

**NVIDIA**

**MICCAI2021**

# NVIDIA AT MICCAI

September 27 - October 1, 2021 - Welcome to the NVIDIA Virtual Booth



**Nadim Daher**

*Healthcare Ecosystem  
Development Lead  
at NVIDIA*

**Moderator**



**Prerna Dogra**

*Sr. Product Manager  
at NVIDIA &  
Community Adoption &  
Outreach Lead for MONAI*

**Healthcare Product  
Management**



**Nicola Rieke**

*Head of Healthcare &  
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Architecture EMEA  
at NVIDIA*

**NVFlare**



**Marc Edgar**

*Sr. Alliance Manager for Medical  
Devices & Developer Relations  
at NVIDIA*

**Clara AGX**

# Prerna Dogra

Sr. Product Manager at NVIDIA &  
Community Adoption & Outreach Lead for MONAI

*Healthcare Product Management*

September 27 - October 1, 2021





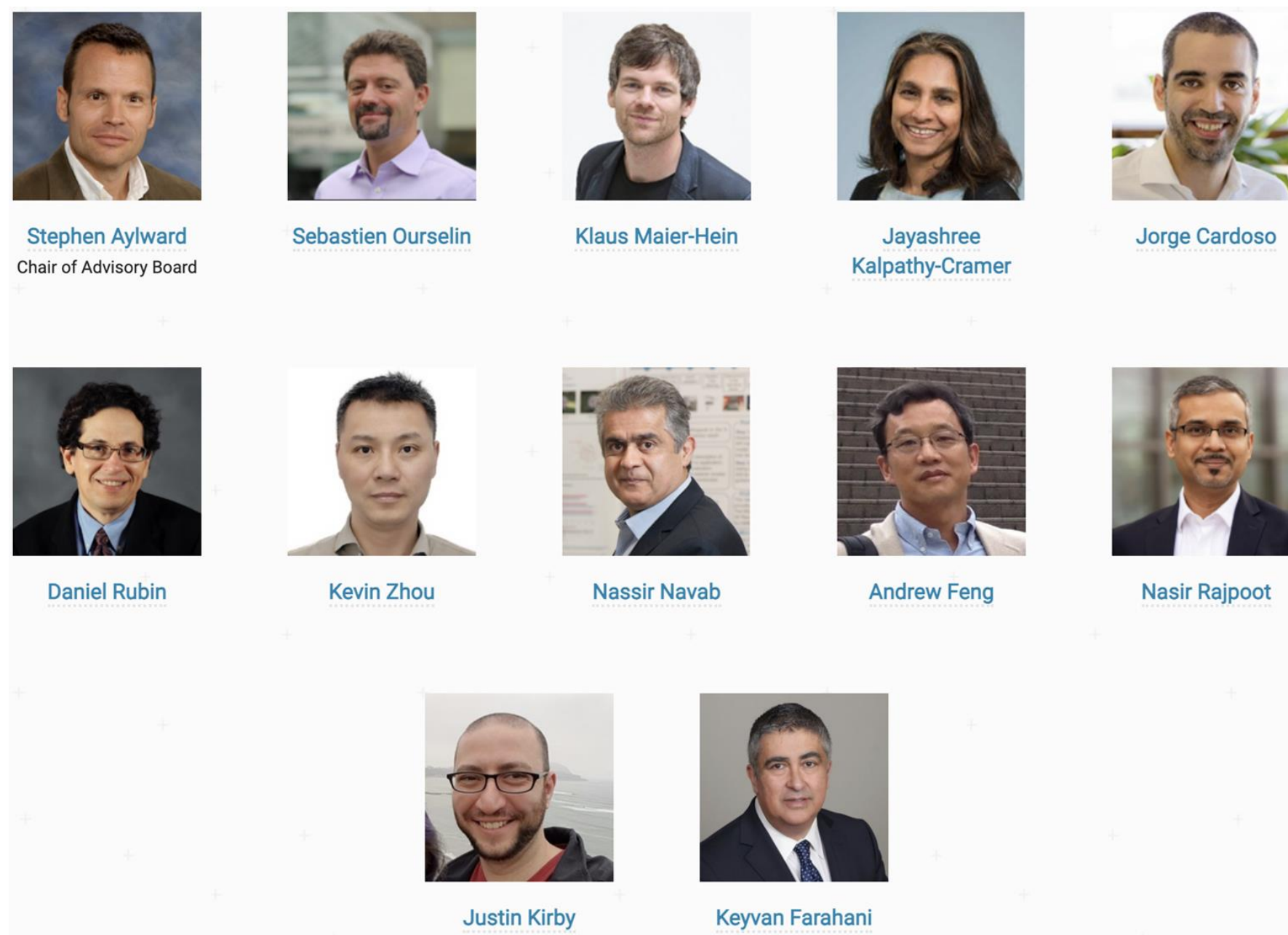
# Medical Open Network for AI

Prerna Dogra: Sr. Product Manager, Community Adoption & Outreach Lead for MONAI

# WHAT IS MONAI?

## Medical Open Network for AI

*Project MONAI is a collaborative open-source initiative built by academic & industry leaders to establish and standardize the best practices for deep learning in healthcare imaging to accelerate the pace of innovation”*



*Project MONAI is guided by Advisory Board chaired by Dr Stephen Aylward*

# WHAT IS MONAI?

Accelerate Pace of Research Innovation With a Common Foundation



*MONAI Label, an intelligent open-source image labeling and learning tool*

*That helps researchers and clinicians collaborate, create annotated datasets, and build AI models in a standardized MONAI paradigm.*

*MONAI Label v0.1*

*MONAI, the core Pytorch-based library for deep learning in healthcare imaging.*

*Provides domain-optimized foundational capabilities for developing healthcare imaging training workflows*

*MONAI Label v0.7*

*The very first release of MONAI Deploy App SDK that allows users to create applications from AI models in minutes*

*MONAI Deploy App SDK v0.1*

*Coming Soon !*

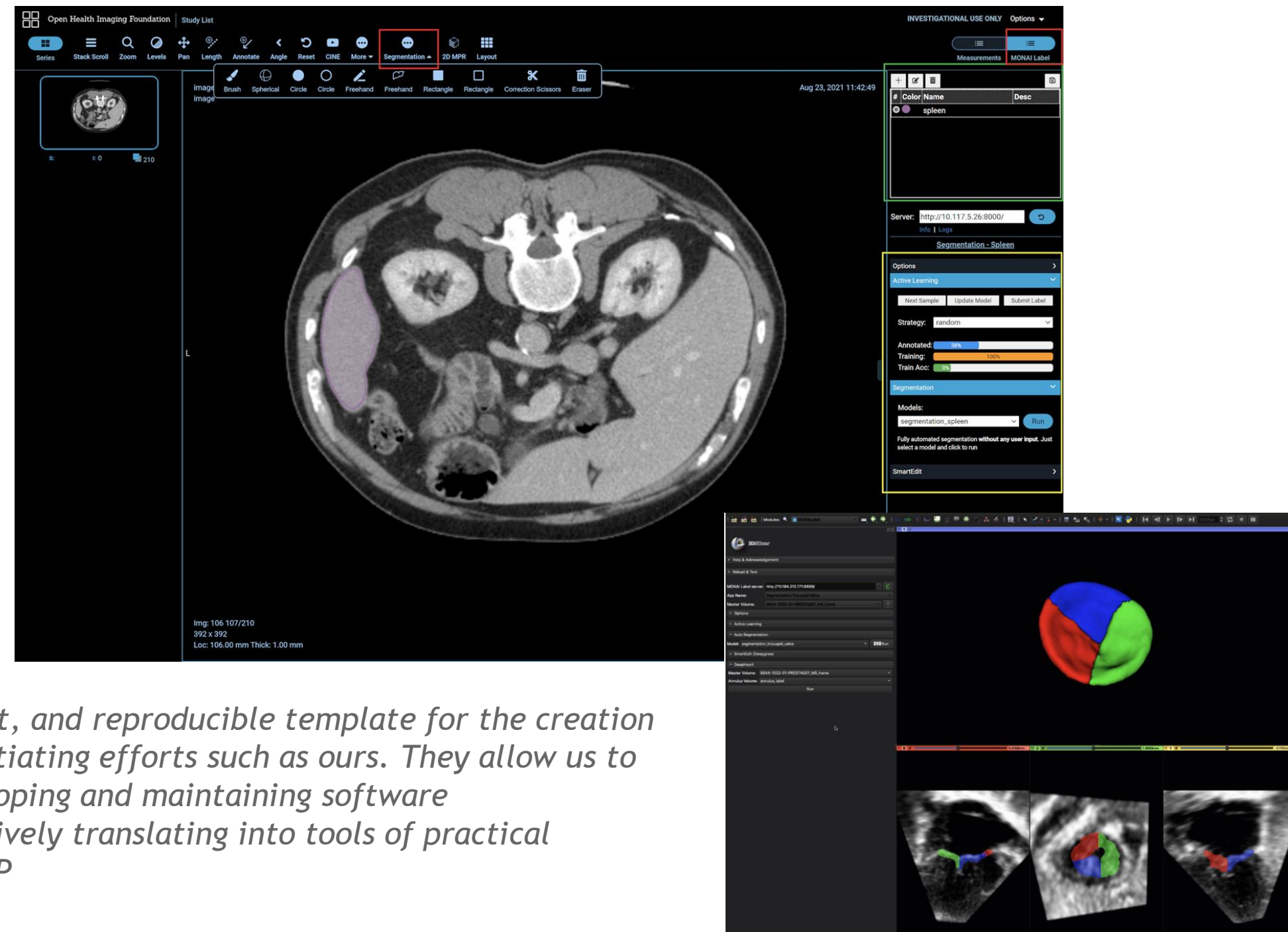


# MONAI LABEL V0.2

An intelligent open-source image labeling and learning tool

MONAI Label helps researchers and clinicians collaborate, create annotated datasets and build AI models in a standardized MONAI paradigm.

- MONAI Label v0.2 now includes:
  - Support for OHIF, a zero-footprint web viewer, now get started with MONAI Label with no local installations
  - Support for DICOM web & new MONAI Label application Scribbles
  - New DL based Active Learning strategies



*Open-source frameworks like Project MONAI provide a standardized, transparent, and reproducible template for the creation of, and deployment of medical imaged-focused machine learning models, potentiating efforts such as ours. They allow us to focus on investigating novel algorithms and their application, rather than developing and maintaining software infrastructure. This in turn has accelerated research progress which we are actively translating into tools of practical relevance to the pediatric community we serve” - Dr. Matthew Jolley, MD, CHOP*

