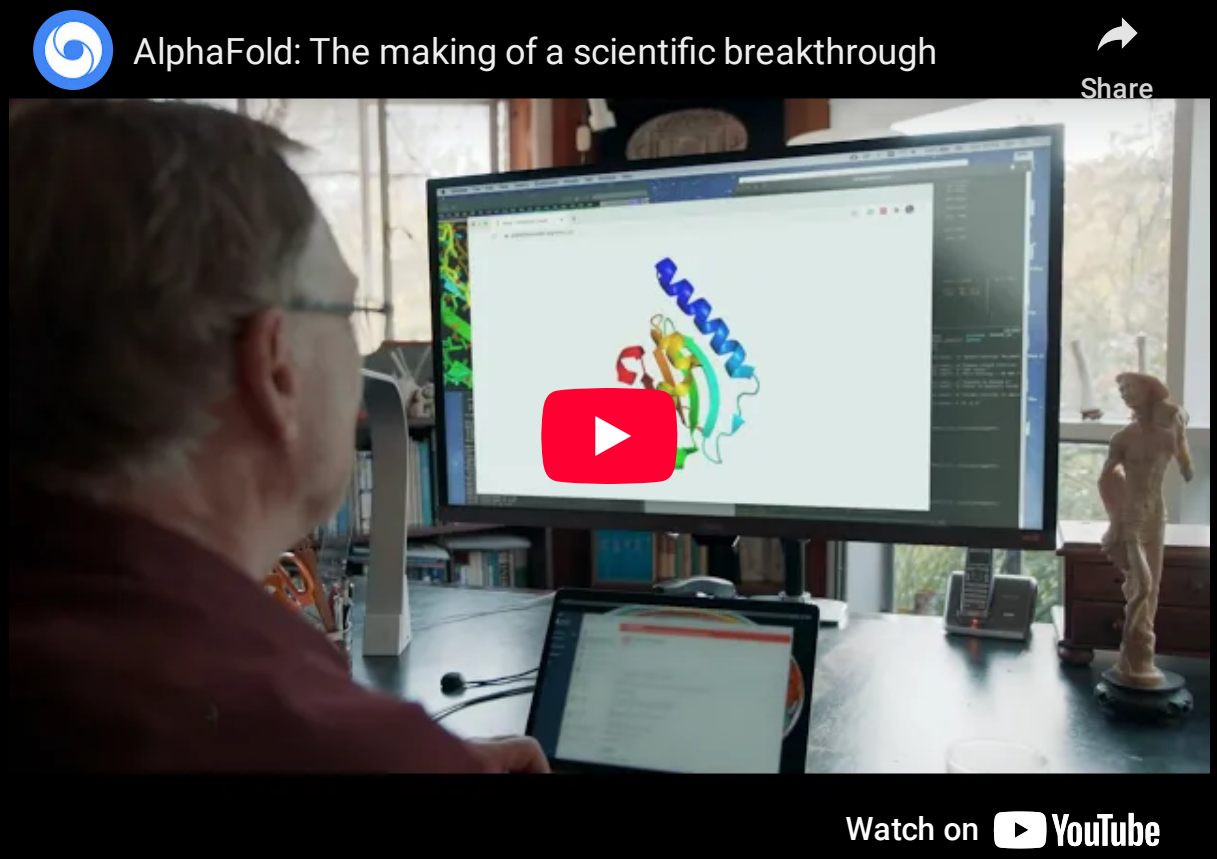
1.42m Accesses | **12k** Citations | **3493** Altmetric | Metrics

Abstract

Proteins are essential to life, and understanding their structure can facilitate a mechanistic understanding of their function. Through an enormous experimental effort[1,2,3,4], the structures of around 100,000 unique proteins have been determined[5], but this represents a small fraction of the billions of known protein sequences[6,7]. Structural coverage is bottlenecked by the months to years of painstaking effort required to determine a single protein structure. Accurate computational approaches are needed to address this gap and to enable large-scale structural bioinformatics. Predicting the three-dimensional structure that a protein will adopt based solely on its amino acid sequence—the structure prediction component of the 'protein folding problem'[8]—has been an important open research problem for more than 50 years[9]. Despite recent progress[10,11,12,13,14], existing methods fall far short of atomic accuracy, especially when no homologous structure is available. Here we provide the

John Jumper

(The 2024 Nobel Prize in Chemistry)



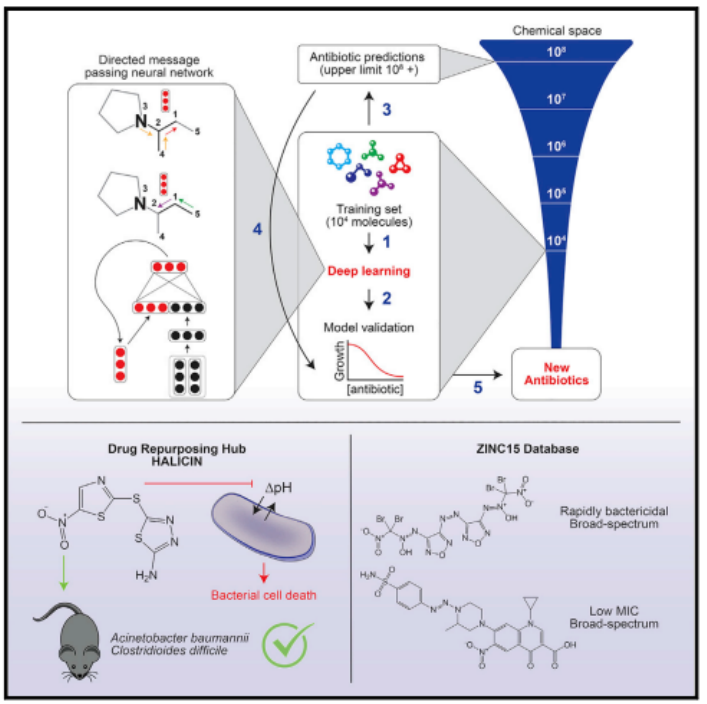
AI for Science (Deepmind, AlphaFold, 2020)

Drug discovery with graph neural networks

Cell

A Deep Learning Approach to Antibiotic Discovery

Graphical Abstract



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Jonathan M. Stokes, Kevin Yang, Kyle Swanson, ..., Tommi S. Jaakkola, Regina Barzilay, James J. Collins

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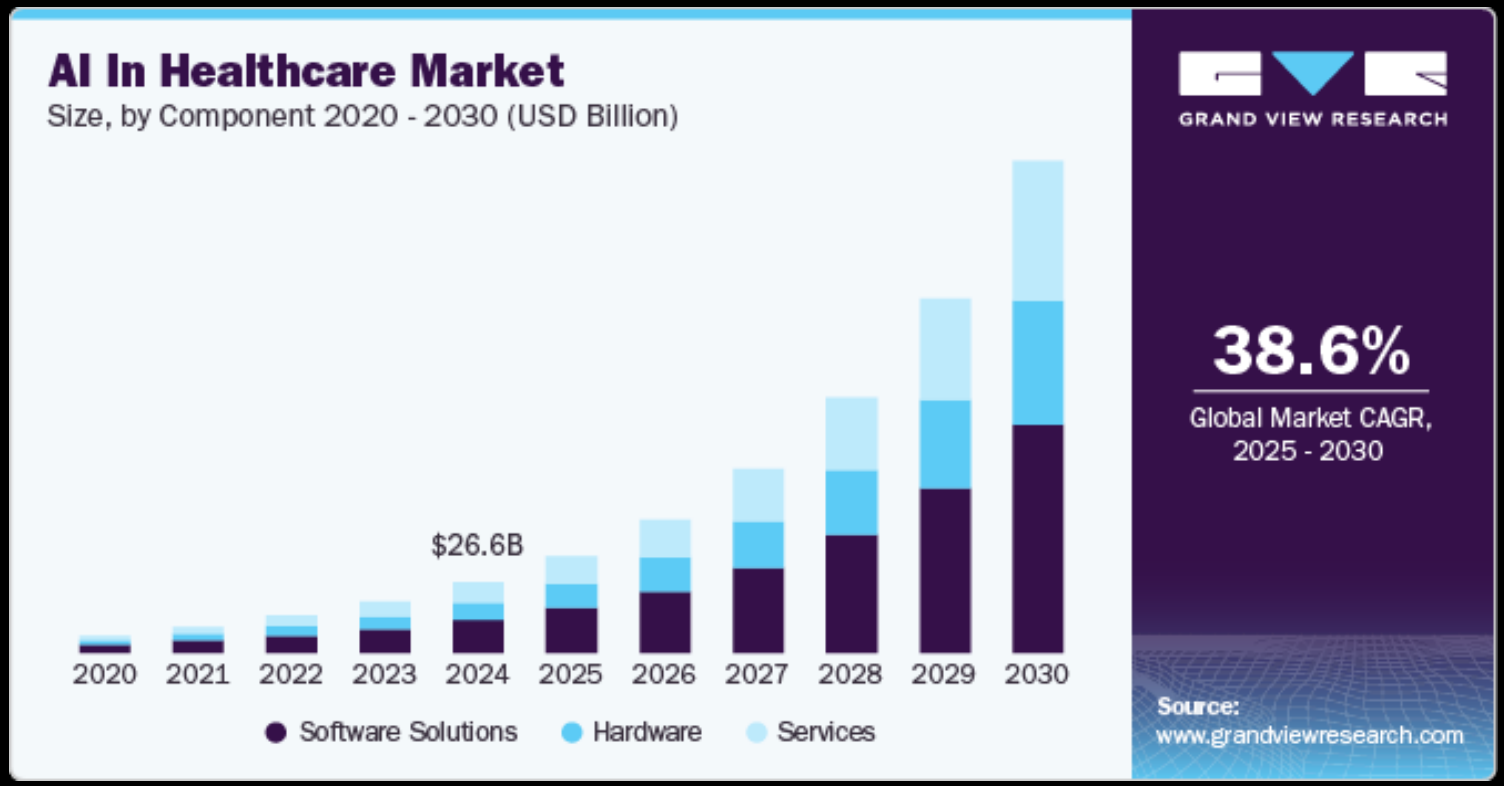
In Brief

