Peregrine: A Scalable In-Situ Process Monitoring Software Stack using Artificial Intelligence

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Acknowledgements
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Stephanie Cooper, Christine Cummings, Michael Heiden
Gerry Knapp, Chris Ledford, Fred List, Larry Lowe, Selda Nayir
Dylan Richardson, Alex Rogers, Julio Ortega Rojas, Alka Singh
Michael Sprayberry, Logan Sturm, Jamie Stump, Amir Ziabari

Special thanks to collaborators at
AFRL, ANL, KCNSC, LANL, LLNL, NNPL, NUWC, Pantex Plant
PNNL, SNL, SRNL

About the Speaker

Dr. Luke Scime

Luke is a Staff Scientist at **Oak Ridge National Laboratory** (ORNL) in the Manufacturing Systems Analytics (MSA) group at the **Manufacturing Demonstration Facility** (MDF) https://www.ornl.gov/facility/mdf. He specializes in real-time data acquisition, multi-modal image segmentation, machine learning, and data visualization and management with applications focused on powder bed additive manufacturing. Luke joined the laboratory as a postdoctoral researcher in the Imaging, Signals, & Machine Learning (IS&ML) group in 2018 after completing his Ph.D. in mechanical engineering at Carnegie Mellon University. Luke also volunteers extensively with FIRST robotics programs which seek to engage elementary through high school students in STEM.

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How Data can Support AM Qualification Efforts

I.	II.	III.	IV.
record keeping	**enhanced understanding**	**property prediction**	**accelerated design**
• Data and metadata are recorded primarily for provenance purposes. • Data are painstakingly reviewed manually to identify problems. • In-situ sensor data are of generally low quality and minimal volume. • Historical datasets are difficult to access and may be inconsistently formatted.	• Data and metadata are consistently recorded for every build and are used to better understand the process. • Artificial intelligence is used to automatically analyze in-situ data and identify anomalies and flaw indications. • In-situ sensor data are of high quality and require large storage volumes. • Sensors and algorithms are sufficiently robust to determine if a given build was printed under nominal conditions.	• In-situ data are spatially registered with ex-situ characterization data, at scale. • Process simulations are performed at scale and linked to in-situ data. • The correlation between anomalies (indications) and flaws is understood with statistical methods. • Artificial intelligence and physics-based modeling are used to predict local material properties. • Physics-based models are used to predict part performance based on the in-situ data (i.e., is a flaw truly a defect).	• Each part's digital thread can be used to simulate its digital twin. • In-situ data, process simulations, and local property predictions are leveraged during the design process. • Artificial intelligence is used to automatically iterate both the part design and the manufacturing process steps.