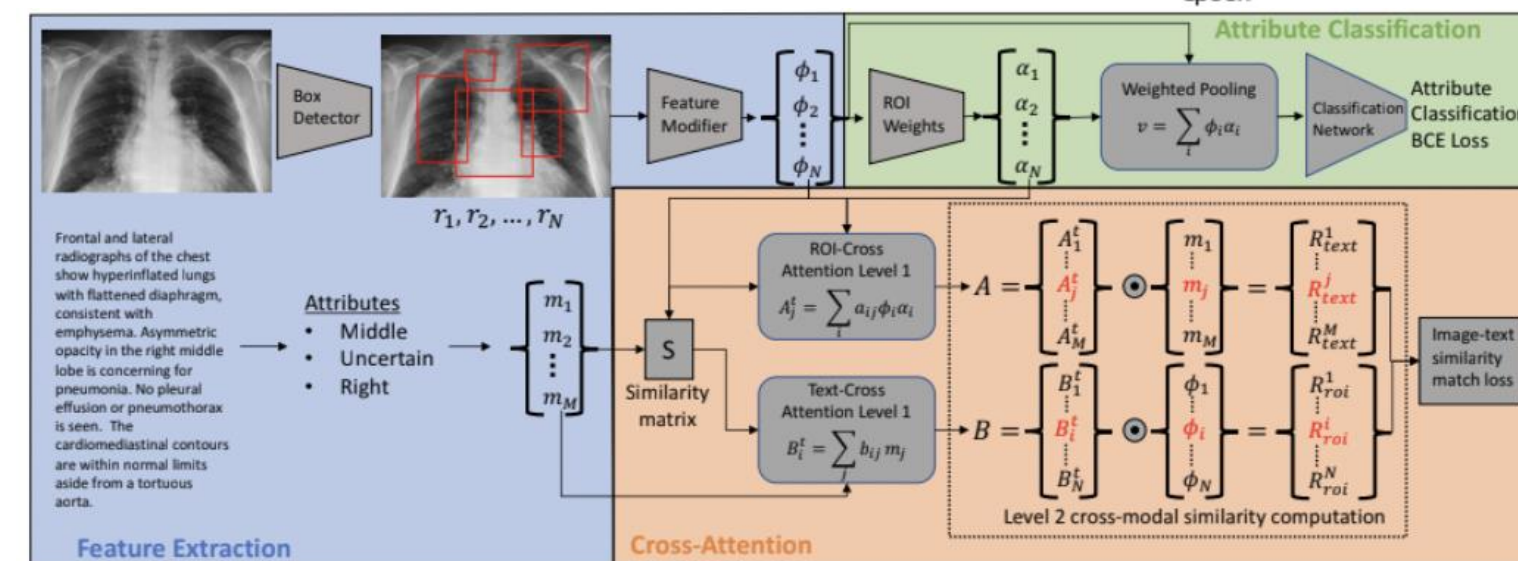
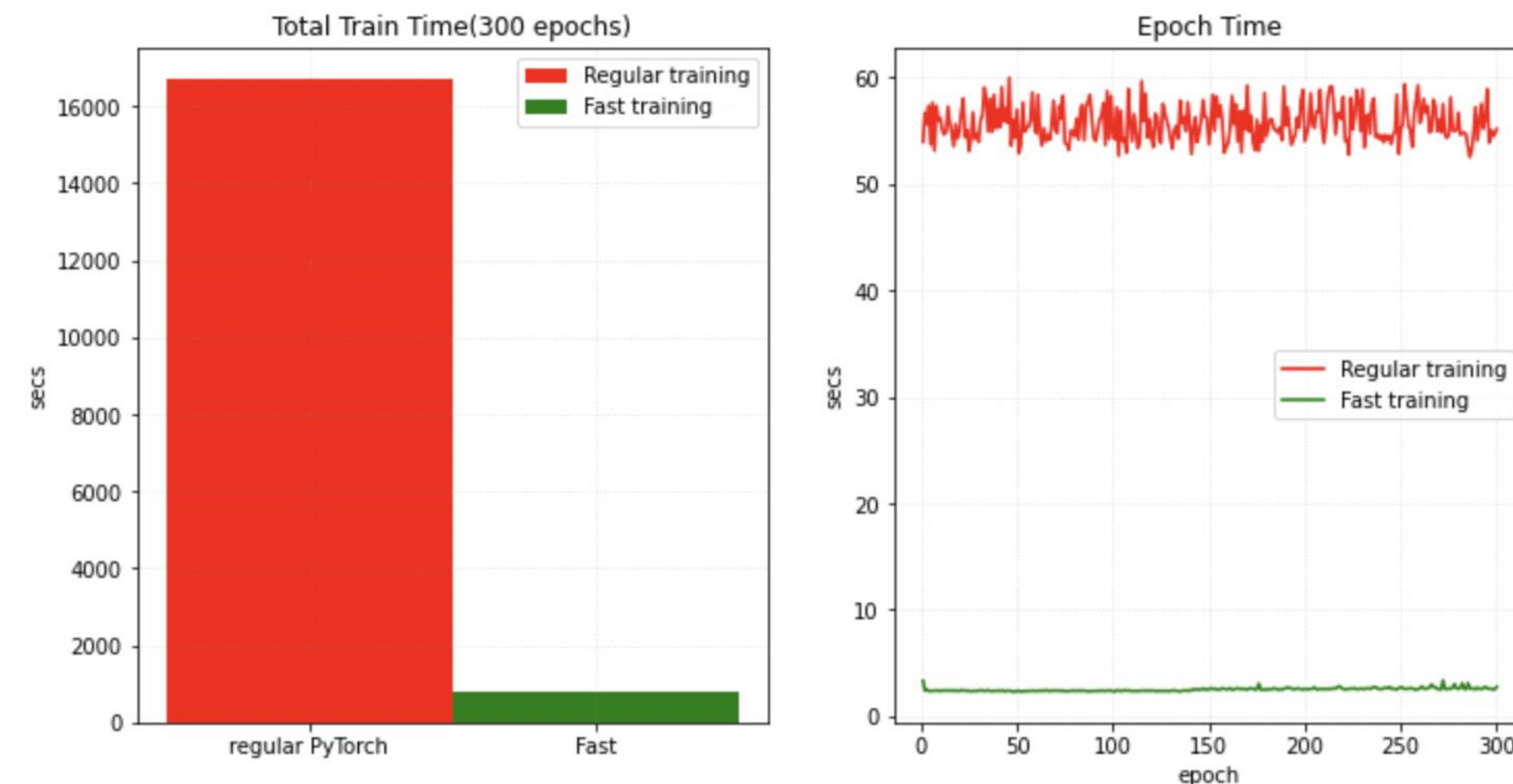
# MONAI V0.7

## Flagship domain specialized training library

*MONAI, the flagship library of Project Monai providing domain specialized best practices for building AI models in healthcare imaging*

• MONAI v0.7 now includes:

- Perf features, enabling up to 20x faster training with developers guides on building state of the art high performing training pipelines using MONAI
- New tutorials showcasing reference Kaggle top performing methods implemented as MONAI pipelines.
- MICCAI Research powered by MONAI, Attention driven visual grounding for disease localization



**Fig. 1.** Network architecture for training the attention based image-text matching for localization.



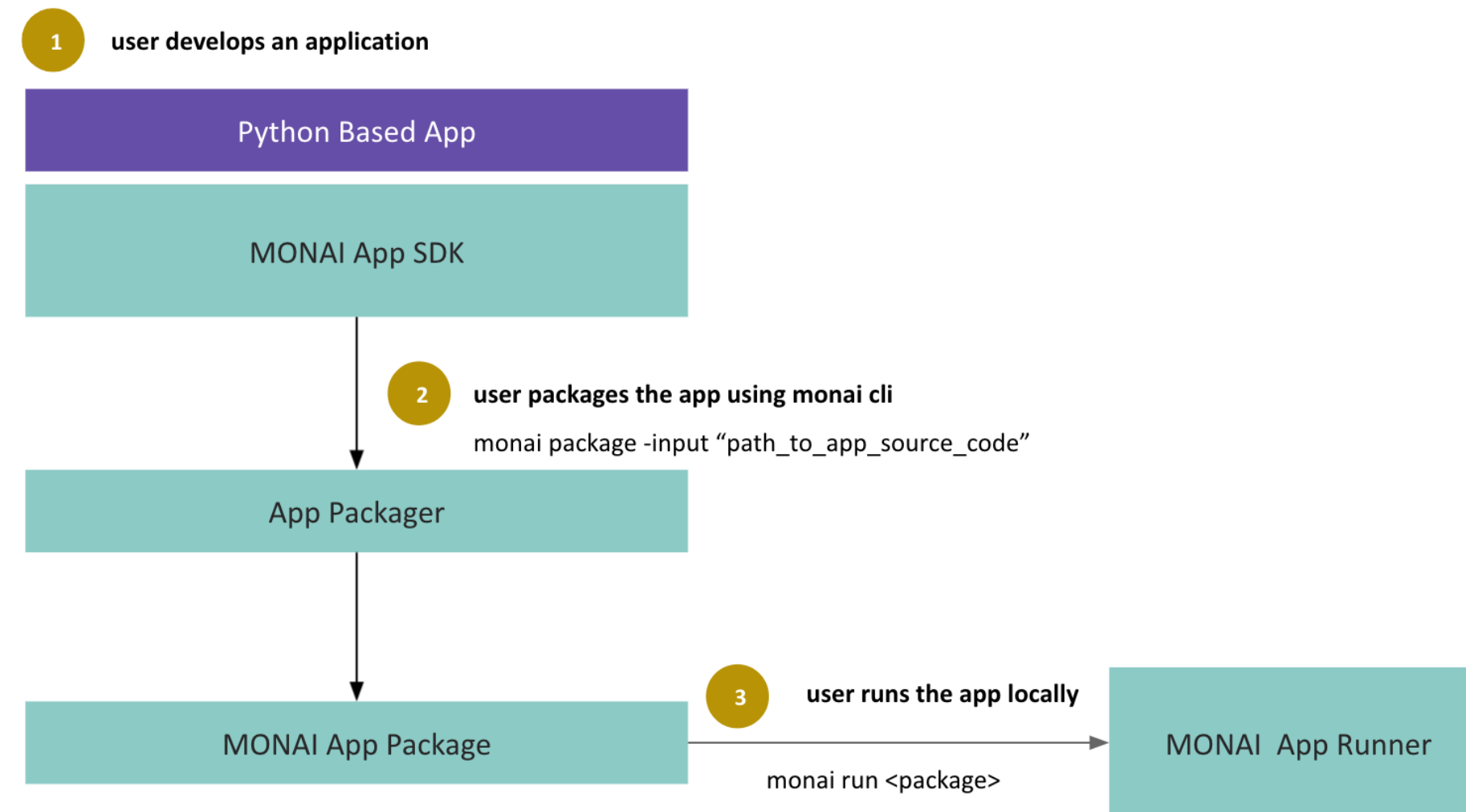
# MONAI DEPLOY V0.1

Develop and test medical applications from AI trained models, in minutes!

*MONAI Deploy App SDK offers a framework and associated tools to design, develop and verify AI-driven applications in the healthcare imaging domain.*

- V0.1.0 includes

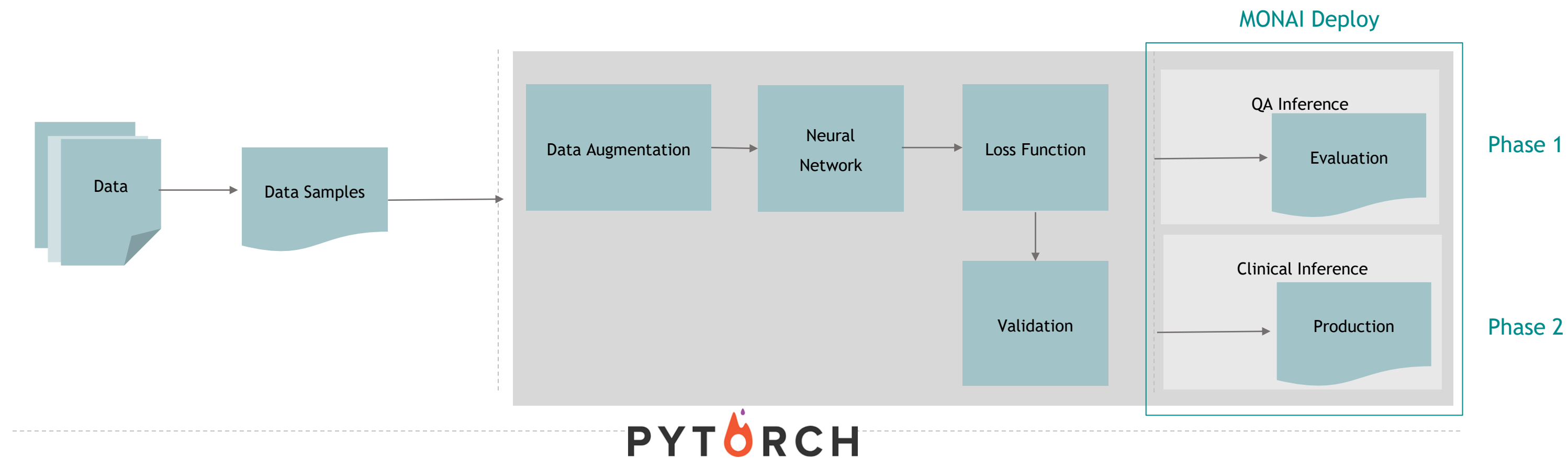
- Pythonic framework for app development
- API documentation and user's guide
- A mechanism to locally run a MONAI Deploy App via App Runner
- Sample applications for a simple Image processing app, MedNist Classifier app and an organ segmentation app



# MONAI DEPLOY

## Bridging the gap from research innovation to clinical production

- **MONAI Deploy** aims to become the de-facto standard for developing, testing, deploying and running medical AI applications in clinical production.
- *For Researchers & developers*, MONAI Deploy provides an easy way to develop MONAI Deploy application packages (MAPs)
- *For Hospital Operations*, MONAI Deploy will define what a clinical infrastructure to run AI should look like, and how to interoperate with medical imaging systems over standards like DICOM and FHIR.