A trained deep neural network predicts antibiotic activity in molecules that are structurally different from known antibiotics, among which Halicin exhibits efficacy against broad-spectrum bacterial infections in mice.

Market Size & Trends

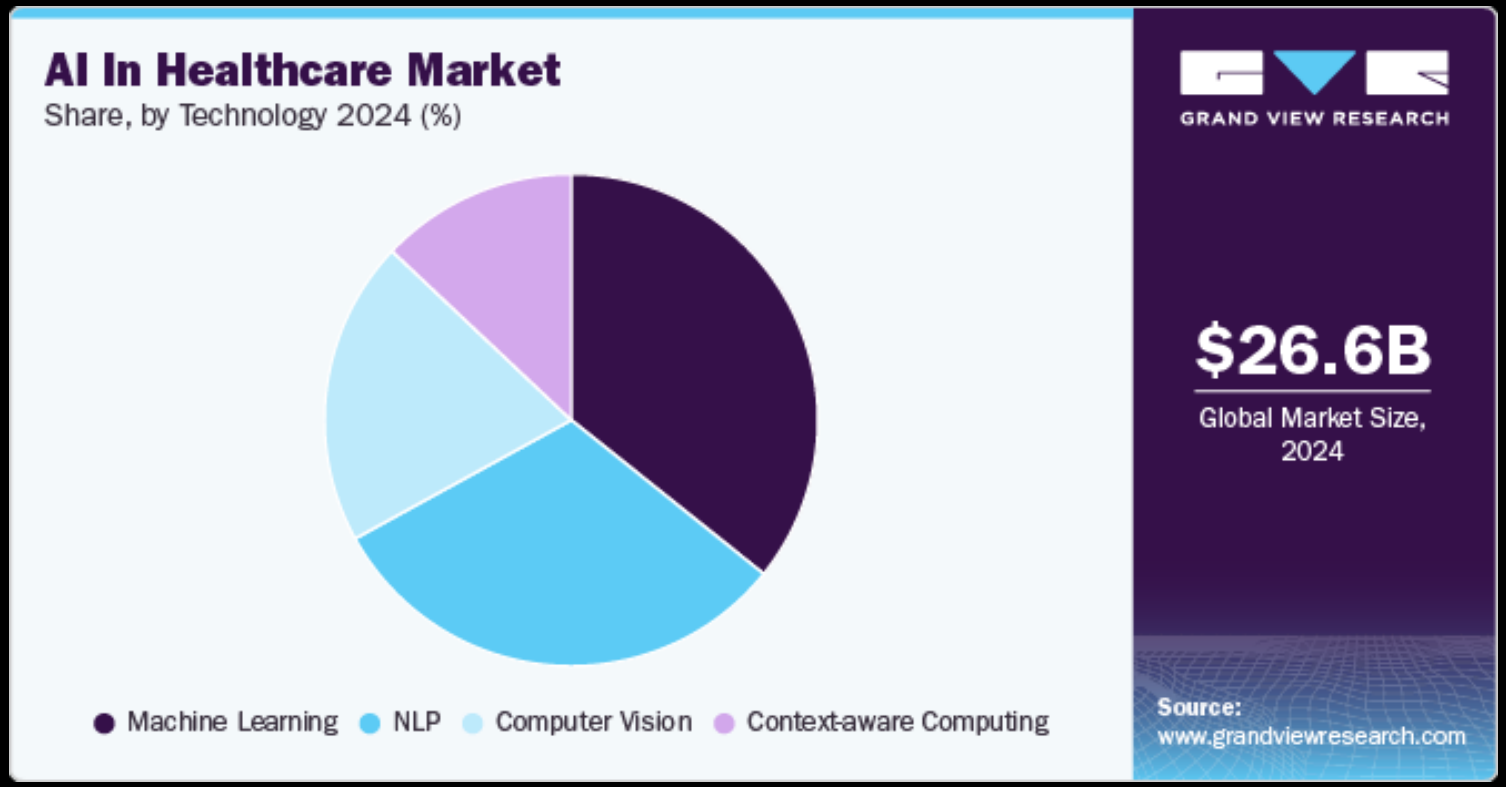


CAGR (Compound Annual Growth Rate)

A **key factor** driving market growth is the increasing demand in the healthcare sector for enhanced efficiency, accuracy, and better patient outcomes.

—

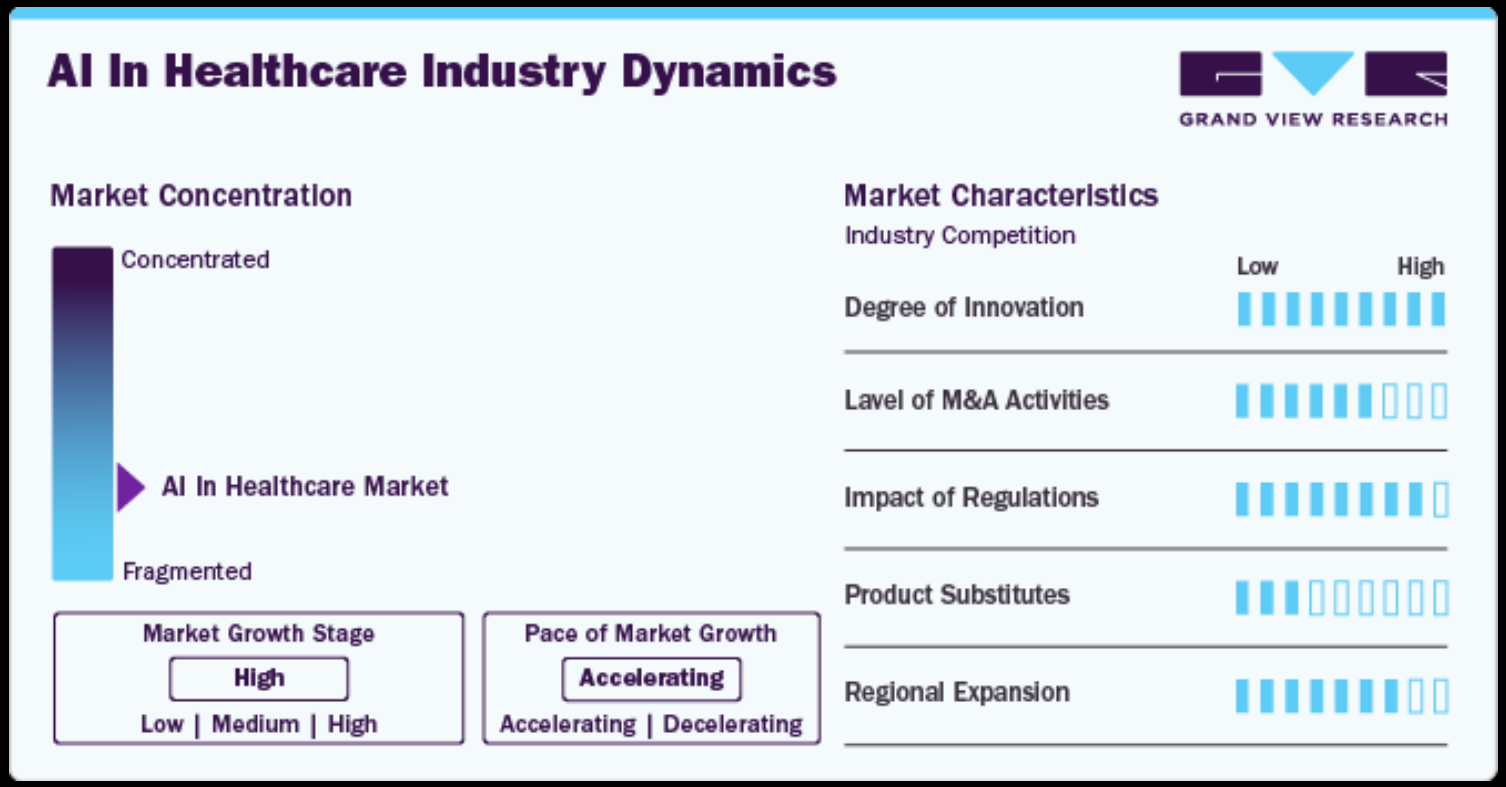
Credit: AI In Healthcare Market Size, Share, And Trends Analysis Report By Component (Hardware, Services), By Application, By End Use, By Technology, By Region (North America, Europe, APAC, Latin America, MEA), And Segment Forecasts, 2025 - 2030.