Scaled Deployment of the *Peregrine* Software and Datasets

- **15** U.S. government labs are using and collaboratively developing *Peregrine*
- **14** R&D licenses have been granted to industry partners and international laboratories
- **3** CRADAs have leveraged *Peregrine*
- **3** different universities have received copies of Peregrine for research purposes
- **15+** companies and universities have downloaded Peregrine datasets containing over **400 GB** of in-situ and ex-situ data
  - https://doi.ccs.ornl.gov/ui/doi/341
  - https://doi.ccs.ornl.gov/ui/doi/417
  - https://doi.ccs.ornl.gov/ui/doi/451
  - https://doi.ccs.ornl.gov/ui/doi/452
  - https://doi.ccs.ornl.gov/ui/doi/454
- **6** journal papers and **1** U.S. patent are related to *Peregrine* technologies
  - https://doi.org/10.1016/j.addma.2020.101453
  - https://doi.org/10.1016/j.mfglet.2021.05.007
  - https://doi.org/10.3389/fmech.2021.767444
  - https://doi.org/10.1016/j.addma.2022.103298
  - https://doi.org/10.1016/j.mfglet.2023.01.003
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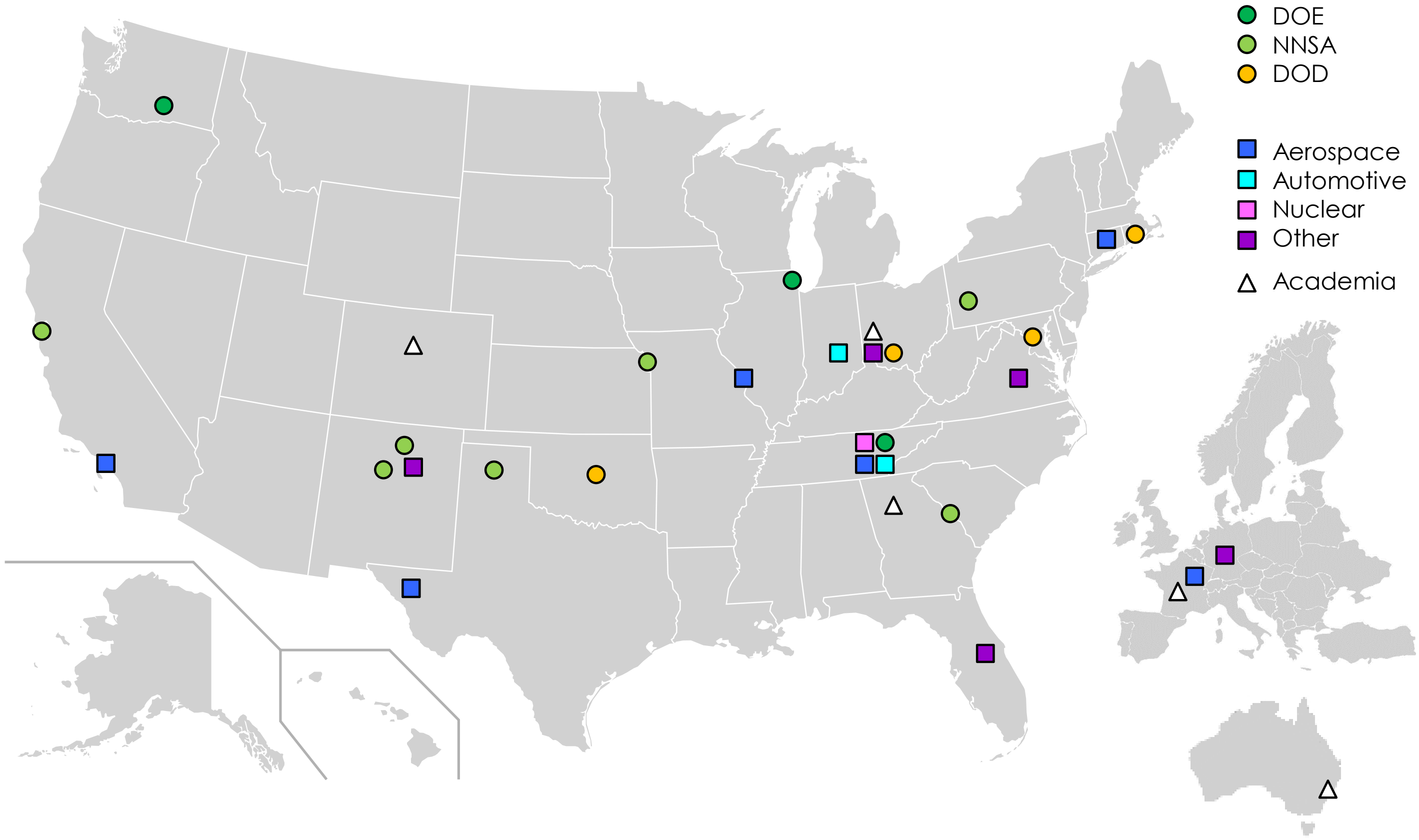
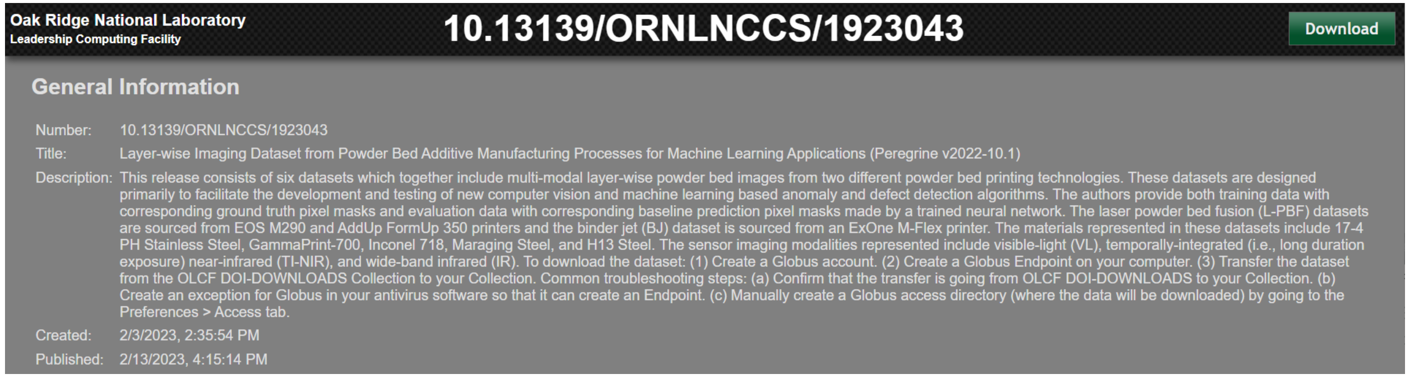
  - https://doi.org/10.1016/j.addma.2023.103817





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10.13139/ORNLNCCS/1923043

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General Information

Number: 10.13139/ORNLNCCS/1923043

Title: Layer-wise Imaging Dataset from Powder Bed Additive Manufacturing Processes for Machine Learning Applications (Peregrine v2022-10.1)

Description: This release consists of six datasets which together include multi-modal layer-wise powder bed images from two different powder bed printing technologies. These datasets are designed primarily to facilitate the development and testing of new computer vision and machine learning based anomaly and defect detection algorithms. The authors provide both training data with corresponding ground truth pixel masks and evaluation data with corresponding baseline prediction pixel masks made by a trained neural network. The laser powder bed fusion (L-PBF) datasets are sourced from EOS M290 and AddUp FormUp 350 printers and the binder jet (BJ) dataset is sourced from an ExOne M-Flex printer. The materials represented in these datasets include 17-4 PH Stainless Steel, GammaPrint-700, Inconel 718, Maraging Steel, and H13 Steel. The sensor imaging modalities represented include visible-light (VL), temporally-integrated (i.e., long duration exposure) near-infrared (TI-NIR), and wide-band infrared (IR). To download the dataset: (1) Create a Globus account. (2) Create a Globus Endpoint on your computer. (3) Transfer the dataset from the OLCF DOI-DOWNLOADS Collection to your Collection. Common troubleshooting steps: (a) Confirm that the transfer is going from OLCF DOI-DOWNLOADS to your Collection. (b) Create an exception for Globus in your antivirus software so that it can create an Endpoint. (c) Manually create a Globus access directory (where the data will be downloaded) by going to the Preferences > Access tab.