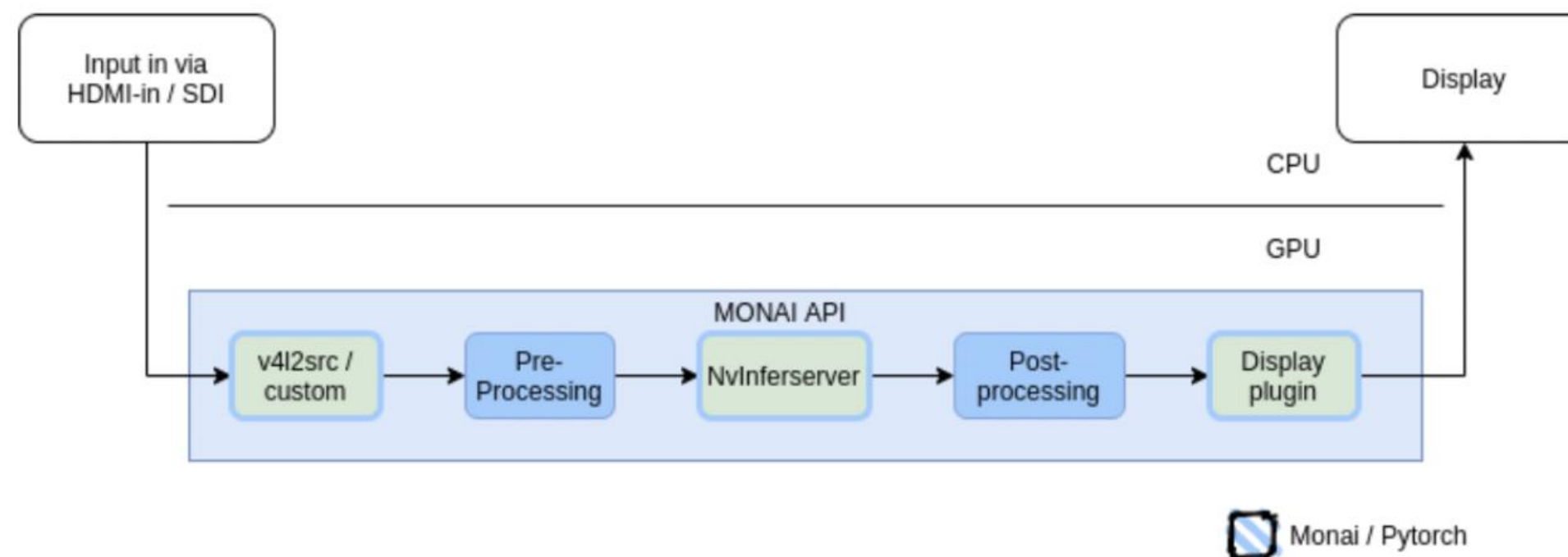
# MONAI STREAM

## Accelerating Research Prototyping for Streaming Applications

- [Announcing MONAI Stream](#), enables faster prototyping for data streaming research into real-time imaging and computer-assisted interventions.
- Dr. Tom Vercauteren, Professor at King's College London would be leading the MONAI Stream working group.
- Please stay tuned to learn more !



Dr. Tom Vercauteren  
MONAI Stream Lead



# MONAI MOMENTUM IS EXPLODING

Let's build MONAI together

Summary

PyPI link	<a href="https://pypi.org/project/monai">https://pypi.org/project/monai</a>
Total downloads	111,846
Total downloads - 30 days	14,061
Total downloads - 7 days	3,394

*112k Downloads  
105 external projects*

Contributors 76

+ 65 contributors

**Project MONAI**  
AI Toolkit for Healthcare Imaging  
<https://monai.io/> [@ProjectMONAI](#)

*10 Working groups  
80 external contributors*

*Join the open-source force  
of multiple organizations*

# ENGAGE WITH MONAI TODAY

Get Started: <https://github.com/Project-MONAI>

Create AI Model for Healthcare Imaging with MONAI: <https://github.com/Project-MONAI/MONAI>

Create AI models for annotation and integrate with your viewer of choice: <https://github.com/Project-MONAI/MONAILabel>

Create an application from an AI model with MONAI Deploy: <https://github.com/Project-MONAI/monai-deploy-app-sdk>

## We want to hear from you

- MONAI Core GitHub Discussion: <https://github.com/Project-MONAI/MONAI/discussions>
- MONAI Label GitHub Discussion: <https://github.com/Project-MONAI/MONAILabel/discussions>
- MONAI Deploy Discussion: <https://github.com/Project-MONAI/monai-deploy-app-sdk/discussions>

## Contribute

- GitHub
  - Community Guide: <https://github.com/Project-MONAI/MONAI#community>
  - Contributing Guide: <https://github.com/Project-MONAI/MONAI#contributing>
- Join our Slack Channel. Fill out the Google Form here: <https://forms.gle/QTxJq3hFictp31UM9>

# Nicola Rieke

Head of Healthcare & Life Sciences, Solution Architecture EMEA at NVIDIA

*Federated Learning with NVFlare*

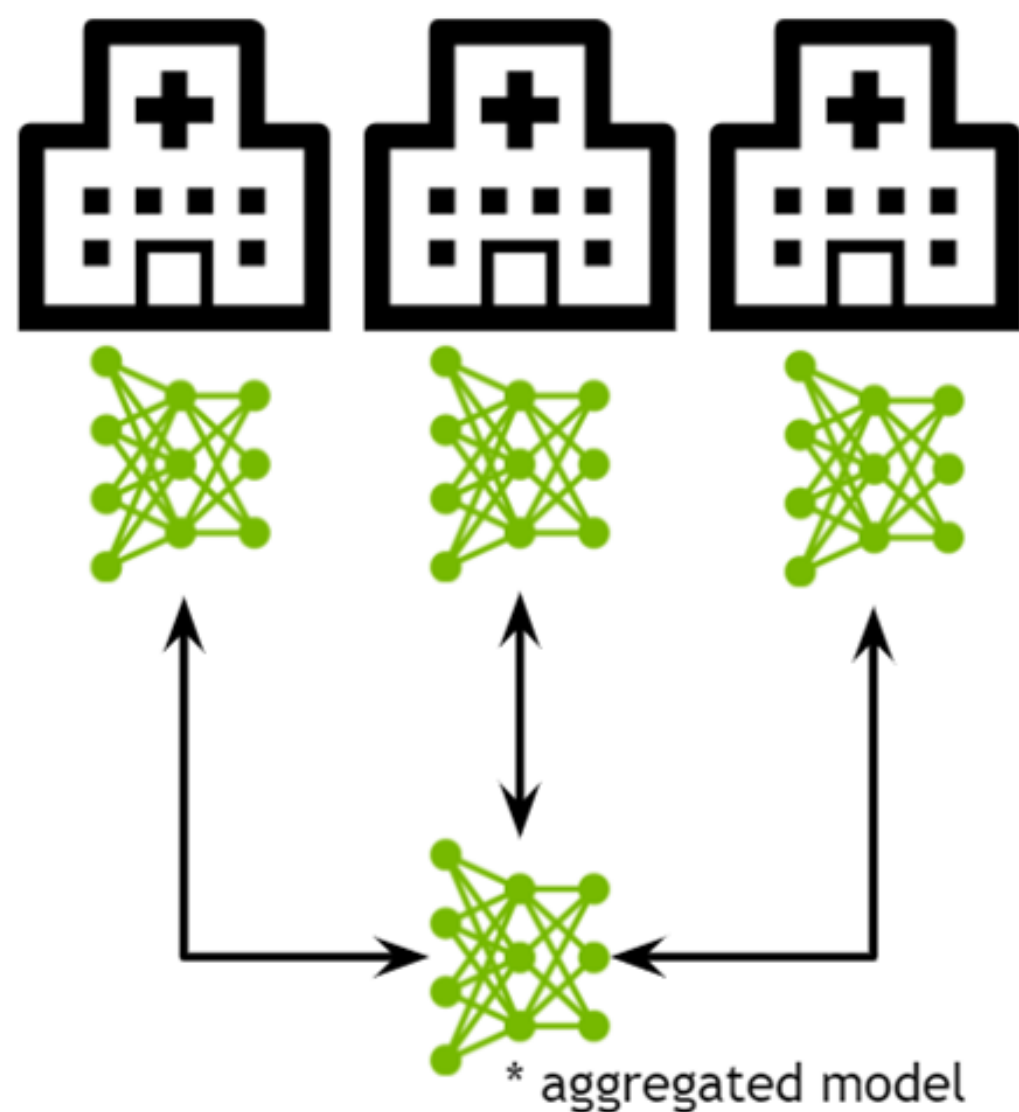
*NVIDIA Federated Learning Application Runtime Environment*

September 27 - October 1, 2021



# FEDERATED EFFORT

## ROBUST MODELS, LARGE SCALE TRAINING



- Training of AI models requires sufficiently large, diverse and curated data sets
- Share **model updates**, not data
- Collaborative Learning without centralizing data
- AI training occurs locally at each participant
- Participant controls data access and the ability to revoke it

# FEDERATED LEARNING

NVIDIA has strong footprints for FL in healthcare



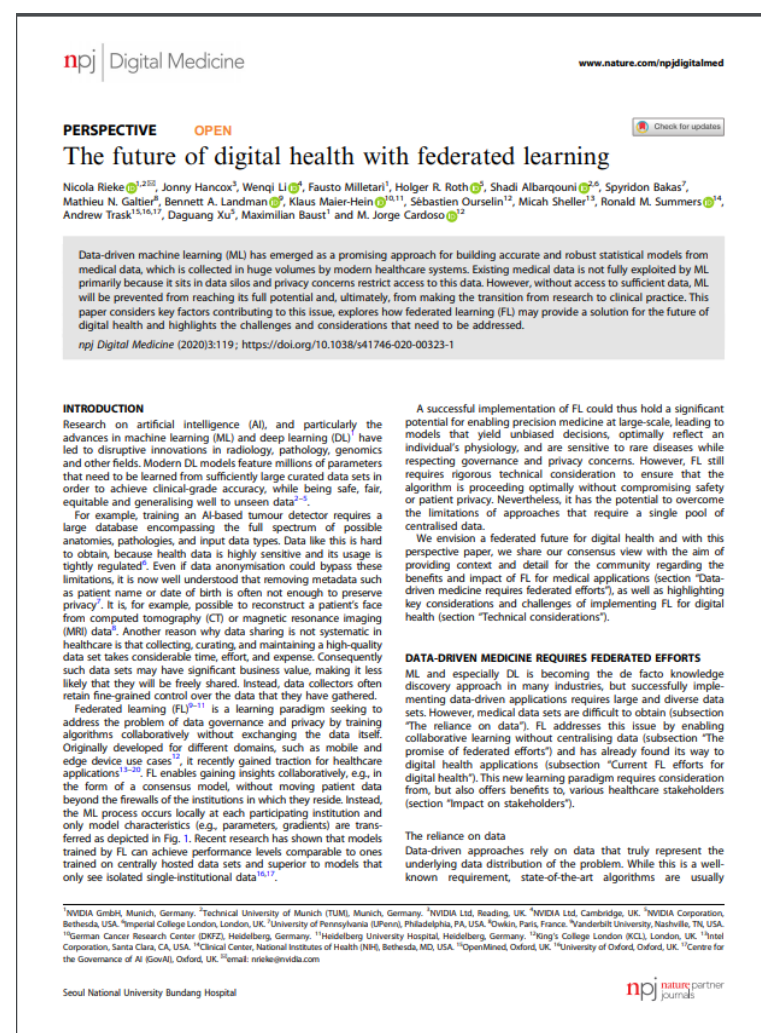
Distributed & Collaborative Learning

1st MICCAI Workshop on  
“Distributed And Collaborative Learning”

FEDERATED LEARNING FOR HEALTHCARE

2<sup>nd</sup> MICCAI DCL Workshop on Oct 1!

<http://dcl-workshop.net/>



npj Digital Medicine

PERSPECTIVE OPEN

The future of digital health with federated learning

Nicola Rieke<sup>1,2,3,4</sup>, Jonny Hancox<sup>1</sup>, Wenqi Li<sup>5</sup>, Fausto Milletari<sup>1</sup>, Holger R. Roth<sup>6</sup>, Shadi Albarqouni<sup>7,8</sup>, Spyridon Bakas<sup>9</sup>, Mathieu N. Galtier<sup>10</sup>, Bennett A. Landman<sup>11</sup>, Klaus Maier-Hein<sup>12,13</sup>, Sébastien Ourselin<sup>14</sup>, Micah Sheller<sup>15</sup>, Ronald M. Summers<sup>16</sup>, Andrew Trask<sup>16,17</sup>, Daguang Xu<sup>1</sup>, Maximilian Baust<sup>1</sup> and M. Jorge Cardoso<sup>18</sup>

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.

npj Digital Medicine (2020) 3:119 | <https://doi.org/10.1038/s41746-020-00323-1>

INTRODUCTION

Research on artificial intelligence (AI), and particularly the advances in machine learning (ML) and deep learning (DL) have led to disruptive innovations in radiology, pathology, genomics and other fields. Modern DL models feature millions of parameters that need to be learned from sufficiently large curated data sets in order to achieve clinical-grade accuracy, while being safe, fair, equitable and generalising well to unseen data<sup>1-4</sup>.

For example, training an AI-based tumour detector requires a large database encompassing the full spectrum of possible anatomies, pathologies, and input data types. Data like this is hard to obtain, because health data is highly sensitive and its usage is tightly regulated<sup>5</sup>. Even if data anonymisation could bypass these limitations, it is now well understood that removing metadata such as patient name or date of birth is often not enough to preserve privacy<sup>6</sup>. It is, for example, possible to reconstruct a patient's face from computed tomography (CT) or magnetic resonance imaging (MRI) data<sup>7</sup>. Another reason why data sharing is not systematic in healthcare is that collecting, curating, and maintaining a high-quality data set takes considerable time, effort, and expense. Consequently such data sets may have significant business value, making it less likely that they will be freely shared. Instead, data collectors often retain fine-grained control over the data that they have gathered.