The **context-aware computing** segment is expected to grow at the fastest CAGR between 2025 and 2030. AI algorithms integrate and analyze diverse data sources such as electronic health records (EHRs), real-time vital signs, medical history, environmental factors, and patient activity to understand patient context dynamically.

—

Credit: AI In Healthcare Market Size, Share, And Trends Analysis Report By Component (Hardware, Services), By Application, By End Use, By Technology, By Region (North America, Europe, APAC, Latin America, MEA), And Segment Forecasts, 2025 - 2030.



The Healthcare AI market exhibits a high degree of innovation, characterized by ongoing advancements in technology. Rapid developments in machine learning, deep learning, natural language processing, and computer vision are driving the evolution of AI-powered healthcare solutions.

—

Credit: AI In Healthcare Market Size, Share, And Trends Analysis Report By Component (Hardware, Services), By Application, By End Use, By Technology, By Region (North America, Europe, APAC, Latin America, MEA), And Segment Forecasts, 2025 - 2030.

North America AI in healthcare industry dominated the global market and accounted for the largest revenue share of over 54% in 2024.

AI in healthcare industry in the UK held the largest market share in the European region in 2024.

—

Credit: AI In Healthcare Market Size, Share, And Trends Analysis Report By Component (Hardware, Services), By Application, By End Use, By Technology, By Region (North America, Europe, APAC, Latin America, MEA), And Segment Forecasts, 2025 - 2030.

Key Companies

The following are the **leading companies** in the AI in healthcare market. These companies collectively hold the largest market share and dictate industry trends:

- Microsoft
- IBM
- Google
- NVIDIA Corporation
- Intel Corporation
- Itrex Group
- GE Healthcare
- Medtronic
- Oracle
- Medidata
- Merck
- IQVIA

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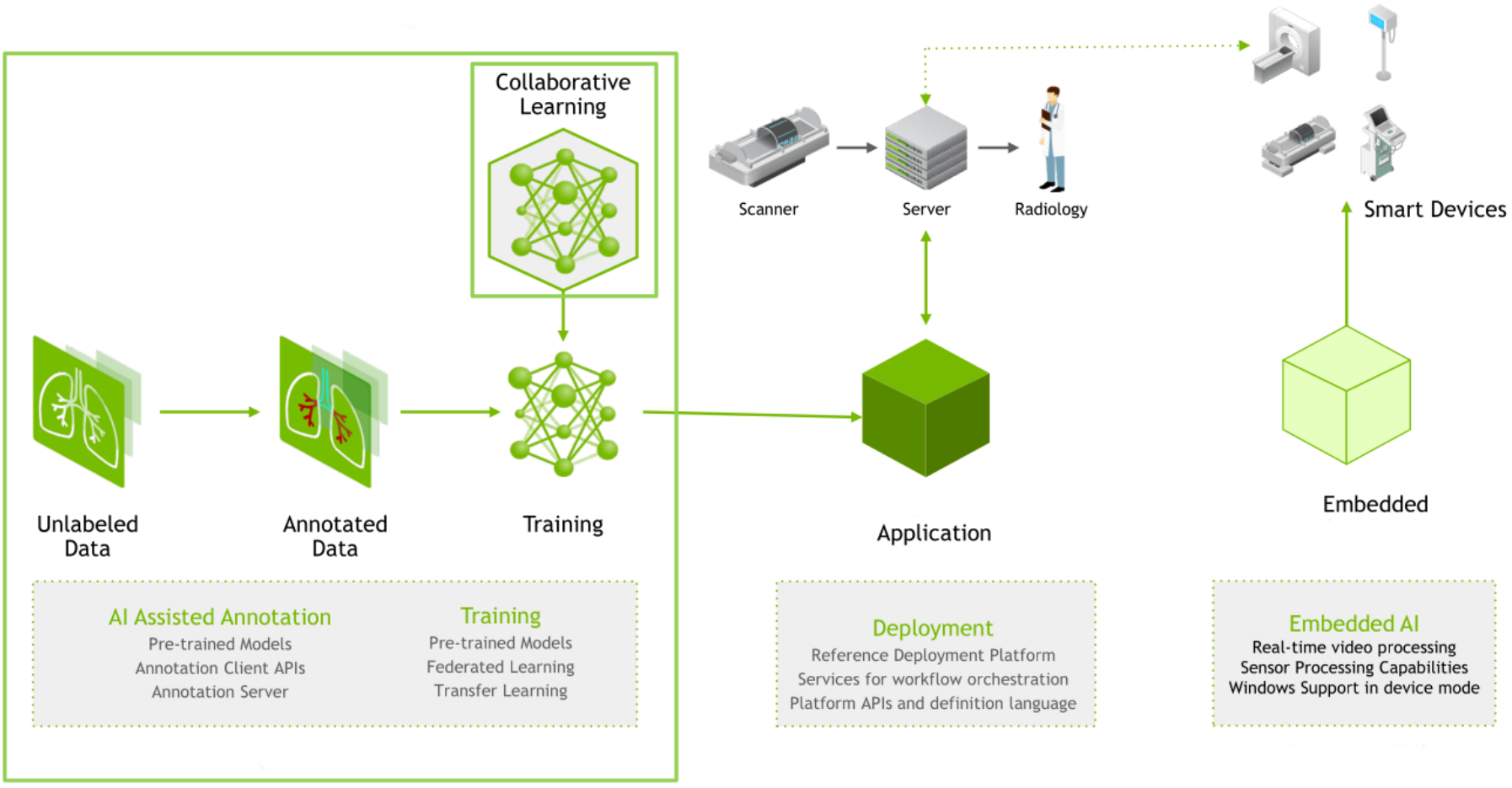
Credit: AI In Healthcare Market Size, Share, And Trends Analysis Report By Component (Hardware, Services), By Application, By End Use, By Technology, By Region (North America, Europe, APAC, Latin America, MEA), And Segment Forecasts, 2025 - 2030.