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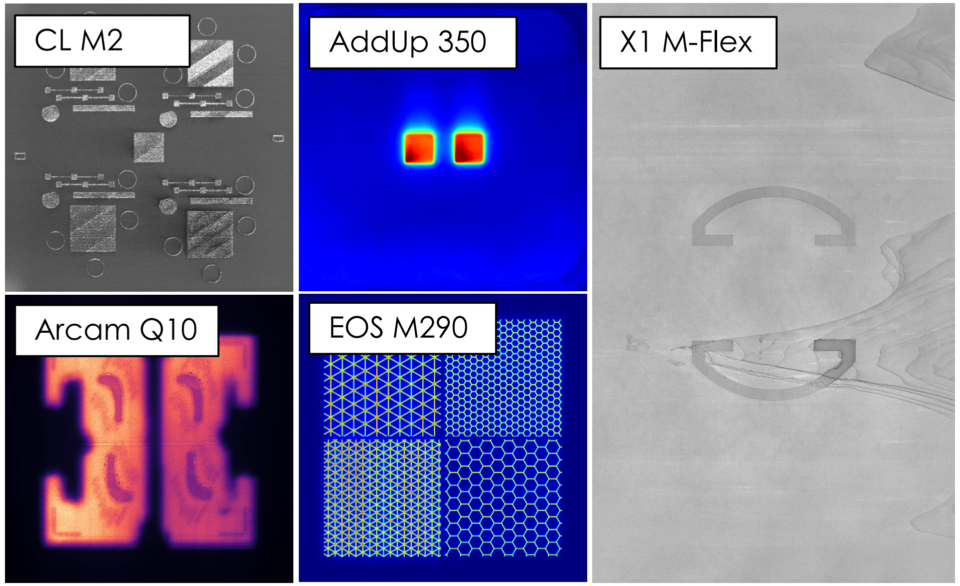
Published: 2/13/2023, 4:15:14 PM

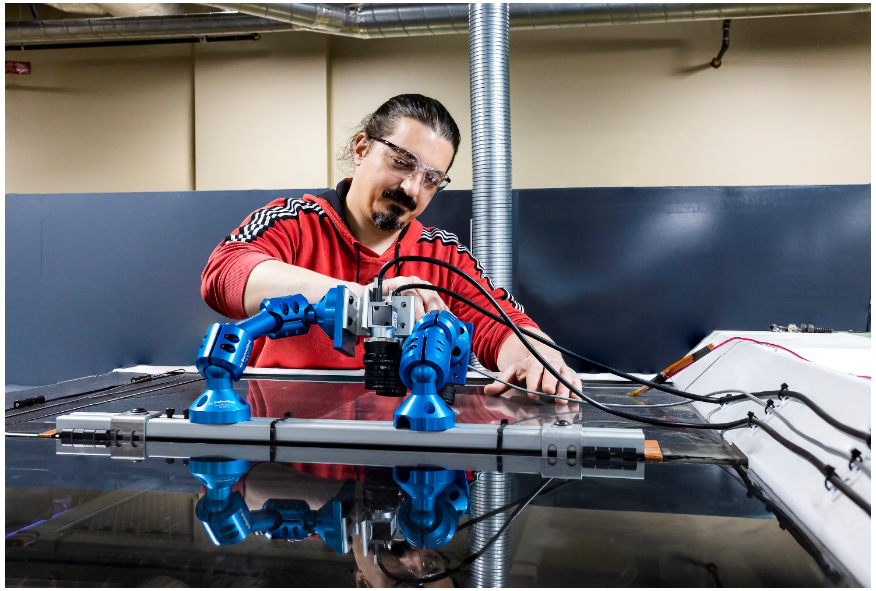
Powder Bed Printing Systems

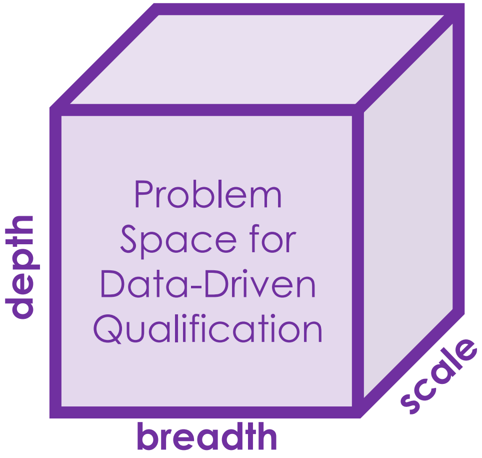
- **9 L-PBF** systems at ORNL
  - Aconity MIDI
  - AddUp FormUp 350
  - Concept Laser M2
  - Concept Laser X-Line 2000R
  - EOS M290
  - Renishaw AM250/AM400
- **4 EB-PBF** systems at ORNL
  - Arcam Q10/Q10+
  - Arcam Spectra H
- **6 Binder Jet** systems at ORNL
  - ExOne 25Pro
  - ExOne Innovent/Innovent+
  - ExOne M-Flex
- **10+** different systems at government and industry partners
  - 3D Systems ProX 320
  - Desktop Metal Shop Printer
  - Digital Metal P2500
  - EOS M280
  - EOS M400
  - GE H2.5
  - SLM 125
  - SLM 280
  - Trumpf TruPrint 1000
- As of **September 2023**, there are **2500+** builds loaded into *Peregrine* and available on the MDF Digital Platform, adding approximately **50** builds per month