Federated learning (FL)<sup>8-11</sup> is a learning paradigm seeking to address the problem of data governance and privacy by training algorithms collaboratively without exchanging the data itself. Originally developed for different domains, such as mobile and edge device use cases<sup>12</sup>, it recently gained traction for healthcare applications<sup>13-15</sup>. FL enables gaining insights collaboratively, e.g., in the form of a consensus model, without moving patient data beyond the firewalls of the institutions in which they reside. Instead, the ML process occurs locally at each participating institution and only model characteristics (e.g., parameters, gradients) are transferred as depicted in Fig. 1. Recent research has shown that models trained by FL can achieve performance levels comparable to ones trained on centrally hosted data sets and superior to models that only see isolated single-institutional data<sup>16,17</sup>.

A successful implementation of FL could thus hold a significant potential for enabling precision medicine at large-scale, leading to models that yield unbiased decisions, optimally reflect an individual's physiology, and are sensitive to rare diseases while respecting governance and privacy concerns. However, FL still requires rigorous technical consideration to ensure that the algorithm is proceeding optimally without compromising safety or patient privacy. Nevertheless, it has the potential to overcome the limitations of approaches that require a single pool of centralised data.

We envision a federated future for digital health and with this perspective paper, we share our consensus view with the aim of providing context and detail for the community regarding the benefits and impact of FL for medical applications (section “Data-driven medicine requires federated efforts”), as well as highlighting key considerations and challenges of implementing FL for digital health (section “Technical considerations”).

DATA-DRIVEN MEDICINE REQUIRES FEDERATED EFFORTS

ML and especially DL is becoming the de facto knowledge discovery approach in many industries, but successfully implementing data-driven applications requires large and diverse data sets. However, medical data sets are difficult to obtain (subsection “The reliance on data”), FL addresses this issue by enabling collaborative learning without centralising data (subsection “The promise of federated efforts”) and has already found its way to digital health applications (subsection “Current FL efforts for digital health”). This new learning paradigm requires consideration from, but also offers benefits to, various healthcare stakeholders (section “Impact on stakeholders”).

The reliance on data

Data-driven approaches rely on data that truly represent the underlying data distribution of the problem. While this is a well-known requirement, state-of-the-art algorithms are usually

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NATURE PARTNER JOURNAL - POSITIONING FL FOR HEALTHCARE

<https://www.nature.com/articles/s41746-020-00323-1>



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Privacy-preserving Federated Brain Tumour Segmentation

Wenqi Li<sup>1</sup>, Fausto Milletari<sup>1</sup>, Daguang Xu<sup>1</sup>, Nicola Rieke<sup>1</sup>, Jonny Hancox<sup>1</sup>, Wentao Zhu<sup>1</sup>, Maximilian Baust<sup>1</sup>, Yan Cheng<sup>1</sup>, Sébastien Ourselin<sup>2</sup>, M. Jorge Cardoso<sup>2</sup>, and Andrew Feng<sup>1</sup>

<sup>1</sup> NVIDIA  
<sup>2</sup> Biomedical Engineering and Imaging Sciences, King's College London, UK

Abstract. Due to medical data privacy regulations, it is often infeasible to collect and share patient data in a centralised data lake. This poses challenges for training machine learning algorithms, such as deep convolutional networks, which often require large numbers of diverse training examples. Federated learning sidesteps this difficulty by bringing code to the patient data owners and only sharing intermediate model training updates among them. Although a high-accuracy model could be achieved by appropriately aggregating these model updates, the model shared could indirectly leak the local training examples. In this paper, we investigate the feasibility of applying differential-privacy techniques to protect the patient data in a federated learning setup. We implement and evaluate practical federated learning systems for brain tumour segmentation on the BraTS dataset. The experimental results show that there is a trade-off between model performance and privacy protection costs.

1 Introduction

Deep Neural Networks (DNN) have shown promising results in various medical applications, but highly depend on the amount and the diversity of training data [1]. In the context of medical imaging, this is particularly challenging since the required training data may not be available in a single institution due to the low incidence rate of some pathologies and limited numbers of patients. At the same time, it is often infeasible to collect and share patient data in a centralised data lake due to medical data privacy regulations.

One recent method that tackles this problem is Federated Learning (FL) [2-4]; it allows collaborative and decentralised training of DNNs without sharing the patient data. Each node trains its own local model and, periodically, submits it to a parameter server. The server accumulates and aggregates the individual contributions to yield a global model, which is then shared with all nodes. It should be noted that the training data remains private to each node and is never shared during the learning process. Only the model's trainable weights or updates are shared, thus keeping patient data private. Consequently, FL succinctly sidesteps many of the data security challenges by leaving the data where they are and enables multi-institutional collaboration.

arXiv:2009.13148v1 [eess.IV] 28 Sep 2020  
arXiv:2009.01871v2 [eess.IV] 17 Sep 2020  
arXiv:1910.00962v1 [cs.CV] 2 Oct 2019

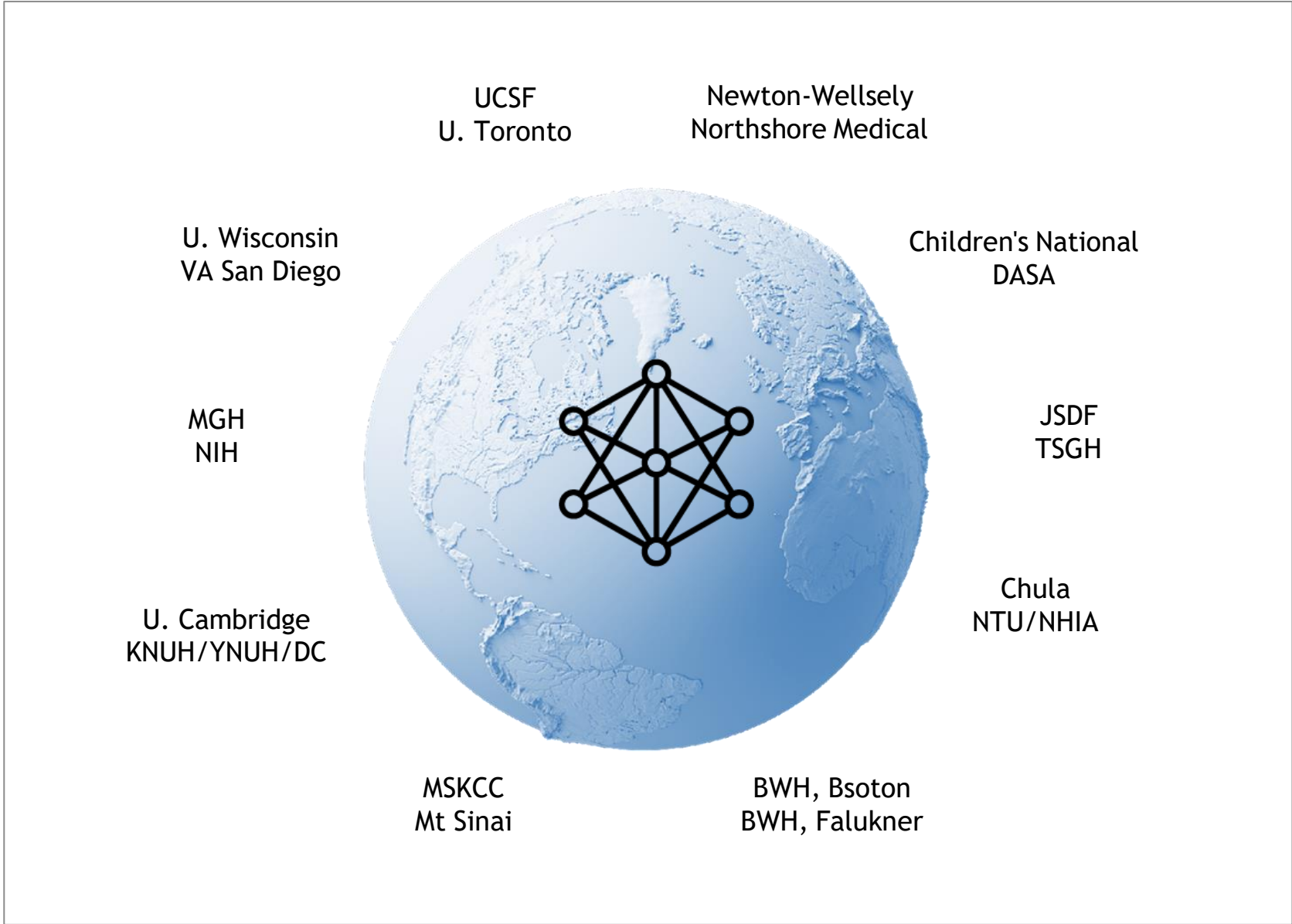
npj Digital Medicine

ADDRESSING OPEN FL RESEARCH QUESTIONS

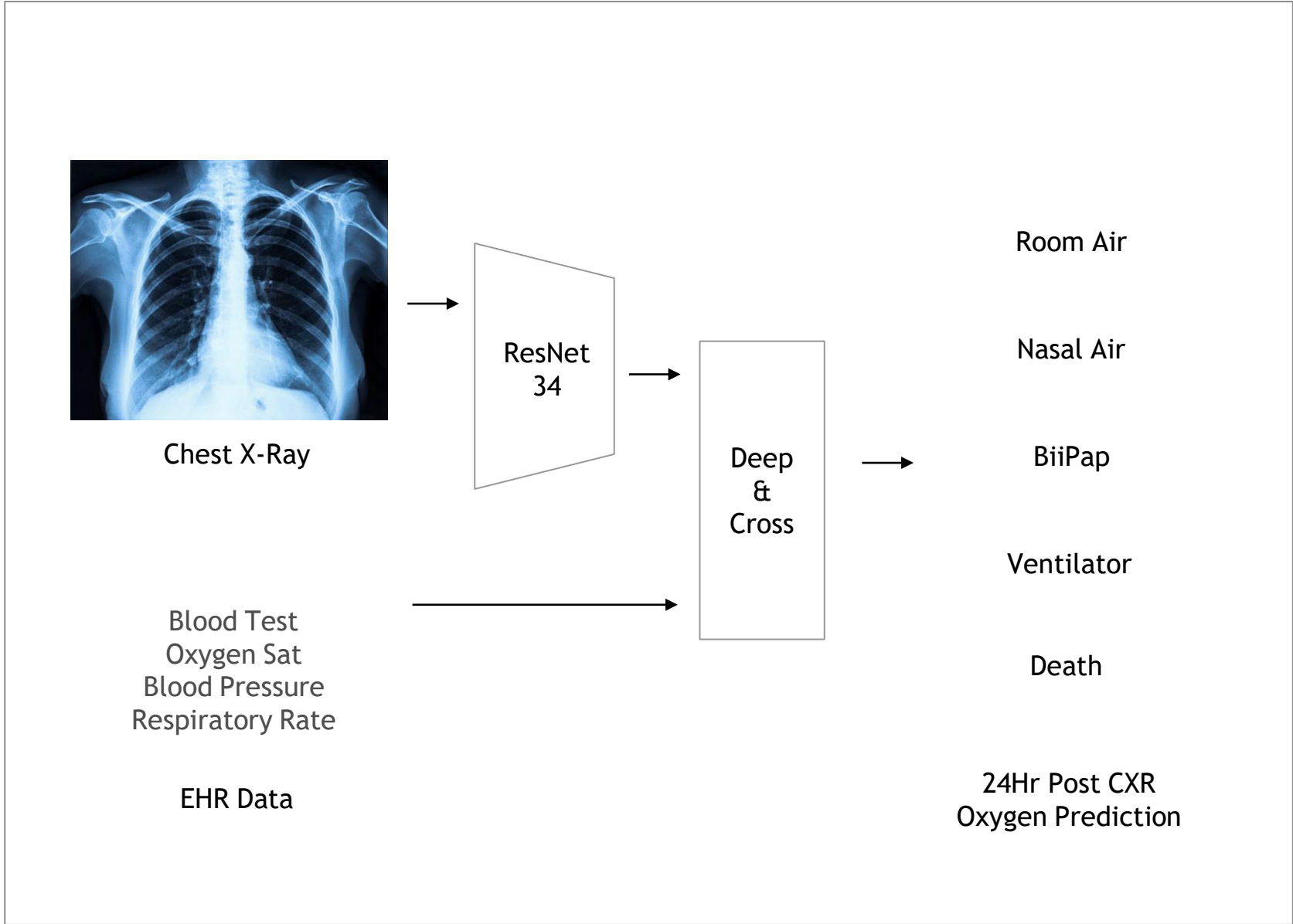
Connect with the NVIDIA Researchers at the NVIDIA booth!