Federated Learning (FL) in Healthcare

Application framework



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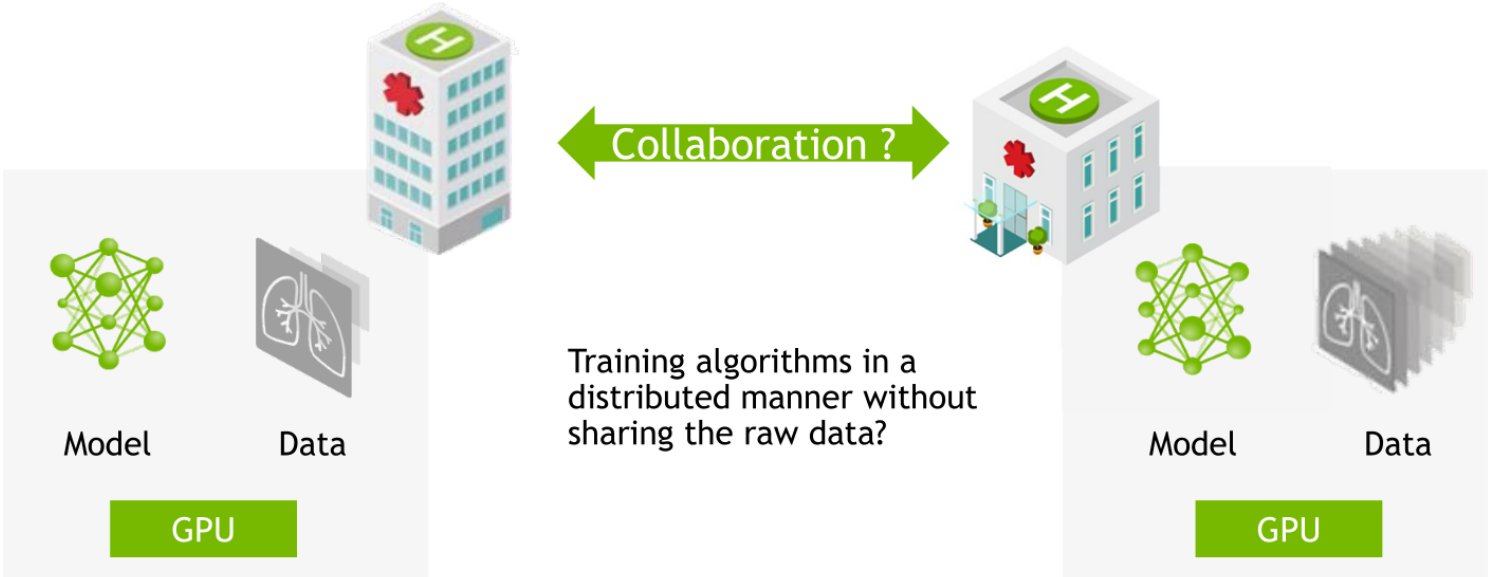
Credit: Nicola Rieke | Sr. Deep Learning Solution Architect - Healthcare - FEDERATED LEARNING USING CLARA TRAIN.

Data-driven medicine requires federated efforts



Possible Solution:

Federated Learning – learning paradigm that allows to integrate knowledge learned from non co-located data that resides within the participating entities into a global machine learning model.

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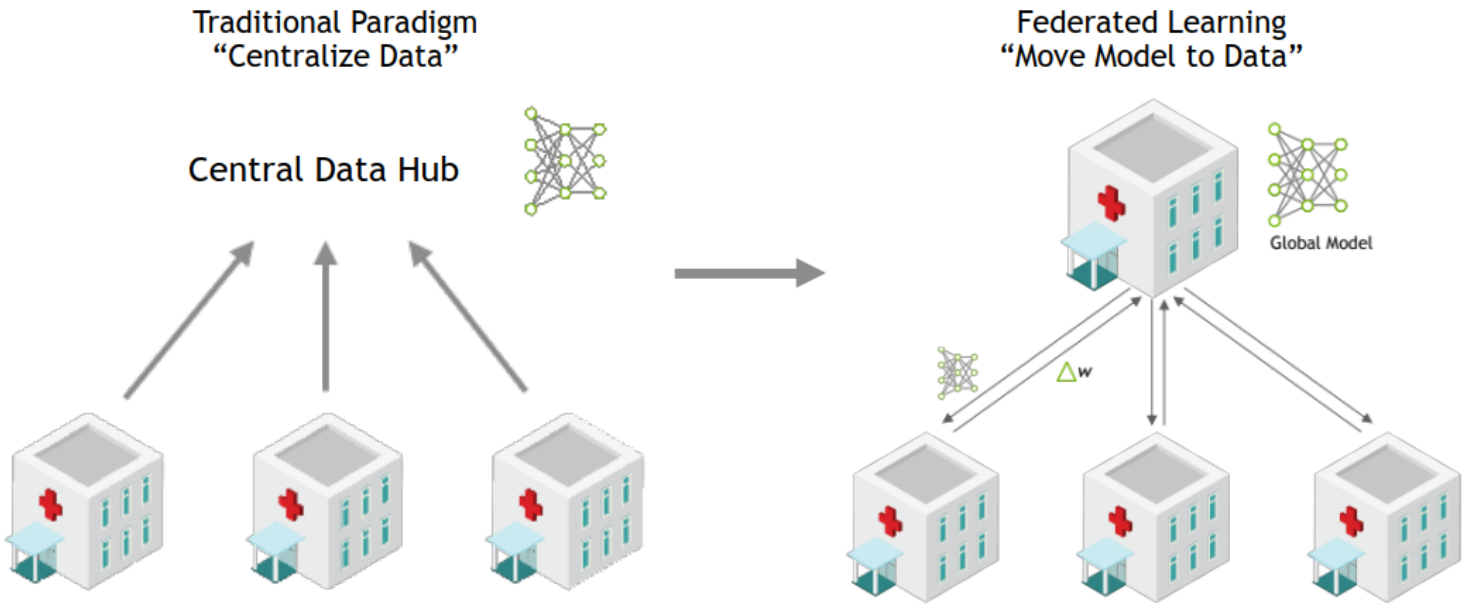
Credit: Nicola Rieke | Sr. Deep Learning Solution Architect - Healthcare - FEDERATED LEARNING USING CLARA TRAIN.

Paradigm Shift



Federated Learning

- Enhanced data privacy and security
- Raw data never leaves the device
- Improved model performance and diversity
- Scalability and efficiency

—

Credit: NVIDIA Deep Learning Institute.

The future of digital health with federated learning

Positioning Federated Learning (FL) for Healthcare

- Consensus view on FL in healthcare
- Benefits and impact of FL for medical applications
- Key challenges of implementing FL

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The future of digital health with federated learning

Nicola Rieke ✉, Jonny Hancox, Wenqi Li, Fausto Milletarì, Holger R. Roth, Shadi Albarqouni, Spyridon Bakas, Mathieu N. Galtier, Bennett A. Landman, Klaus Maier-Hein, Sébastien Ourselin, Micah Sheller, Ronald M. Summers, Andrew Trask, Daguang Xu, Maximilian Baust & M. Jorge Cardoso

npj Digital Medicine **3**, Article number: 119 (2020) | Cite this article

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Abstract

Data-driven machine learning (ML) has emerged as a promising approach for building accurate and robust statistical models from medical data, which is collected in huge volumes by modern healthcare systems. Existing medical data is not fully exploited by ML primarily because it sits in data silos and privacy concerns restrict access to this data. However, without access to sufficient data, ML will be prevented from reaching its full potential and, ultimately, from making the transition from research to clinical practice. This paper considers key factors contributing to this issue, explores how federated learning (FL) may provide a solution for the future of digital health and highlights the challenges and considerations that need to be addressed.

Credit: Rieke, N., Hancox, J., Li, W., Milletari, F., Roth, H. R., Albarqouni, S., ... & Cardoso, M. J. (2020). The future of digital health with federated learning. NPJ digital medicine, 3(1), 119.

Why we need FL?

Data is the Key to Generalizable, Robust AI Models

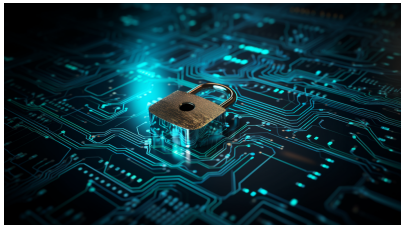
$$\text{Decentralized AI} = \text{federated compute} + \text{decentralized data, model}$$

Regulations

Health data is highly sensitive, subject to regulations and cannot easily be shared.

Data Availability

More data in private domain than public. Distributed data cross-country, rare data siloed and sparsely distributed.



Preserve Privacy

Leveraging private data while preserving data privacy is the mission of **federated learning**.

—
Credit: NVIDIA Deep Learning Institute.

Real-world medical AI development needs **external validation, multiple institutions, prospective data**. Among 500+ published medical AI studies, only 6% of have external validation. Few included multiple institutions.