Peregrine Project Philosophy

- **"We can't keep making unique solutions for each printer"**
- Extreme flexibility to **support any cameras** of scientific or industrial interest
  - Wide range of mounting orientations and lighting configurations
  - Any resolution (<1 MP to 60 MP)
  - Arbitrary number of sensor modalities (e.g., visible, LWIR, NIR)
  - Arbitrary number of images captured per layer
  - Multiple cameras to stich together a large field of view
- Enable data collection from many **different printer manufacturers**
  - Load in OEM images after the build completes
  - Watch an OEM folder for new images during printing
  - Real-time data acquisition over USB cameras
  - Load in OEM log files and scan paths with "parsers"
  - "Workspaces" manage printer-specific settings and configurations
  - Interfaces do not rely on OEM support
- Many **different users** and use-cases
  - Machine operators collect in-situ and meta data
  - Material scientists compare in-situ to ex-situ data
  - Data scientists investigate trends and correlations at scale
  - Managers and regulators want to maintain data provenance
  - Researchers want freedom to make changes while industry wants ease of use
- Must integrate with the **MDF Digital Platform** without relying on it
- Must function via both **graphical** and **scripting** interfaces
- Cannot rely on HPC resources and must function many **different computers**
- Must be **responsive** to feature requests with only a small development team

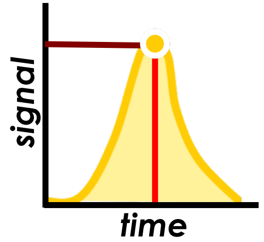


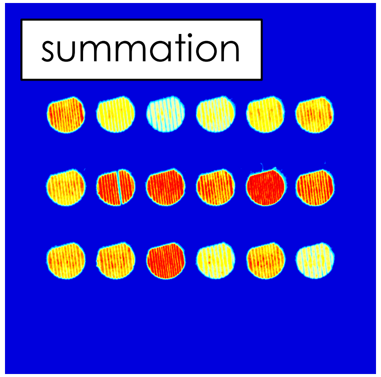


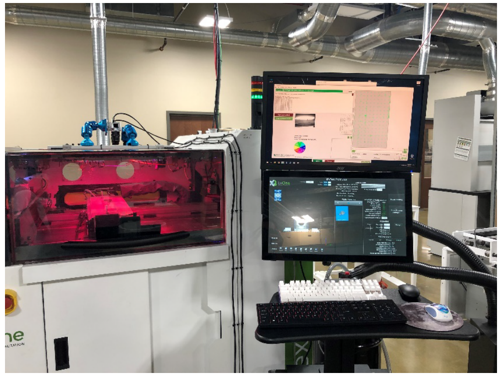
MDF

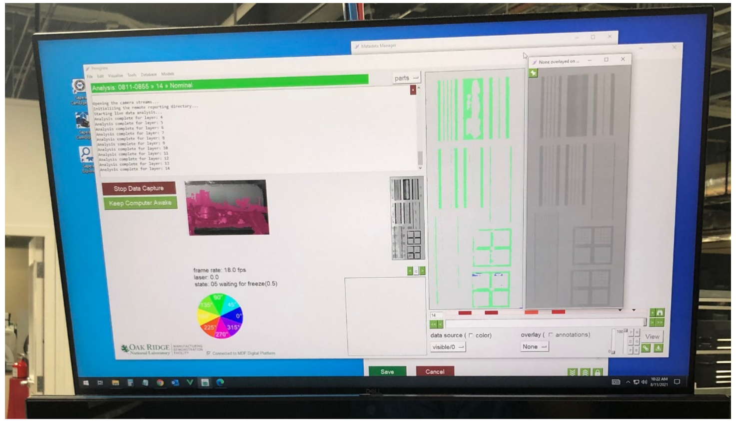
Data Acquisition

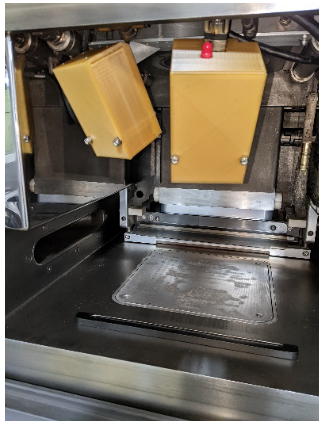
- All data collection and **analysis** can be performed in **real-time** using direct USB connections to multiple cameras
- Cameras, optics, lighting, and mounting are printer-specific
- Data acquisition is printer-agnostic, relying on **motion tracking** and **video analysis** to achieve **camera triggering**
- Advanced **buffering** and **threading** techniques are used to maintain high data acquisition and processing rates
- Typically, layer-wise data are captured as **snapshots**, e.g., a single frame immediately after layer fusion or after powder spreading
- Alternatively, video streams can be rapidly processed into **summation**, **maximum**, and **time-of-maximum** composite images