# CLARA FEDERATED LEARNING FOR COVID-19 PATIENT CARE “EXAM” AI MODEL



Clara Federated Learning  
20 Sites | 8 Countries  
COVID-19 Oxygen Prediction



Global Model Achieved .93AUC  
>25% Relative Improvement  
Every Site Benefited Regardless of Dataset Size

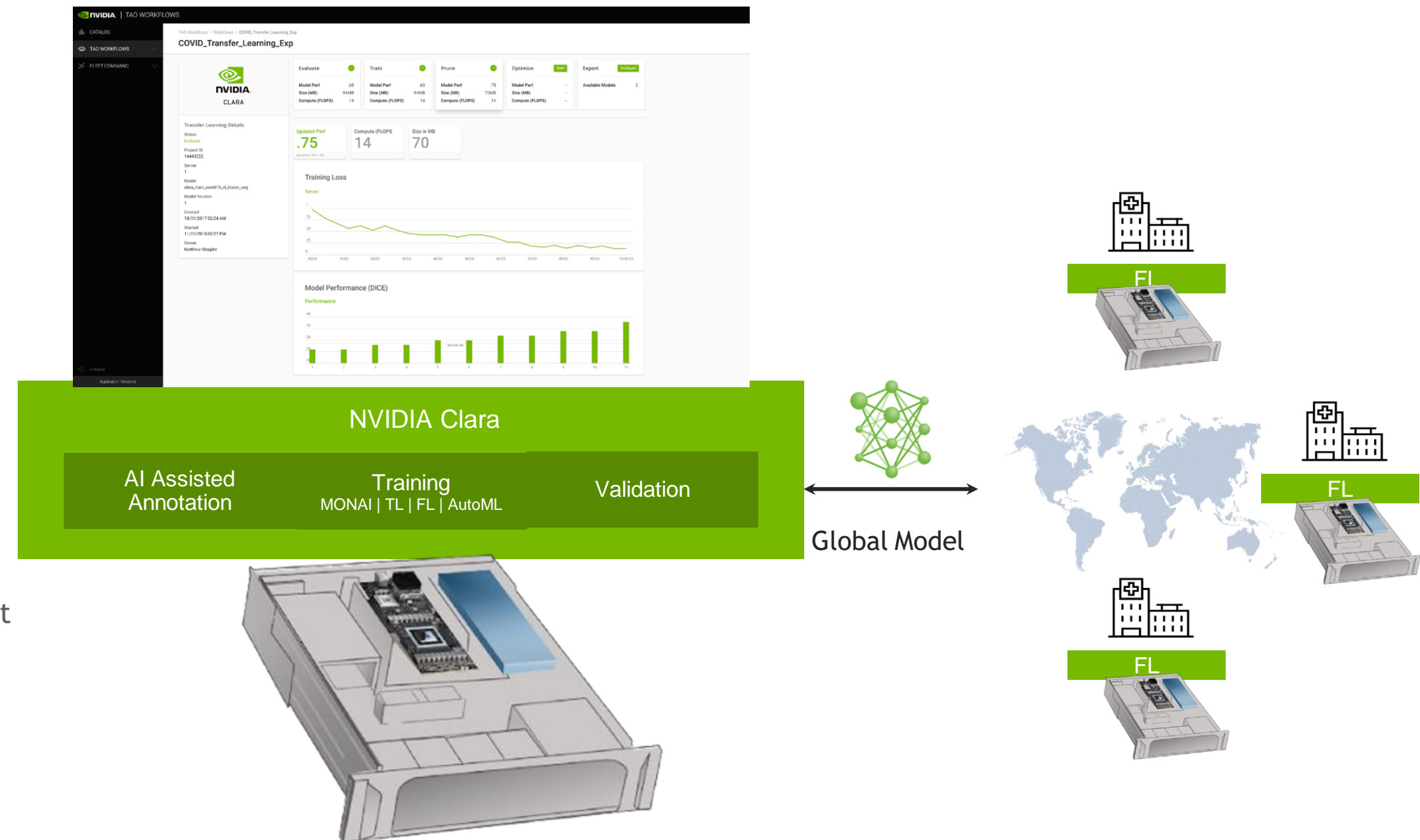
# CLARA FEDERATED LEARNING

Privacy Preserving | Extensible | Ease of provisioning

Privacy-Preserving  
Homomorphic Encryption  
Model Truncation  
Model Noise

## Easy Provisioning & Extensibility

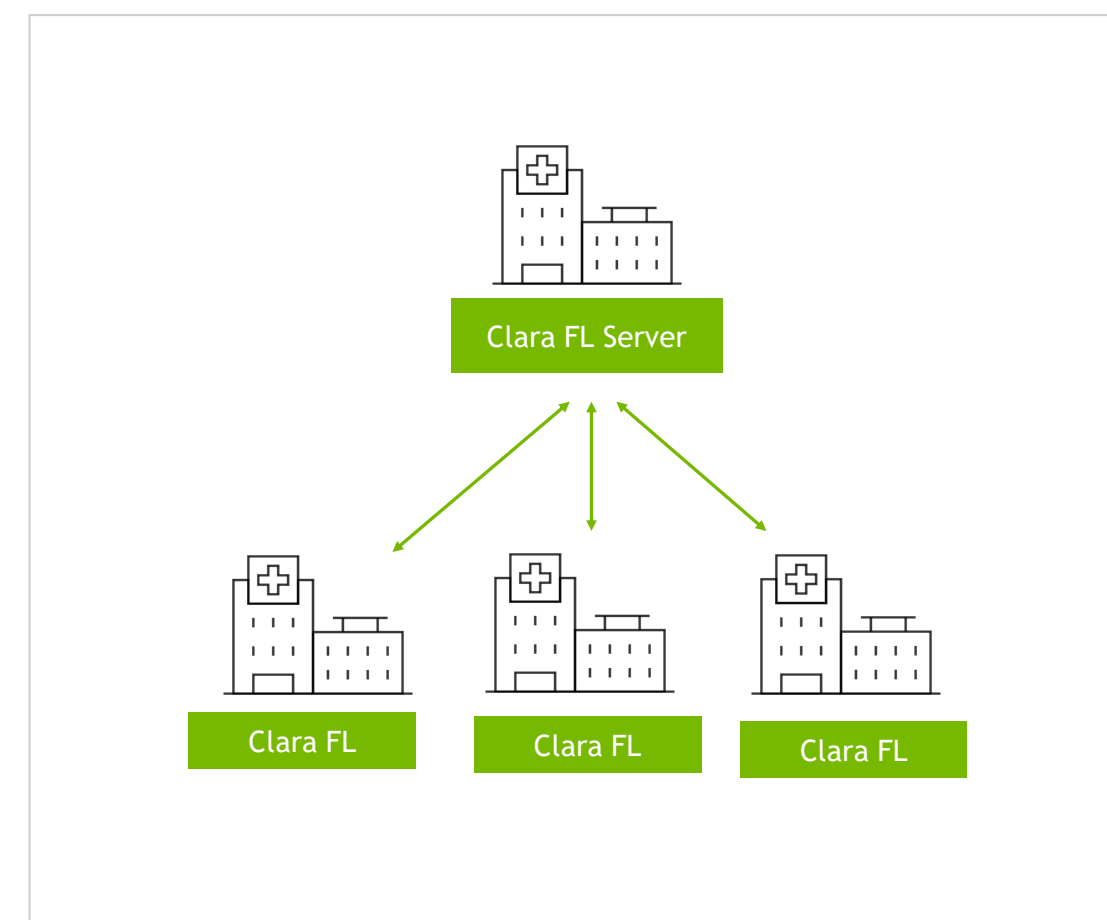
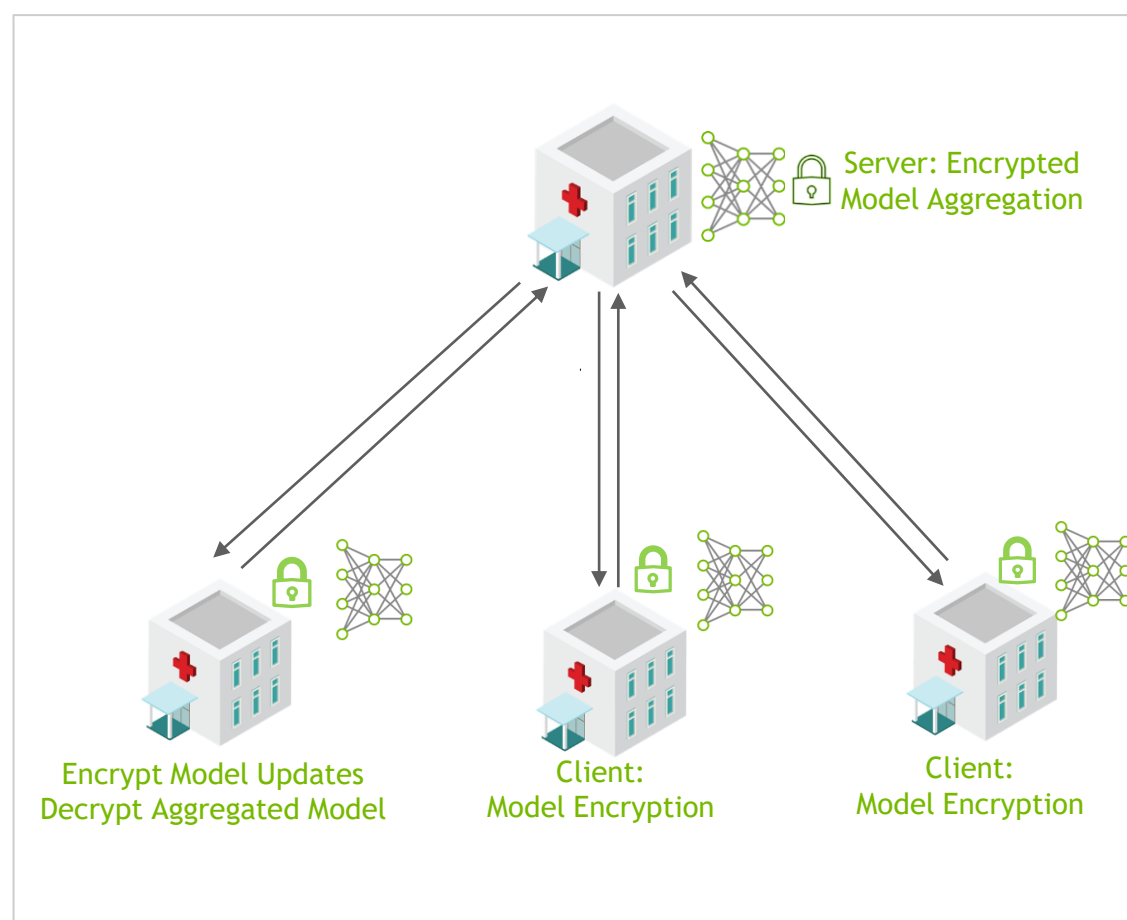
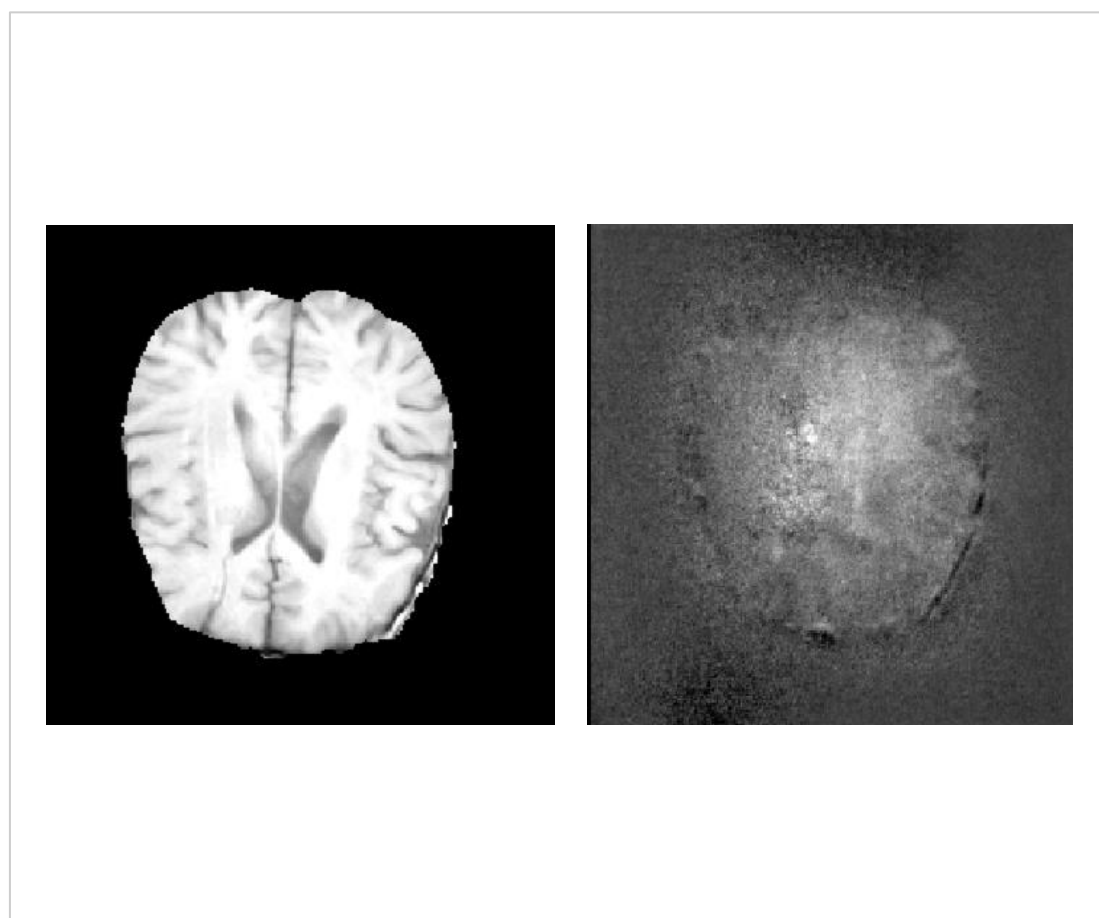
Secure & seamless provisioning  
Extensible with ability to bring your own component  
Certified Deployment with NVIDIA certified servers



[NVIDIA Clara Federated Learning Documentation](#)

# CLARA FEDERATED LEARNING

Privacy Preserving & Extensible Collaborative Learning



**DIFFERENTIAL PRIVACY**  
Prevent data leakage

**HOMOMORPHIC ENCRYPTION**  
Aggregation on Encrypted Models

**EXTENSIBLE**  
Use Cases Beyond Imaging  
Use Preferred Training Framework  
Standalone Python Package for Easy Integration

**PRIVACY PRESERVING**  
Collaborate without compromising privacy

# NVIDIA FEDERATED LEARNING

Secure, Manageable & Scalable Framework

Clara | Drive | Metropolis | TAO | 3<sup>rd</sup> party

FL Simulator

*(Accelerate pace of research & development)*

**Federated Learning API:**

Workflow, Trainer, Aggregator, Validator, Provision

**Learning Components**

Trainers: IDD and non-IDD trainer

Aggregation: Accumulate & in-Time FedAvg, FedAsync

Evaluation: Model Selector, Cross-site Validator

Data: Analytics, *Tracking*

**Federation Workflows**

Fed Avg, *P2P*, Cyclic, etc.