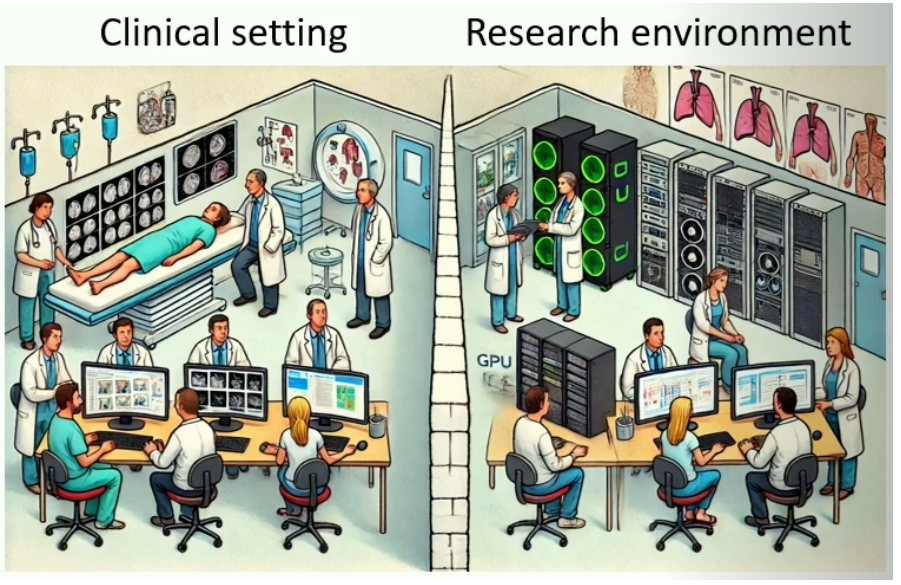
Design Characteristic	All Articles (n = 516)	Articles Published in Medical Journals (n = 437)	Articles Published in Non-Medical Journals (n = 79)	P*
External validation				1.000
Used	31 (6.0)	27 (6.2)	4 (5.1)	
Not used	485 (94.0)	410 (93.8)	75 (94.9)	
In studies that used external validation				
Diagnostic cohort design	5 (1.0)	5 (1.1)	0 (0)	1.000
Data from multiple institutions	15 (2.9)	12 (2.7)	3 (3.8)	0.713
Prospective data collection	4 (0.8)	4 (0.9)	0 (0)	1.000
Fulfillment of all of above three criteria	0 (0)	0 (0)	0 (0)	1.000
Fulfillment of at least two criteria	3 (0.6)	3 (0.7)	0 (0)	1.000
Fulfillment of at least one criterion	21 (4.1)	18 (4.1)	3 (3.8)	1.000

Challenges: data sharing, regulation, legal, privacy, technical …

—

Credit: Kim DW, Jang HY, Kim KW, Shin Y, Park SH. Design Characteristics of Studies Reporting the Performance of Artificial Intelligence Algorithms for Diagnostic Analysis of Medical Images: Results from Recently Published Papers, 2019.

Separation of clinical data and compute

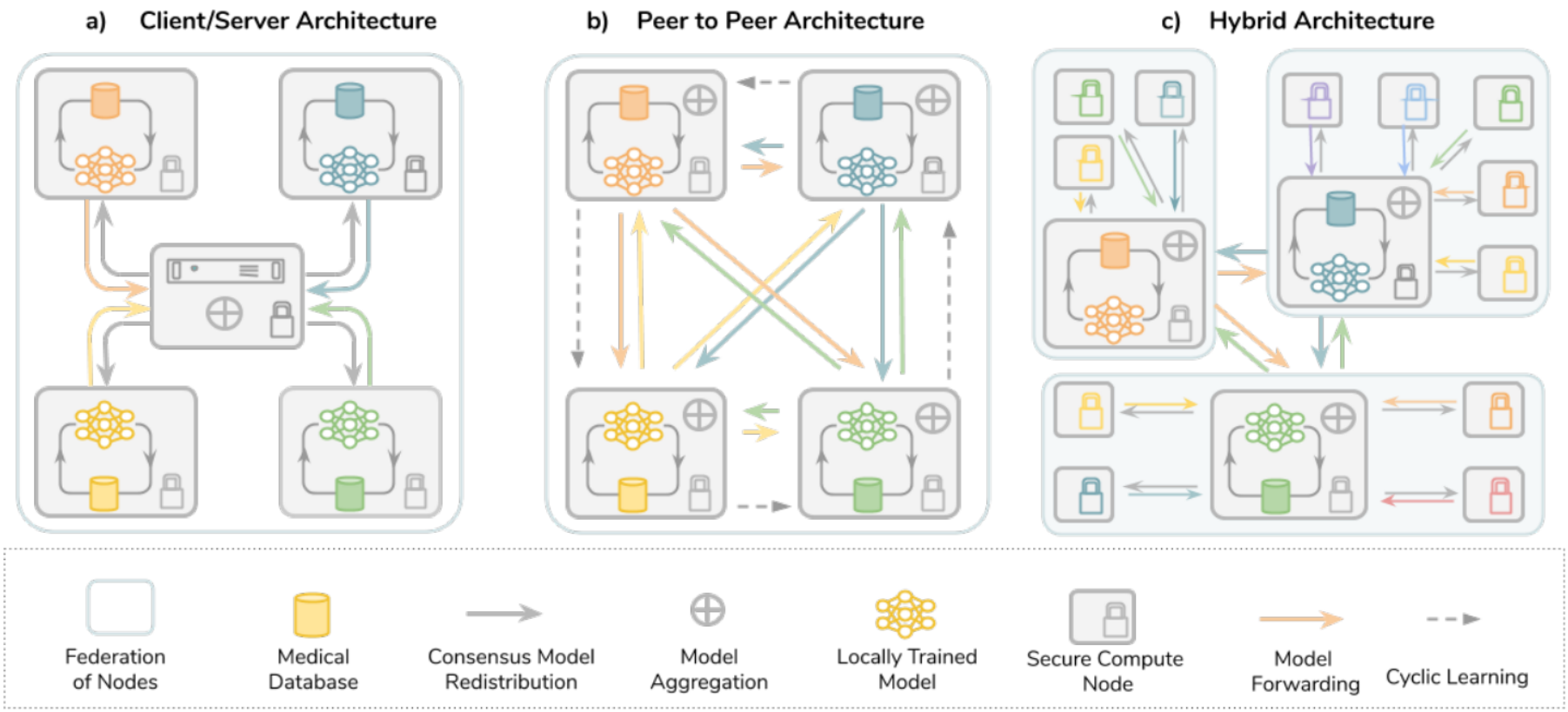


- Compute clusters typically operate outside Protected Health Information (PHI) compliant environments, limiting direct access to medical data.
- Secure, compliant environments often have limited compute resources.
- Strict firewalls and security measures complicate connecting to federated learning servers.

—
Credit: John Garrett.Federated Learning in Medical Imaging: Enhancing Data Privacy and Advancing Healthcare, 2025.

How does FL work?

Communication Architectures



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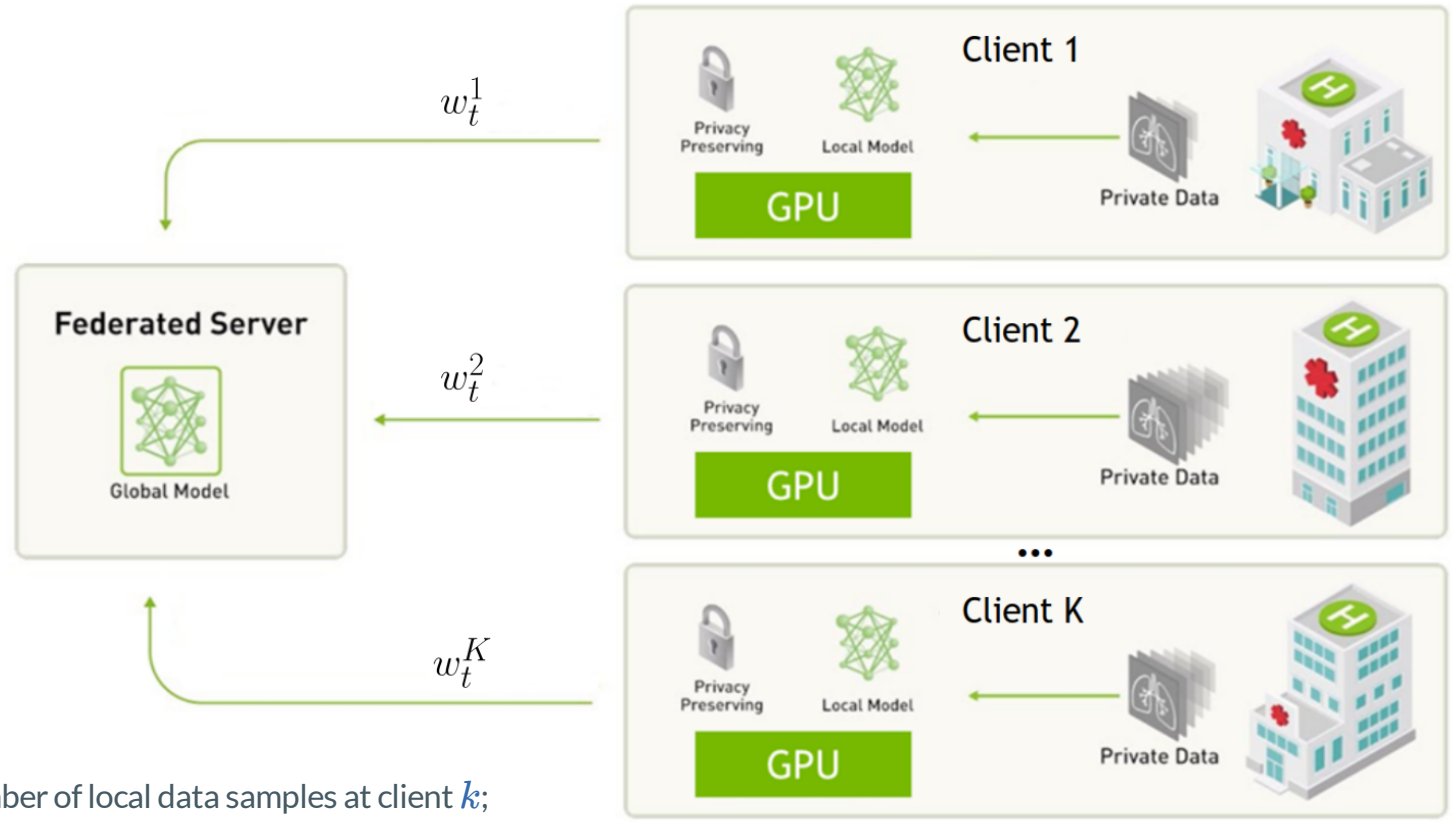
Credit: Nicola Rieke | Sr. Deep Learning Solution Architect - Healthcare - FEDERATED LEARNING USING CLARA TRAIN.