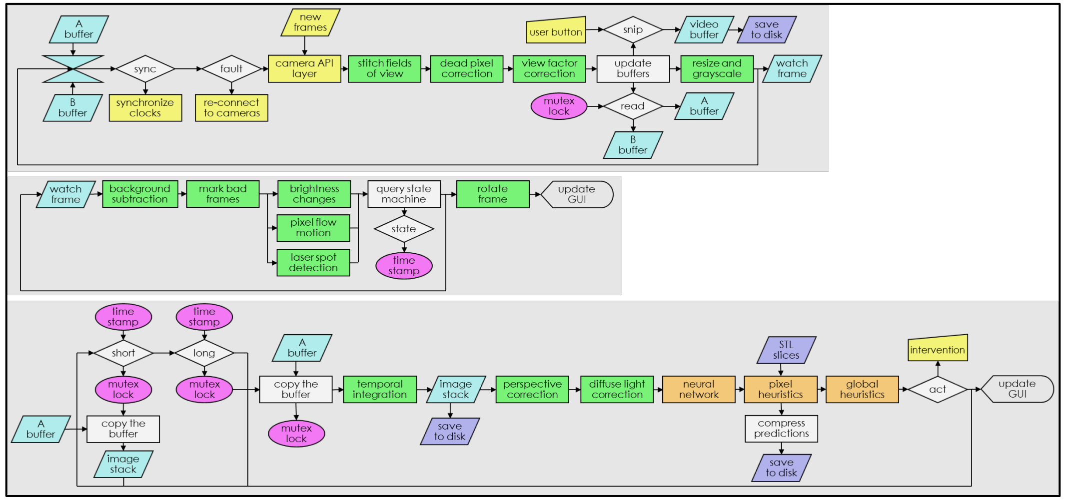




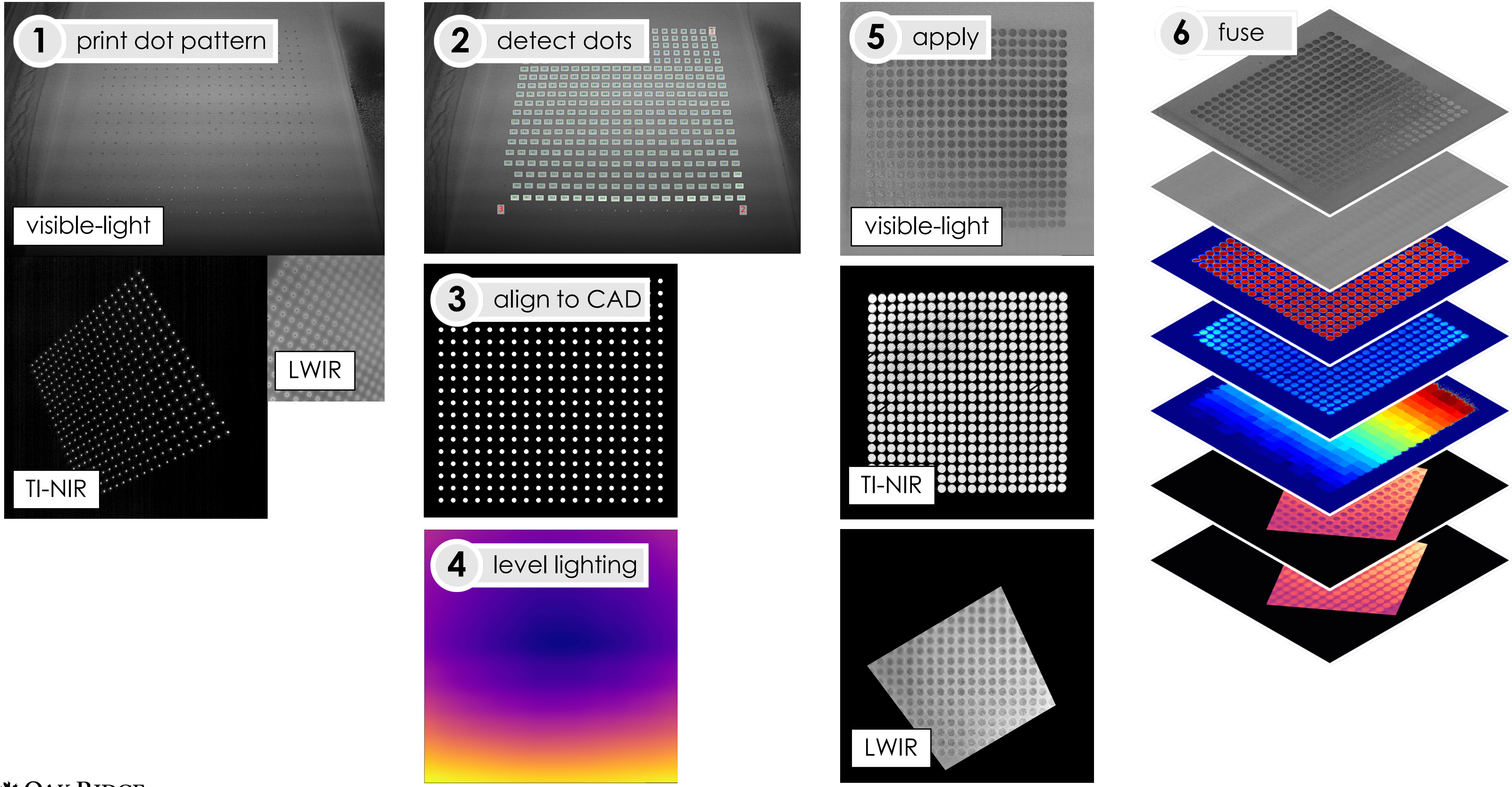