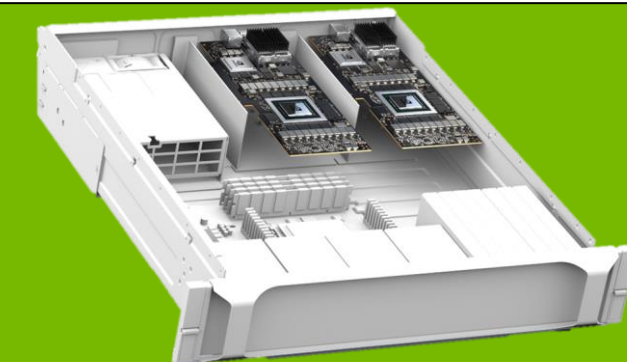
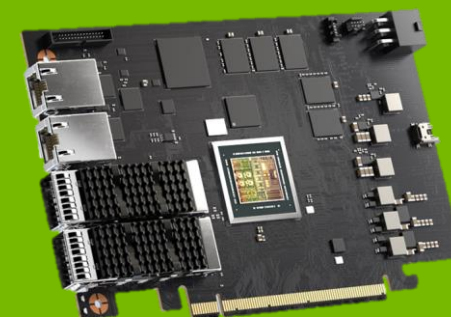
**Orchestration**

Provision,  
Data Prep,  
Study Mgmt,  
System Monitoring,  
Post-study Analysis

**Confidential, Secure, Manageable Compute**

Data: Differential Privacy, Gradient Inversion Protection, Homomorphic Encryption

Manage: Messaging, Identity, Authentication, Authorization



NVFlare

# NVFlare: NVIDIA FEDERATED LEARNING APPLICATION RUNTIME ENVIRONMENT

Enabler of FL application development

- NVFlare is an **enabler** for Federated Learning across industries
  - NVFlare is application agnostic, not framework specific
  - NVFlare is for all kinds of Federated study, not limited to model weights
  - Users are in control, NVFlare helps
- NVFlare is **SDK**, not end-to-end solution
  - We provide reference application in native PT, TF, numpy, Clara Train and MONAI
- How **NVFlare** helps
  - Solve hard real-world problems: comm security, identity, session management, reconnect ...
  - Provide programming framework for FL research/innovation
  - Provide a runtime environment for FL study
  - Provide a set of general-purpose FL components

# NVFlare Examples

## Getting Started

Github: <https://github.com/NVIDIA/NVFlare>

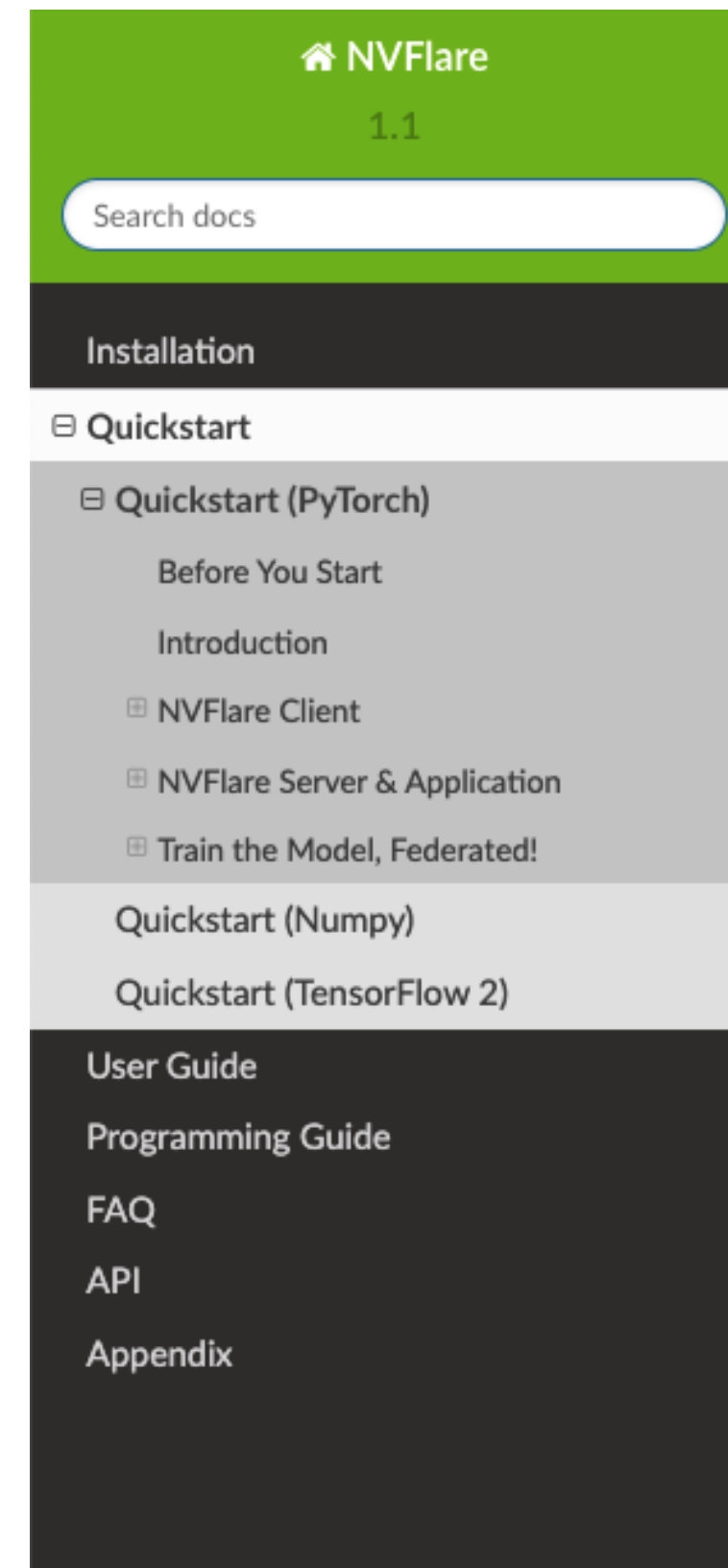
Docs: <https://nvidia.github.io/NVFlare/>

Installation - pip install in a python virtualenv

Quickstart - simple examples illustrating the basic structure of an NVFlare application and flow between server and clients

- Pytorch - hello-pt - simple CNN on CIFAR10
- Numpy - hello-numpy - Fibonacci sequence
- Tensorflow - hellow-tf2 - MNIST
- Coming soon - hello-cross-site-validation, hello-events, mnist-pt

Contact: [FederatedLearning@nvidia.com](mailto:FederatedLearning@nvidia.com)



[Home](#) » [Quickstart](#) » Quickstart (PyTorch)

## Quickstart (PyTorch)

### Before You Start

Feel free to refer to the official [documentation](#) at any point to learn more about the specifics of [NVFlare](#).

Make sure you have an environment with NVFlare installed. You can follow the [installation](#) guide on the general concept of Python virtual environment (the recommended environment) and how to install NVFlare.

### Introduction

Through this exercise, you will integrate NVFlare with the popular deep learning framework [PyTorch](#) and learn how to use NVFlare to train a convolutional network with the CIFAR10 dataset.

# NVFLARE AND MONAI

Project-MONAI / tutorials

<> Code Issues 22 Pull requests 8 Discussions Actions Security Insights

master tutorials / federated\_learning / nvflare /

Go to file

Add file

...



Borda and wyli rename n\_classes (#322) ...

✓ 3249a74 5 days ago History

..

nvflare_example	rename n_classes (#322)	5 days ago
nvflare_example_docker	rename n_classes (#322)	5 days ago
README.md	299 add inference script (#338)	10 days ago

README.md

## Federated learning with NVFlare

The examples here show how to train federated learning models with NVFlare and MONAI-based trainers.

1. [nvflare\\_example](#) shows how to run NVFlare with MONAI on a local machine to simulate an FL setting (server and client communicate over localhost). It also shows how to run a simulated FL experiment completely automated using the admin API. To streamline the experimentation, we have already prepared startup kits for up to 8 clients in this tutorial.
2. [nvflare\\_example\\_docker](#) provides further details on running FL with MONAI and NVFlare using docker containers for the server and each client for easier real-world deployment.

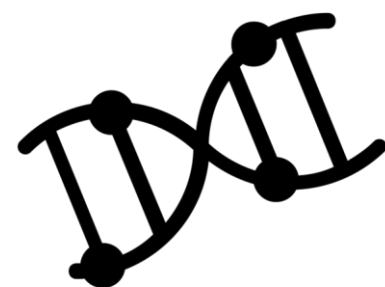
[Example: NVFlare with MONAI](#)

# FEDERATED LEARNING

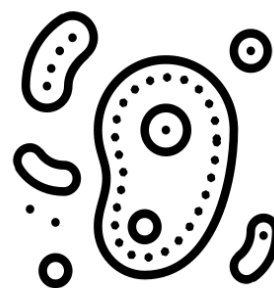
Some application areas... there are many more!



Medical  
Imaging



Genomics



Digital  
Pathology



Drug  
Discovery



Contact: [FederatedLearning@nvidia.com](mailto:FederatedLearning@nvidia.com)



# Marc Edgar

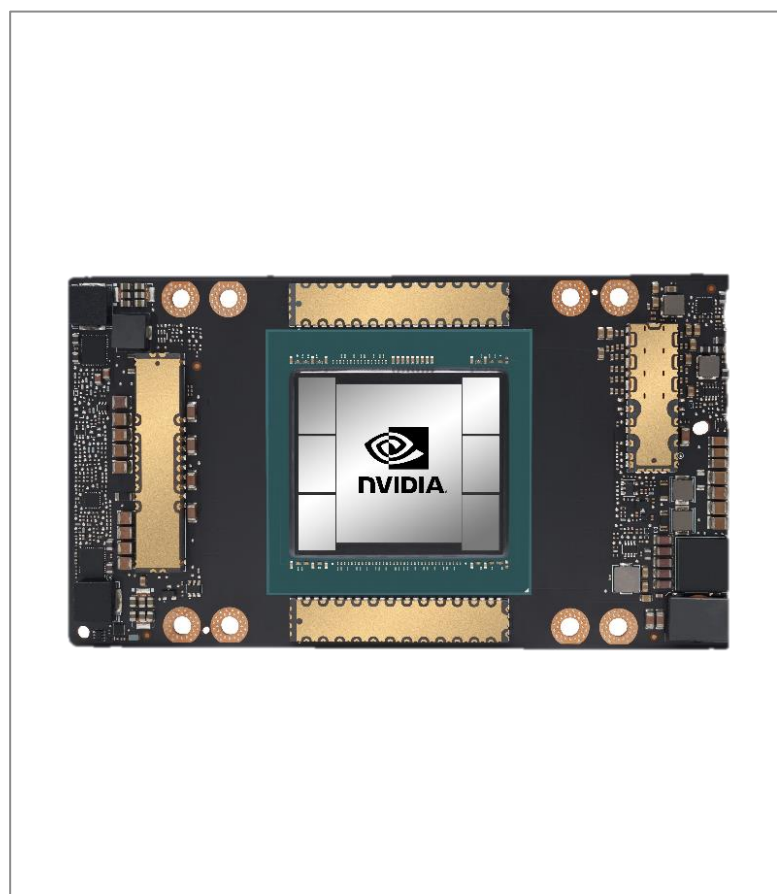
Sr. Alliance Manager for Medical Devices at NVIDIA