Server-Client Federated Learning: Averaging

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^k$$



n_k is the number of local data samples at client k;

n is the total number of samples across all participating clients;

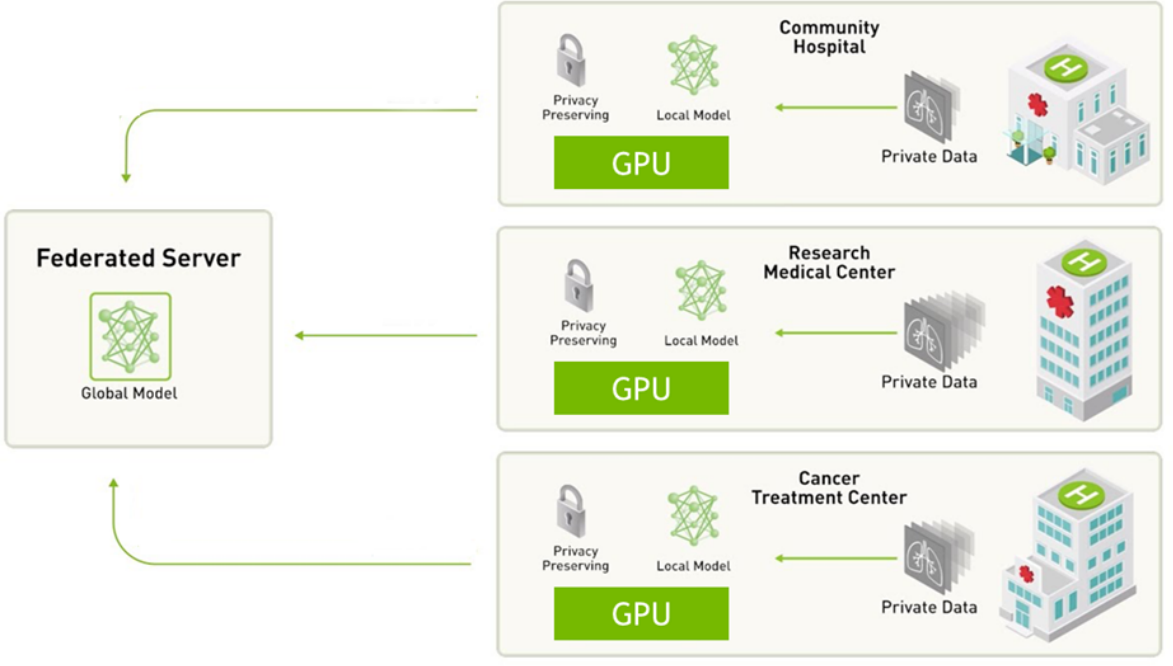
w_t^k — model weights trained locally by client k;

t is a communication round.

—

Server-Client Federated Learning

- **Server:** manages job lifecycle, assigns computation tasks to clients & aggregate.
- **Clients:** perform tasks assigned by the server.
- **Workflow:** a distributed workflow with specific optimization algorithms and communication strategies.



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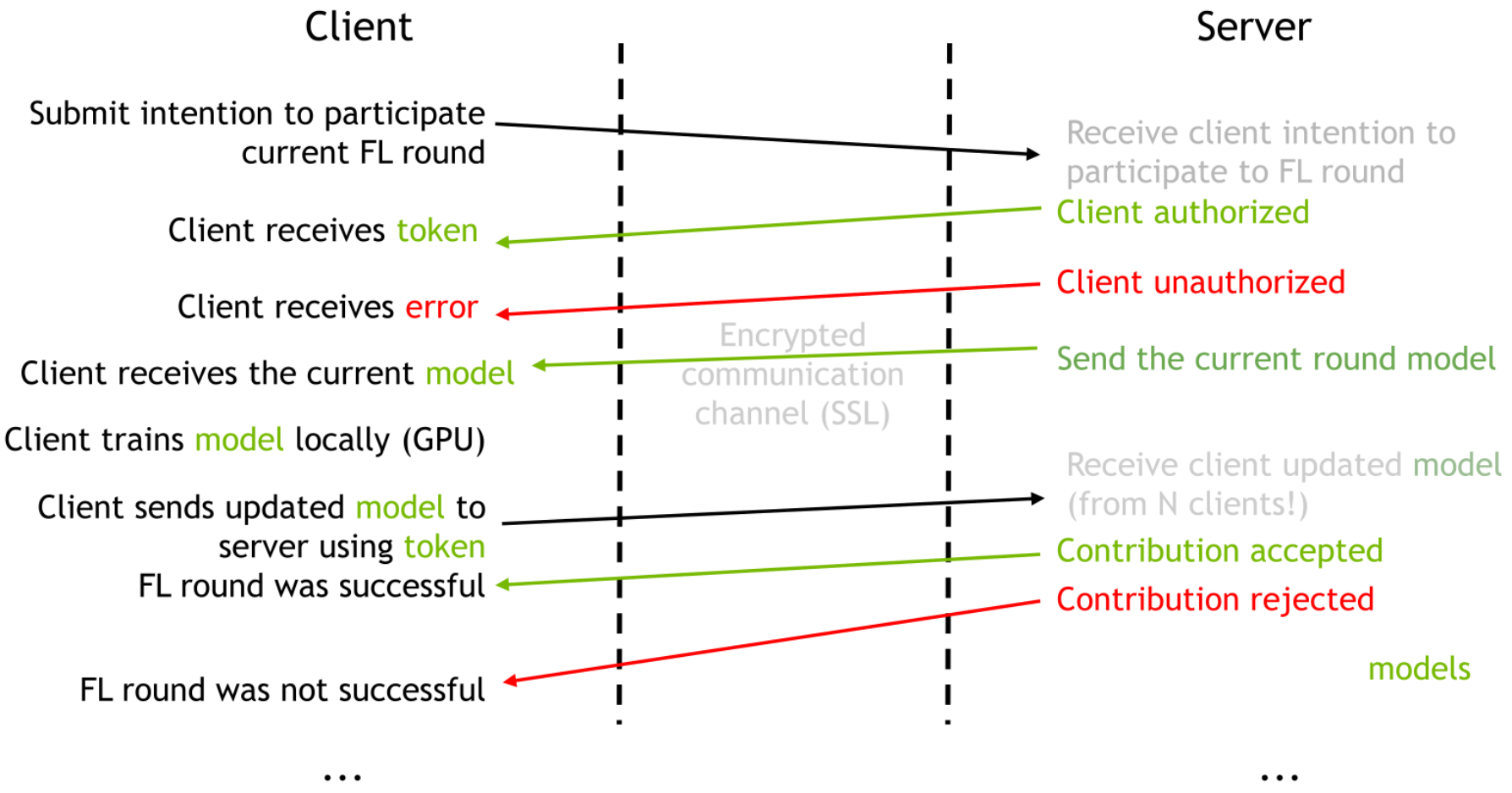
Credit: Nicola Rieke | Sr. Deep Learning Solution Architect - Healthcare - FEDERATED LEARNING USING CLARA TRAIN.