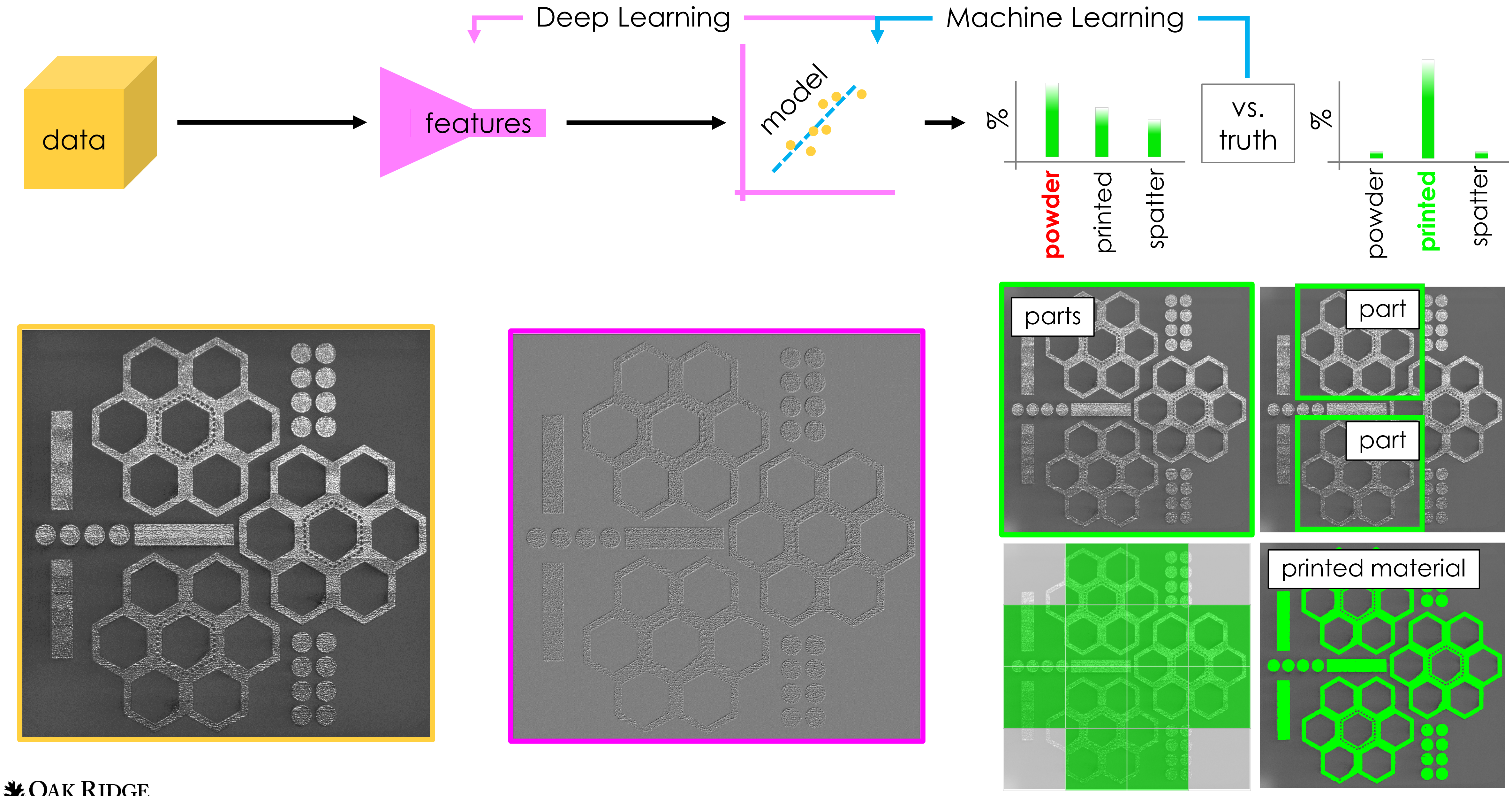




Data Calibration, Registration, and Fusion