*NVIDIA Clara AGX Dev Kit  
The Era of Software Defined Medical Devices*

September 27 - October 1, 2021

# NVIDIA Full-Stack Accelerated Computing for Healthcare

Accelerated | Optimized | Cloud Native | Software Defined | Domain Specific



## GPUs

A100 Ampere  
Largest 7nm Chip  
25B Transistors



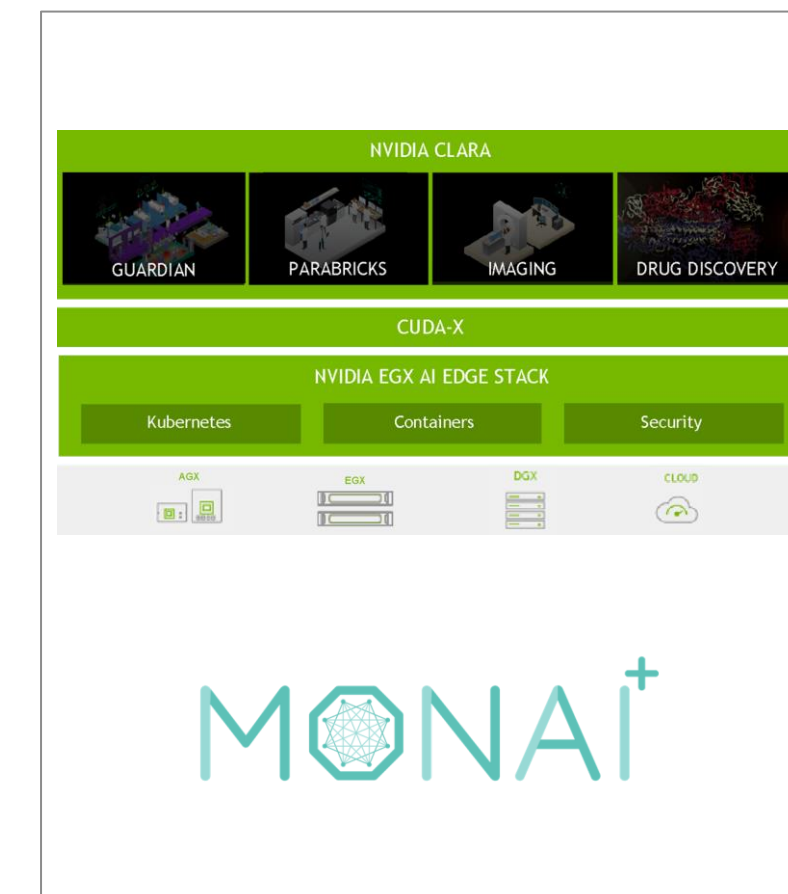
## Systems

AGX for Autonomous/Embedded  
EGX for Edge Computing  
DGX for Datacenter



## Platforms

AI Accelerated Hybrid Edge-Cloud  
Remote Management & Security  
Software Defined Infrastructure



## Application Frameworks and Algorithms

Domain Specific / Healthcare Specific  
Optimized Performance  
Accelerate Dev to Deploy

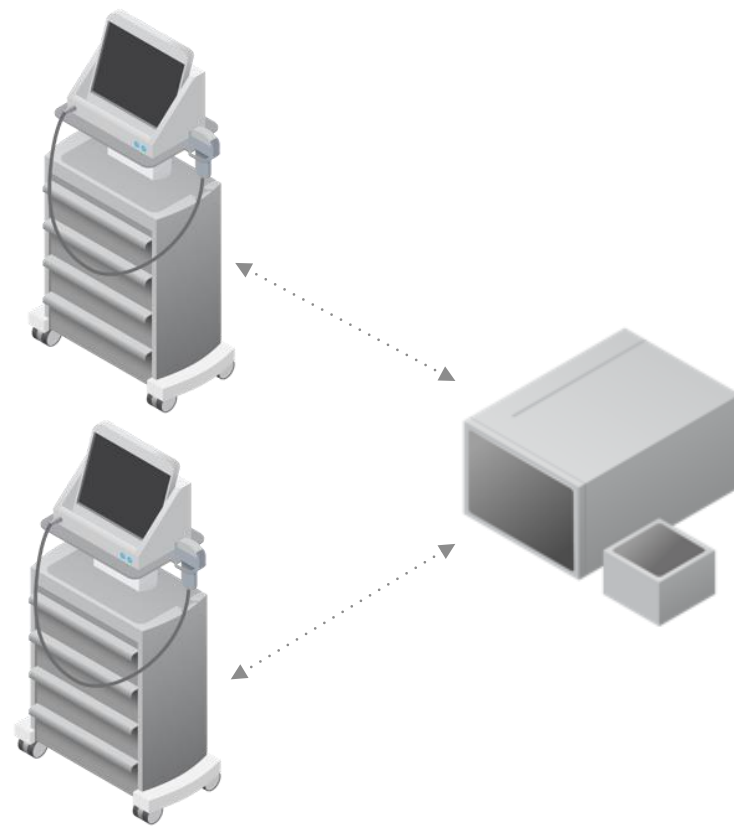
# SOFTWARE DEFINED MEDICAL DEVICES

A NEW ERA OF ACCELERATED INNOVATION



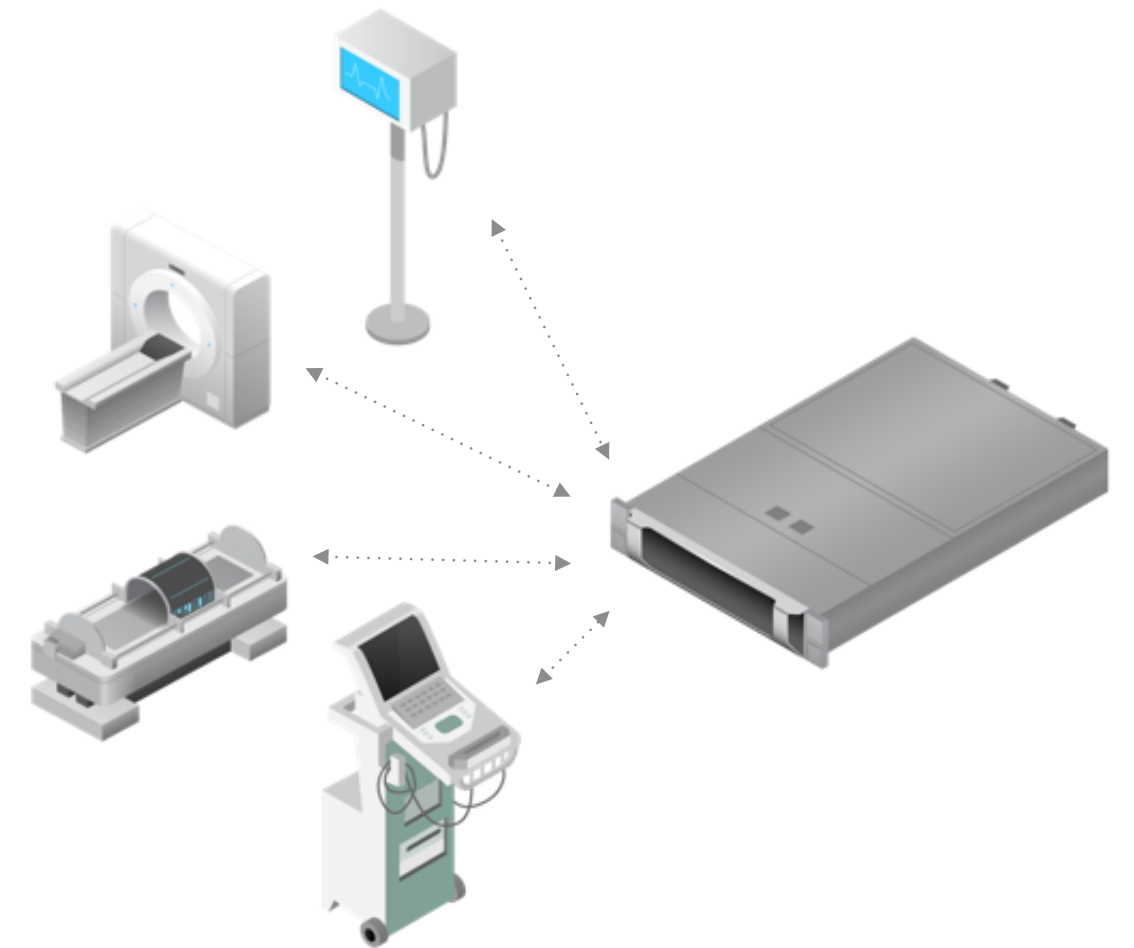
Embedded AI

Accelerated, Compact, Low Power



Sidecar AI

Add AI to unmodified medical devices



Streaming AI

Multiple Connected Devices

Clara AGX for Development to Translational Study to Commercialization

# CLARA AGX DEV KIT

- 1 NVIDIA® JETSON AGX XAVIER™
- 2 NVIDIA RTX™ 6000
- 3 NVIDIA CONNECTX®-6 SmartNIC  
-QSFP28 FOR 100GbE and RJ45 for 10GbE
- 4 HDMI 2.0 INPUT
- 5 2X PCIE GEN4x8 SLOTS
- 6 250GB M.2 SATA STORAGE

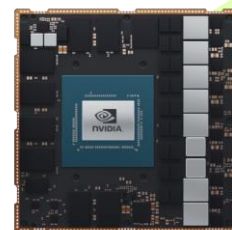


# NVIDIA CLARA AGX ROADMAP

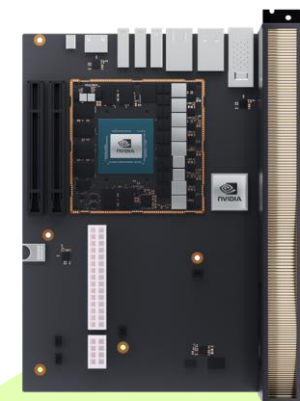
Develop Today for Tomorrow's Embedded Solution



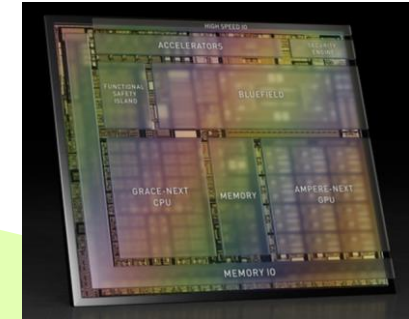
**Developer Kit**  
Clara AGX Xavier  
8 Carmel ARM Cores  
200+ TOPS  
100 GbE