High-level implementation



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Data harmonization challenges for FL

- **Protocol and equipment variability**
  - Differences in imaging methods and machines between institutions.

—
Credit: John Garrett.Federated Learning in Medical Imaging: Enhancing Data Privacy and Advancing Healthcare, 2025.

- **Protocol and equipment variability**
  - Differences in imaging methods and machines between institutions.
- **Data interoperability**
  - Using common formats and processing methods for easier analysis.
  - In medical imaging DICOM standard is widespred, though clinical data such as labs is less standardized.

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Credit: John Garrett.Federated Learning in Medical Imaging: Enhancing Data Privacy and Advancing Healthcare, 2025.

- **Protocol and equipment variability**
  - Differences in imaging methods and machines between institutions.
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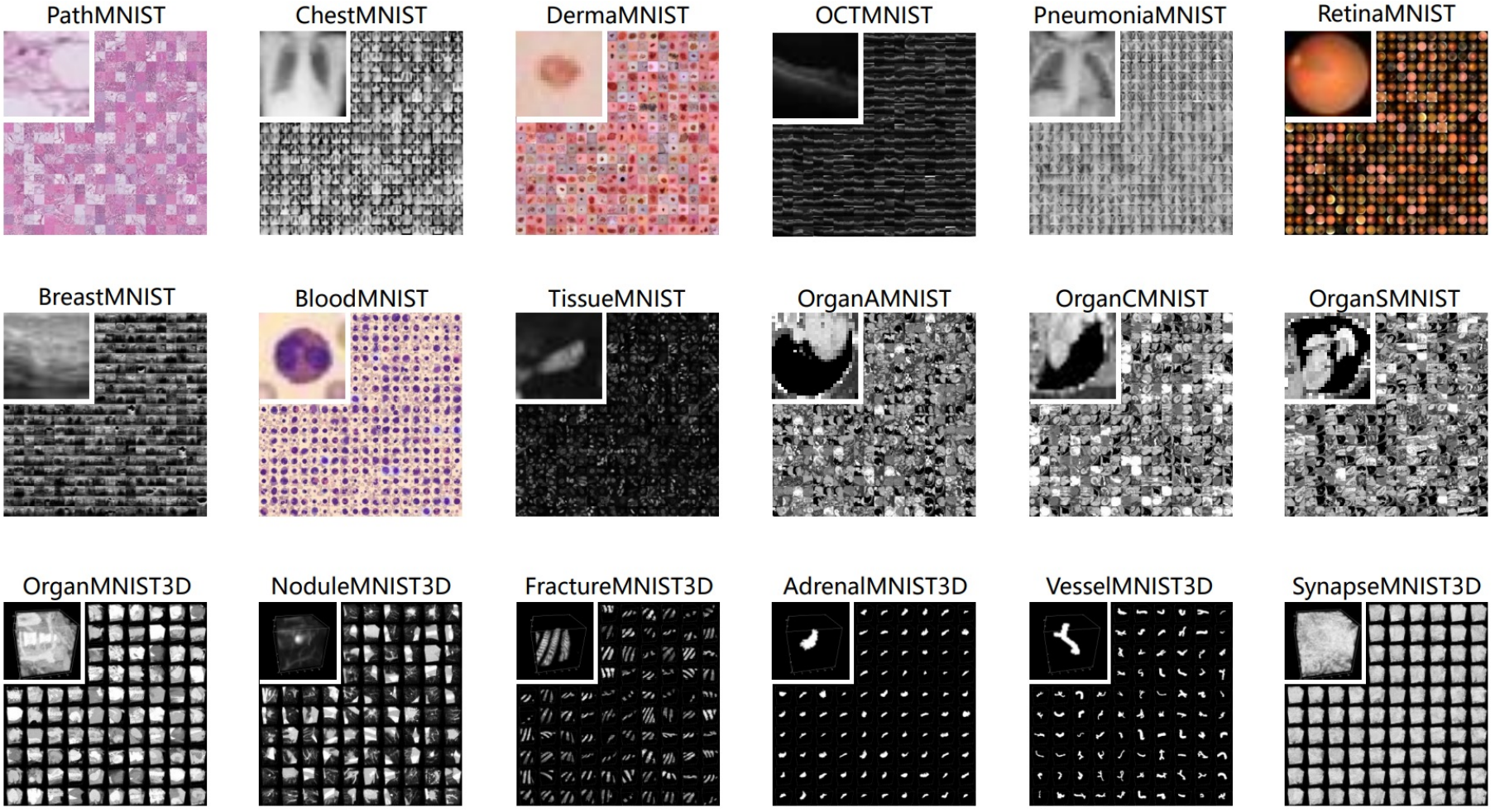
  - Using common formats and processing methods for easier analysis.
  - In medical imaging DICOM standard is widespred, though clinical data such as labs is less standardized.
- **Labeling differences**
  - Inconsistent terminology and labels are used across different organizations.

—

Credit: John Garrett.Federated Learning in Medical Imaging: Enhancing Data Privacy and Advancing Healthcare, 2025.

Large-scale standardized dataset (MedMNIST)

The **MedMNIST** dataset consists of 12 datasets for 2D and 6 datasets for 3D. Covers key medical imaging modalities (X-Ray, OCT, Ultrasound, CT, Electron Microscopy). Supports tasks (binary/multi-class classification, ordinal regression, multi-label), and scales from 10^2 to 10^5 samples. Multiple size options: 28 (MNIST-Like), 64, 128, and 224.



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Credit: MedMNIST. 18x Standardized Datasets for 2D and 3D Biomedical Image Classification with Multiple Size Options: 28 (MNIST-Like), 64, 128, and 224, 2020.

MedMNIST2D

MedMNIST2D	Data Modality	Tasks (# Classes/Labels)	# Samples	# Training / Validation / Test
PathMNIST	Colon Pathology	Multi-Class (9)	107,180	89,996 / 10,004 / 7,180
ChestMNIST	Chest X-Ray	Multi-Label (14) Binary-Class (2)	112,120	78,468 / 11,219 / 22,433
DermaMNIST	Dermatoscope	Multi-Class (7)	10,015	7,007 / 1,003 / 2,005
OCTMNIST	Retinal OCT	Multi-Class (4)	109,309	97,477 / 10,832 / 1,000
PneumoniaMNIST	Chest X-Ray	Binary-Class (2)	5,856	4,708 / 524 / 624
RetinaMNIST	Fundus Camera	Ordinal Regression (5)	1,600	1,080 / 120 / 400
BreastMNIST	Breast Ultrasound	Binary-Class (2)	780	546 / 78 / 156
BloodMNIST	Blood Cell Microscope	Multi-Class (8)	17,092	11,959 / 1,712 / 3,421
TissueMNIST	Kidney Cortex Microscope	Multi-Class (8)	236,386	165,466 / 23,640 / 47,280
OrganAMNIST	Abdominal CT	Multi-Class (11)	58,830	34,561 / 6,491 / 17,778
OrganCMNIST	Abdominal CT	Multi-Class (11)	23,583	12,975 / 2,392 / 8,216
OrganSMNIST	Abdominal CT	Multi-Class (11)	25,211	13,932 / 2,452 / 8,827

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Credit: MedMNIST. 18x Standardized Datasets for 2D and 3D Biomedical Image Classification with Multiple Size Options: 28 (MNIST-Like), 64, 128, and 224, 2020.

MedMNIST3D

MedMNIST3D	Data Modality	Tasks (# Classes/Labels)	# Samples	# Training / Validation / Test
OrganMNIST3D	Abdominal CT	Multi-Class (11)	1,742	971 / 161 / 610
NoduleMNIST3D	Chest CT	Binary-Class (2)	1,633	1,158 / 165 / 310
AdrenalMNIST3D	Shape from Abdominal CT	Binary-Class (2)	1,584	1,188 / 98 / 298
FractureMNIST3D	Chest CT	Multi-Class (3)	1,370	1,027 / 103 / 240
VesselMNIST3D	Shape from Brain MRA	Binary-Class (2)	1,908	1,335 / 191 / 382
SynapseMNIST3D	Electron Microscope	Binary-Class (2)	1,759	1,230 / 177 / 352

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Credit: MedMNIST. 18x Standardized Datasets for 2D and 3D Biomedical Image Classification with Multiple Size Options: 28 (MNIST-Like), 64, 128, and 224, 2020.