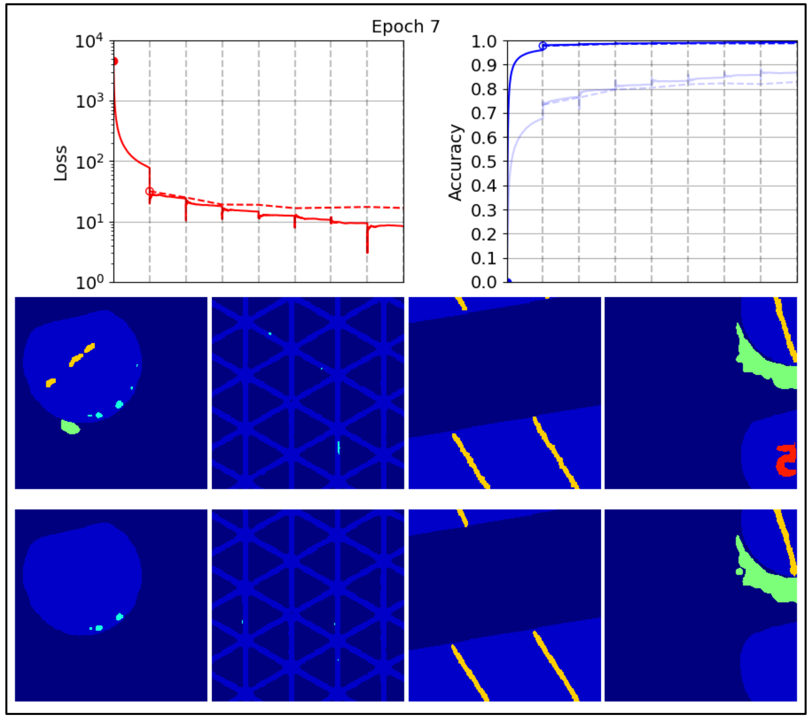


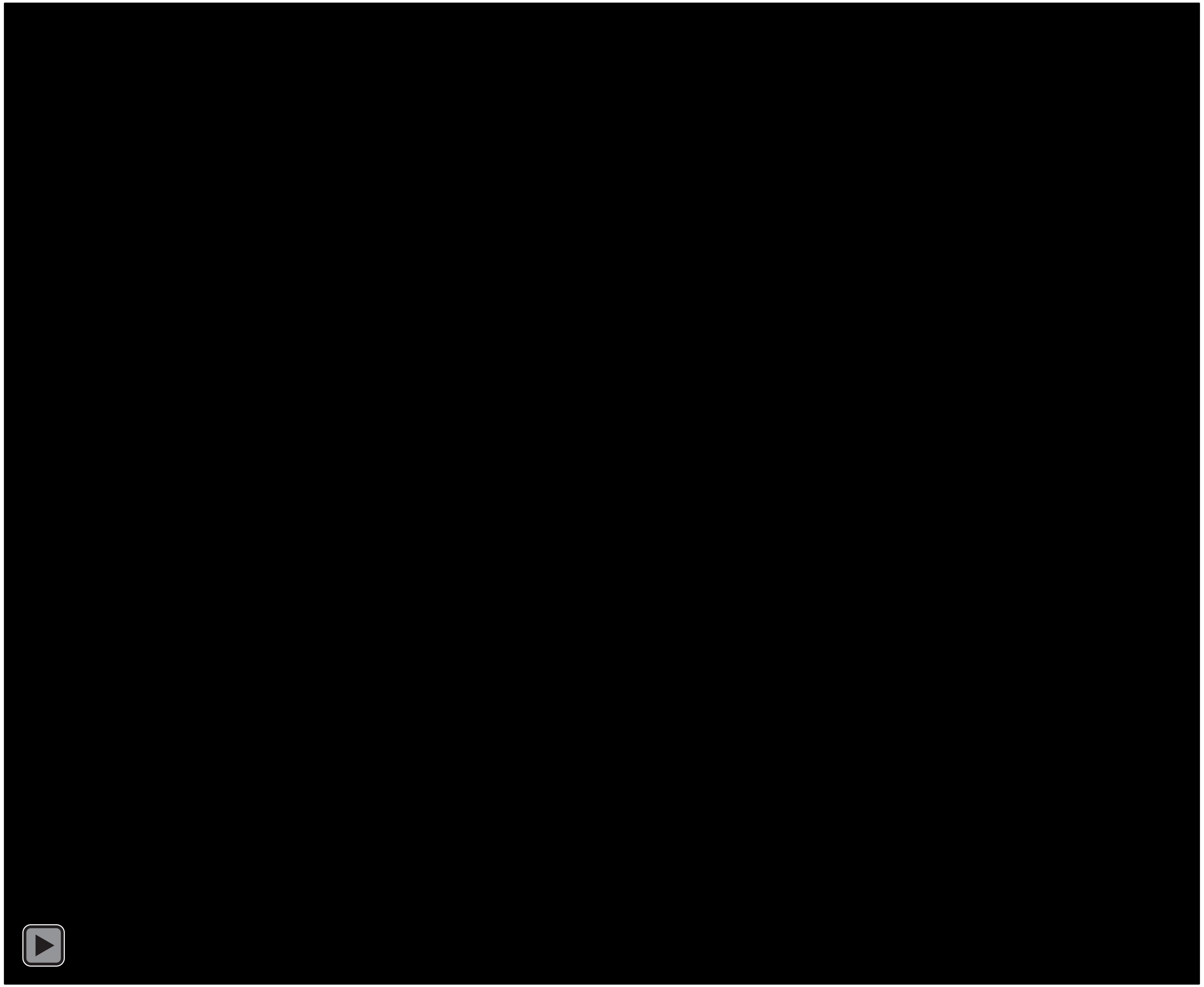
What is Deep Learning?