**Commercialization Platform**  
AGX Orin  
12 Cortex-A78 ARM Cores  
250+ TOPS  
4x 10 GbE



**Developer Kit**  
Clara AGX Orin  
12 Cortex-A78 ARM Cores  
400+ TOPS  
200 GbE



**Atlas**  
1000 TOPS

2021

2022

2023

2024

29

# APPLICATIONS OF CLARA AGX

Real-time Embedded AI + Connectivity

## Modalities : Vertical Applications



**Endoscopy  
Laparoscopy**



**Ultrasound**



**Surgical  
Robotics**



**Connected  
OR / ICU**



**Interventional  
Radiology**



**Digital  
Pathology**



**Desktop  
Genomics**

## Horizontal Applications



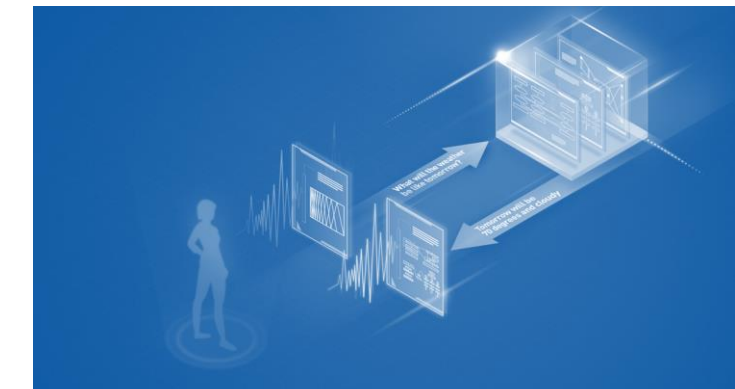
**Low-latency  
AI Inference**



**Streaming Video AI  
and Rendering**

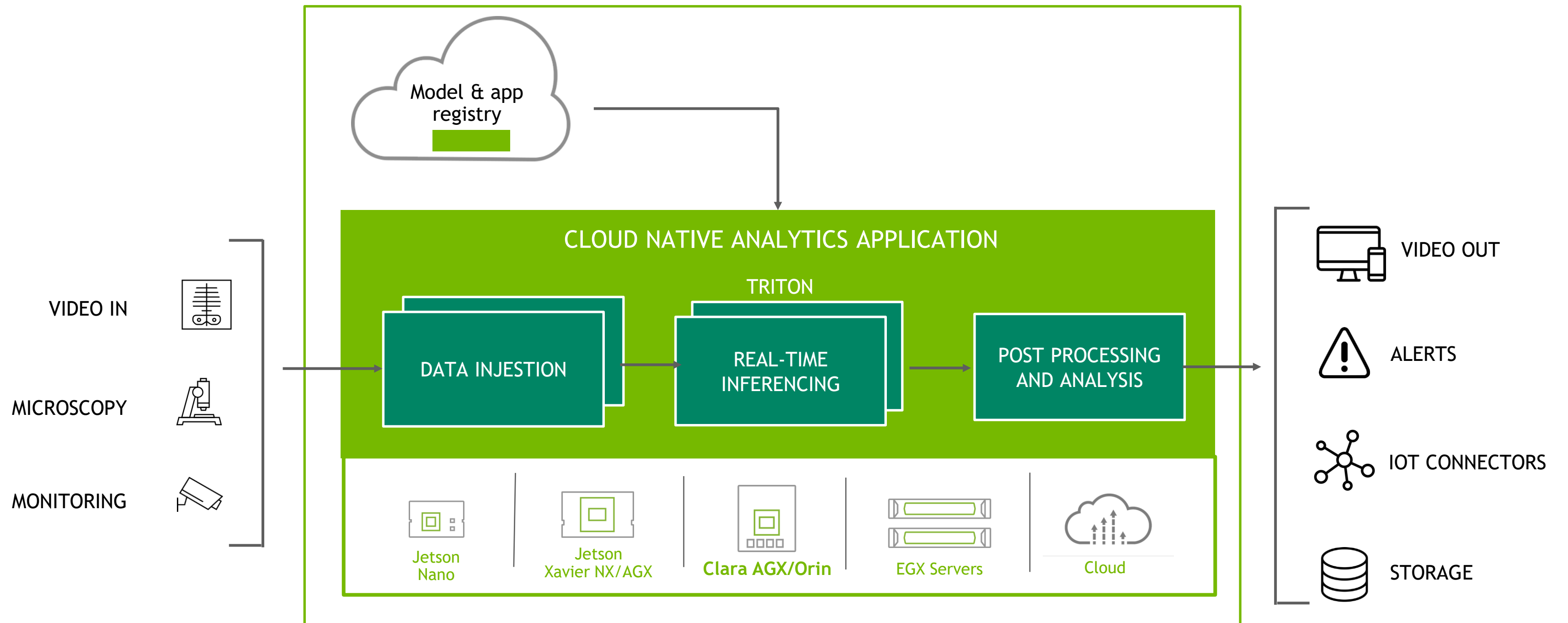


**Data Collection**



**Conversational AI  
NLU**

# DEEPSTREAM PIPELINE AI-POWERED VIDEO APPLICATIONS

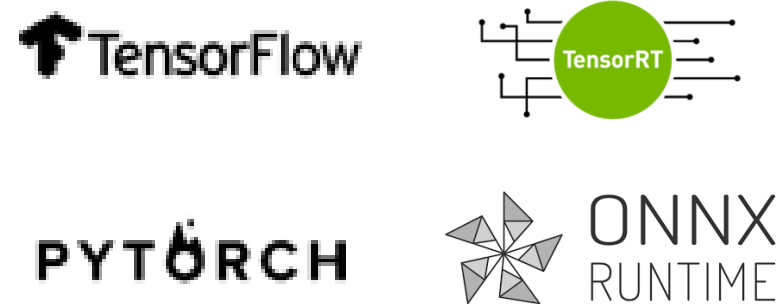


Easy to use, low-latency acquisition, transfer and processing

# TRITON INFERENCING SERVER

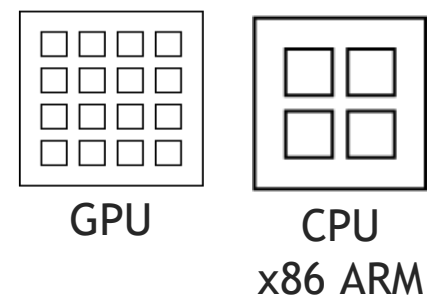
Simplifying the execution and deployment of AI models

Multiple Frameworks



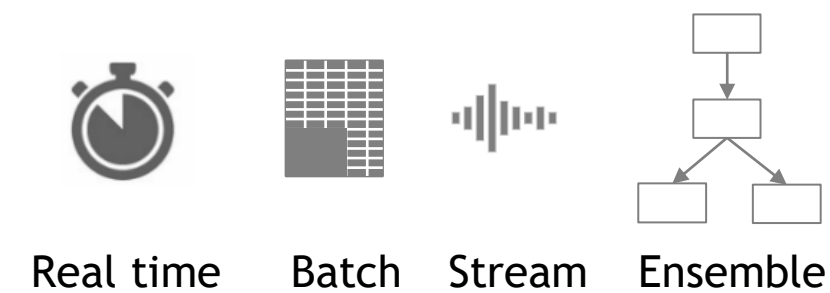
Supports All Major Frameworks  
Consistent API

Inferencing on GPU and CPU



Cloud | Data Center | Edge  
Bare metal | Virtualized

Queue Strategies



Support for Use Cases

Maximize Throughput



Dynamic Batching Optimizes Latency Constraints  
Concurrent Model Execution  
Zero Down Time Updates

Open Source: <https://github.com/triton-inference-server>



# CLARA AGX ECOSYSTEM OF SENSORS



**us4us**

Software defined ultrasound development platform



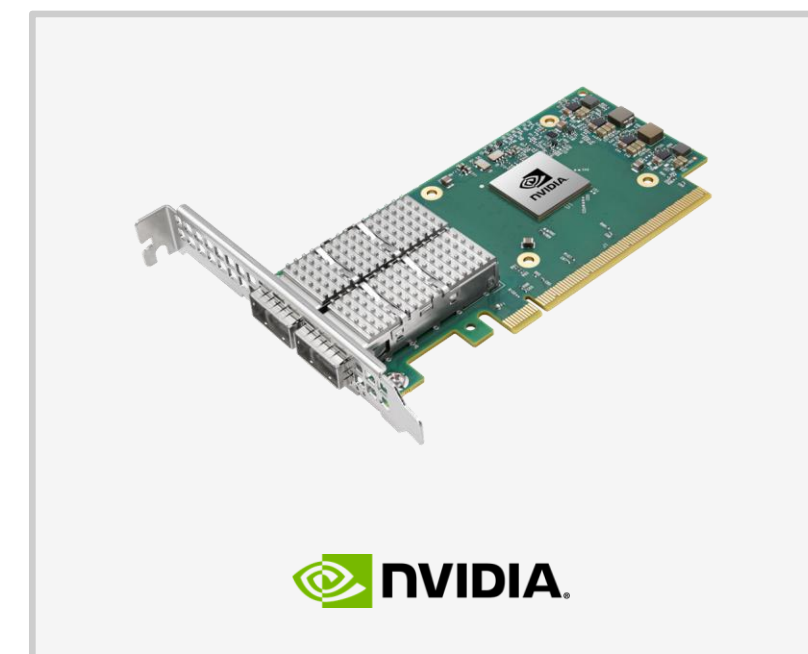
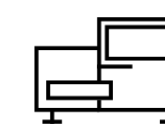
**AJA**  
VIDEO SYSTEMS

High res video capture



**KAYA**  
INSTRUMENTS

Highspeed frame grabber



**NVIDIA**

High speed networking  
ConnectX-6



# GETTING STARTED WITH CLARA AGX

## NVIDIA Clara AGX

**NVIDIA Clara AGX Development Kit**

The NVIDIA Clara AGX Development Kit delivers real-time AI and imaging for medical devices. By combining low-powered, NVIDIA Jetson AGX Xavier and RTX GPU with the NVIDIA Clara AGX SDK and the NVIDIA EGX stack, it's easy to securely provision and remotely manage fleets of distributed medical instruments.

[Request Clara AGX Developer Kit](#)

**NVIDIA Clara AGX Software**

NVIDIA Clara AGX SDK runs on the NVIDIA Clara AGX and Jetson platform and provides developers with capabilities to build end-to-end streaming workflows for medical imaging. It includes advanced samples for ultrasound video and endoscopy. Access to the NVIDIA Clara AGX SDK requires an NVIDIA Developer Account.

[Download Clara AGX SDK](#)

<https://developer.nvidia.com/clara-agx-devkit>

Over 150 customers the Development Partner Program

Including ....



# CLARA AGX DEV KIT

## SOFTWARE DEFINED MEDICAL DEVICE CHALLENGE

NVIDIA will donate a Clara AGX to an educational institution to develop an innovative application

- 1 Go to: <https://developer.nvidia.com/clara-agx-devkit>
- 2 Click on “Request Clara AGX Developer Kit”
- 3 Answer the question: “What use case are you going to use Clara AGX Dev Kit for?”
  - Describe how you would use a Clara AGX Developer Kit to create an innovative and impactful software defined medical device.
  - No more than 500 words
  - Include the words “MICCAI 2021 CHALLENGE”
- 4 Submissions must be received before October 14, 2021


NVIDIA Clara AGX | NVIDIA Developer

developer.nvidia.com/clara-agx-devkit

NVIDIA DEVELOPER HOME BLOG FORUMS DOCS DOWNLOADS TRAINING JOIN

### NVIDIA Clara AGX

HOME PRODUCTS DOCUMENTATION RESEARCH



NVIDIA Jetson AGX Xavier  
NVIDIA Mellanox ConnectX-6  
NVIDIA RTX 6000

#### NVIDIA Clara AGX Development Kit

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2 Request Clara AGX Developer Kit Download Clara AGX SDK

# RESOURCES

# RESOURCES - FEDERATED LEARNING

## NVIDIA Clara Imaging & NVFlare

### NVIDIA Clara Imaging:

- Clara v4.0 : <https://ngc.nvidia.com/catalog/containers/nvidia:clara-train-sdk>
- Clara Notebooks/Tutorial: <https://github.com/NVIDIA/clara-train-examples>
- Clara Documentation: <https://docs.nvidia.com/clara/clara-train-sdk/index.html> , in particular [https://docs.nvidia.com/clara/clara-train-sdk/federated-learning/federated\\_learning.html](https://docs.nvidia.com/clara/clara-train-sdk/federated-learning/federated_learning.html)
- Clara Dev Forum: <https://forums.developer.nvidia.com/c/healthcare/clara-train-transfer-learning-toolkit-for-medi/154>

### NVFlare:

- Github: <https://github.com/NVIDIA/NVFlare>
- Docs: <https://nvidia.github.io/NVFlare/>
- 101 examples: <https://github.com/NVIDIA/NVFlare/tree/main/examples>
- MONAI Example: [https://github.com/Project-MONAI/tutorials/tree/master/federated\\_learning/nvflare](https://github.com/Project-MONAI/tutorials/tree/master/federated_learning/nvflare)

# RESOURCES - FEDERATED LEARNING

## GTC talks on NVIDIA on demand

- General:

- Overview of NVIDIA and Federated Learning: Federated Learning for Medical AI [S32530], Mona Flores: <https://www.nvidia.com/en-us/on-demand/session/gtcspring21-s32530/>
- Example of Clara FL in Industry: Accelerating Health Care at Bayer with Science@Scale and Federated Learning [E32541], David Ruau: <https://www.nvidia.com/en-us/on-demand/session/gtcspring21-e32541/>
- Federated Learning - Scientific Perspective: Developing Robust Medical Imaging AI Applications: Federated Learning and Other Approaches [S32014], Daniel Rubin: <https://www.nvidia.com/en-us/on-demand/session/gtcspring21-s32014/>
- Collaborative Learning in Medical Imaging: Opportunities and Challenges [S32449], Jayashree Kalpathy-Cramer: <https://www.nvidia.com/en-us/on-demand/session/gtcspring21-s32449/>

- Clara 4.0:

- Clara Train 4.0 - 201 Federated Learning [SE3208]: <https://www.nvidia.com/en-us/on-demand/session/gtcspring21-se3208/>
- Clara 4.0 (Overview): <https://www.nvidia.com/en-us/on-demand/session/gtcspring21-s32482/>

# RESOURCES - FEDERATED LEARNING

## NVIDIA Publications (a selection)

- Federated learning for predicting clinical outcomes in patients with COVID-19 (Nature Medicine, <https://www.nature.com/articles/s41591-021-01506-3>)
- The future of digital health with federated learning (npj Digital medicine, <https://www.nature.com/articles/s41746-020-00323-1> )
- Federated semi-supervised learning for COVID region segmentation in chest CT using multi-national data from China, Italy, Japan (Medical Image Analysis (2021): 101992 , <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7864789/> )
- Federated learning improves site performance in multicenter deep learning without data sharing (Journal of the American Medical Informatics Association (2021), <https://academic.oup.com/jamia/advance-article/doi/10.1093/jamia/ocaa341/6127556> )
- Federated Learning for Breast Density Classification: A Real-World Implementation (MICCAI DCL 2020 workshop, <https://arxiv.org/pdf/2009.01871.pdf> )
- Privacy-preserving Federated Brain Tumour Segmentation (MICCAI MLMI 2019 workshop, <https://arxiv.org/pdf/1910.00962.pdf> )

MICCAI 2021 Workshop focusing on medical Federated Learning: <http://dcl-workshop.net/>



# THANK YOU

Visit our Virtual Booth for more information (# 209)

  
MICCAI2021



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