Benchmarking

Methods	PathMNIST		ChestMNIST		DermaMNIST		OCTMNIST		PneumoniaMNIST		RetinaMNIST	
	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC
ResNet-18 (28)	0.983	0.907	0.768	0.947	0.917	0.735	0.943	0.743	0.944	0.854	0.717	0.524
ResNet-18 (224)	0.989	0.909	0.773	0.947	**0.920**	0.754	0.958	0.763	0.956	0.864	0.710	0.493
ResNet-50 (28)	**0.990**	**0.911**	0.769	0.947	0.913	0.735	0.952	0.762	0.948	0.854	0.726	0.528
ResNet-50 (224)	0.989	0.892	0.773	**0.948**	0.912	0.731	0.958	**0.776**	0.962	0.884	0.716	0.511
auto-sklearn	0.934	0.716	0.649	0.779	0.902	0.719	0.887	0.601	0.942	0.855	0.690	0.515
AutoKeras	0.959	0.834	0.742	0.937	0.915	0.749	0.955	0.763	0.947	0.878	0.719	0.503
Google AutoML Vision	0.944	0.728	**0.778**	**0.948**	0.914	**0.768**	**0.963**	0.771	**0.991**	**0.946**	**0.750**	**0.531**

Methods	BreastMNIST		BloodMNIST		TissueMNIST		OrganAMNIST		OrganCMNIST		OrganSMNIST	
	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC
ResNet-18 (28)	0.901	**0.863**	**0.998**	0.958	0.930	0.676	0.997	0.935	0.992	0.900	0.972	0.782
ResNet-18 (224)	0.891	0.833	**0.998**	0.963	0.933	0.681	**0.998**	**0.951**	**0.994**	**0.920**	0.974	0.778
ResNet-50 (28)	0.857	0.812	0.997	0.956	0.931	0.680	0.997	0.935	0.992	0.905	0.972	0.770
ResNet-50 (224)	0.866	0.842	0.997	0.950	0.932	0.680	**0.998**	0.947	0.993	0.911	**0.975**	0.785
auto-sklearn	0.836	0.803	0.984	0.878	0.828	0.532	0.963	0.762	0.976	0.829	0.945	0.672
AutoKeras	0.871	0.831	**0.998**	0.961	**0.941**	**0.703**	0.994	0.905	0.990	0.879	0.974	**0.813**
Google AutoML Vision	**0.919**	0.861	**0.998**	**0.966**	0.924	0.673	0.990	0.886	0.988	0.877	0.964	0.749

Benchmarking Performance on MedMNIST2D.

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Credit: MedMNIST. 18x Standardized Datasets for 2D and 3D Biomedical Image Classification with Multiple Size Options: 28 (MNIST-Like), 64, 128, and 224, 2020.

Methods	OrganMNIST3D		NoduleMNIST3D		FractureMNIST3D		AdrenalMNIST3D		VesselMNIST3D		SynapseMNIST3D	
	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC
ResNet-18 + 2.5D	0.977	0.788	0.838	0.835	0.587	0.451	0.718	0.772	0.748	0.846	0.634	0.696
ResNet-18 + 3D	**0.996**	**0.907**	0.863	0.844	0.712	0.508	0.827	0.721	0.874	0.877	0.820	0.745
ResNet-18 + ACS	0.994	0.900	0.873	0.847	0.714	0.497	**0.839**	0.754	**0.930**	**0.928**	0.705	0.722
ResNet-50 + 2.5D	0.974	0.769	0.835	0.848	0.552	0.397	0.732	0.763	0.751	0.877	0.669	0.735
ResNet-50 + 3D	0.994	0.883	0.875	0.847	0.725	0.494	0.828	0.745	0.907	0.918	**0.851**	**0.795**
ResNet-50 + ACS	0.994	0.889	0.886	0.841	**0.750**	**0.517**	0.828	0.758	0.912	0.858	0.719	0.709
auto-sklearn	0.977	0.814	**0.914**	**0.874**	0.628	0.453	0.828	**0.802**	0.910	0.915	0.631	0.730
AutoKeras	0.979	0.804	0.844	0.834	0.642	0.458	0.804	0.705	0.773	0.894	0.538	0.724

Benchmarking Performance on MedMNIST3D.

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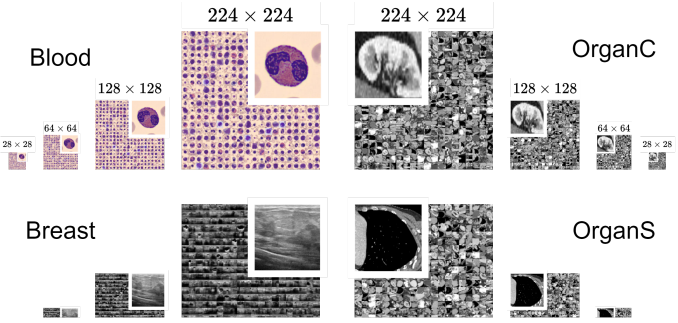
Credit: MedMNIST. 18x Standardized Datasets for 2D and 3D Biomedical Image Classification with Multiple Size Options: 28 (MNIST-Like), 64, 128, and 224, 2020.



Methods	Accuracy (ACC)				Area Under the ROC Curve (AUC)			
	28 × 28	64 × 64	128 × 128	224 × 224	28 × 28	64 × 64	128 × 128	224 × 224
END-TO-END								
VGG16	**82.34**±0.88	**85.33**±1.16	86.64±0.82	86.70±0.93	**92.66**±0.41	**94.24**±0.28	**95.16**±0.27	**95.30**±0.22
AlexNet	78.92±0.81	82.94±0.78	85.04±0.74	85.74±0.64	91.14±0.43	92.72±0.33	94.29±0.30	94.90±0.23
ResNet-18	79.66±0.74	83.42±0.65	85.73±0.66	86.22±0.58	90.92±0.28	92.49±0.50	93.91±0.27	94.51±0.24
DenseNet-121	80.32±0.93	84.62±0.80	**87.13**±0.56	**87.11**±0.64	91.75±0.55	93.59±0.23	94.57±0.21	95.03±0.23
EfficientNet-B4	73.18±1.61	79.37±1.10	82.52±0.79	82.44±1.11	87.04±0.82	90.07±0.65	91.89±0.39	91.64±0.73
ViT-B/16	78.23±0.88	83.17±0.92	84.94±0.93	86.06±0.92	90.54±0.47	92.53±0.69	93.25±0.35	94.08±0.38
CLIP ViT-B/16	76.73±0.80	80.39±0.99	82.33±1.02	82.75±1.01	89.22±1.11	90.91±0.51	91.51±0.31	91.83±0.58

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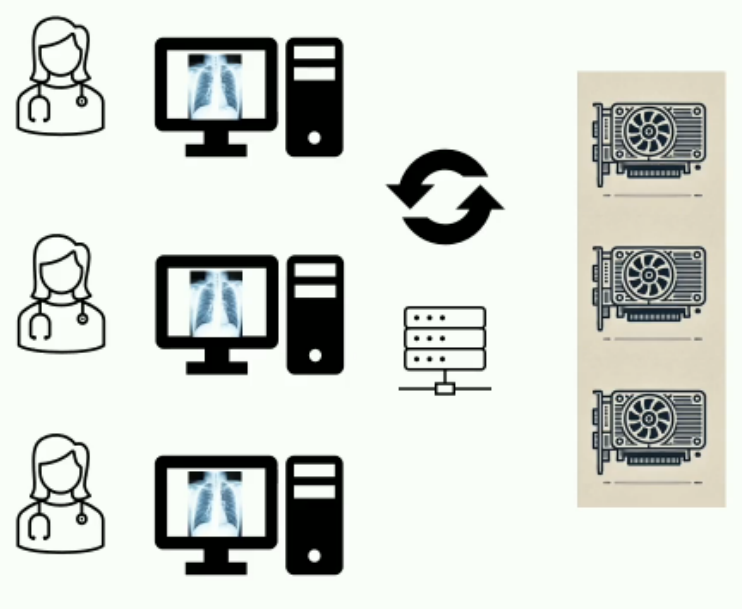
Credit: Rethinking model prototyping through the MedMNIST+ dataset collection, 2025.

Future directions for FL in Healthcare

Real time updates to clinical models



Today basically all imaging AI models deployed and used clinically are static.

Though there's a need to work with the FDA, federated learning may soon facilitate real time refinement and updates of deployed models.

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Credit: John Garrett.Federated Learning in Medical Imaging: Enhancing Data Privacy and Advancing Healthcare, 2025.