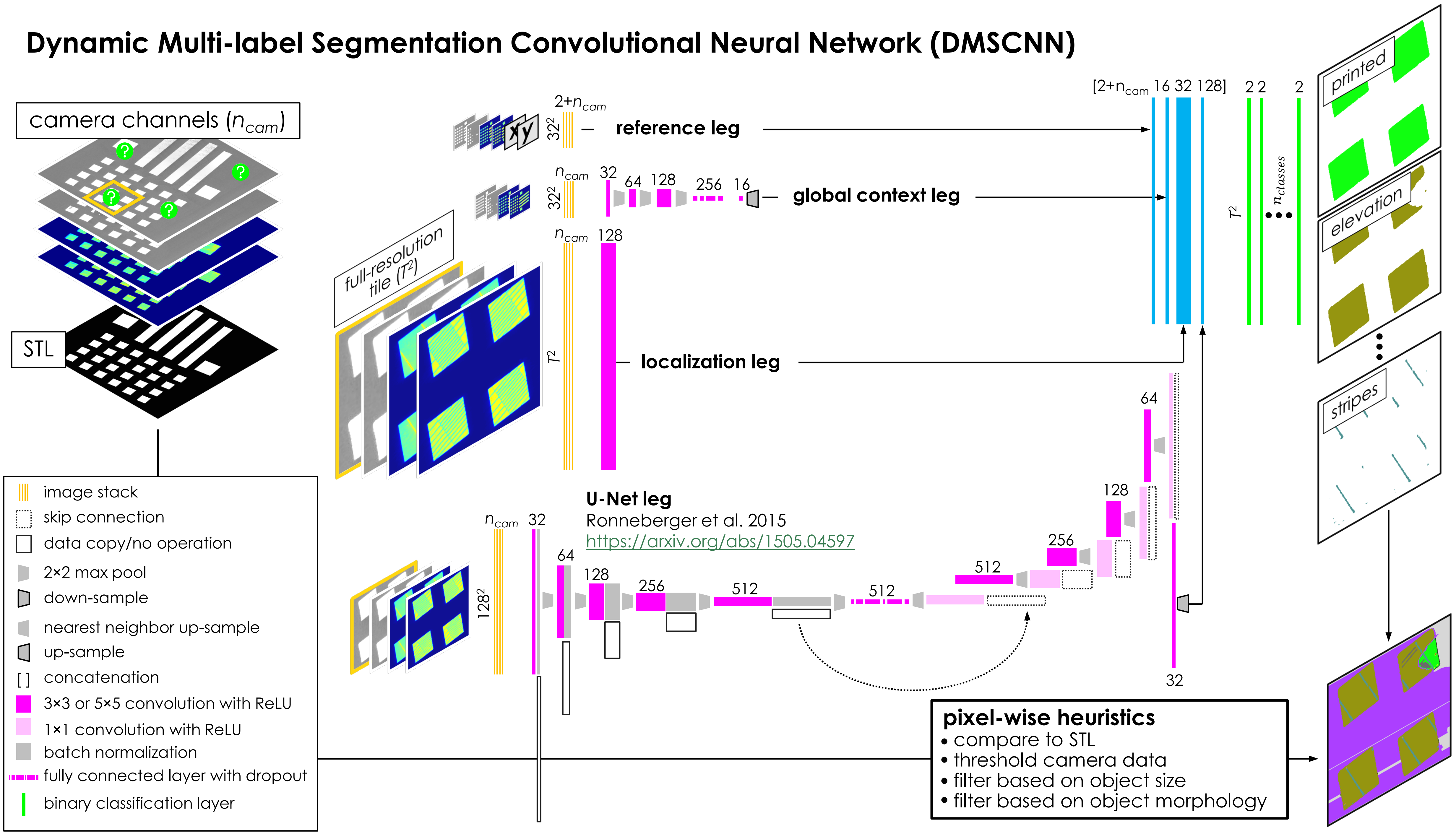
Data Annotation and Training

- Humans annotate pixels from in-situ data, and can use **X-CT** as ground truths
- Training an initial model typically requires **four layers**, or about **20 million pixels**
- Initial annotation and training can be completed within a **48-hour period**
- Data augmentation and **transfer learning** reduces the annotation burden





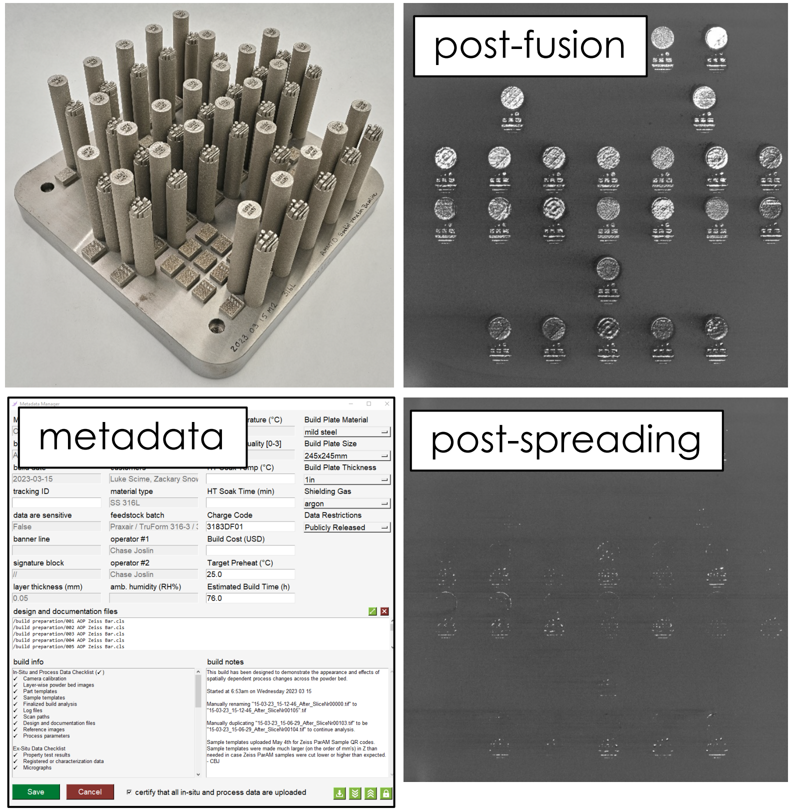
Dynamic Multi-label Segmentation Convolutional Neural Network (DMSCNN)

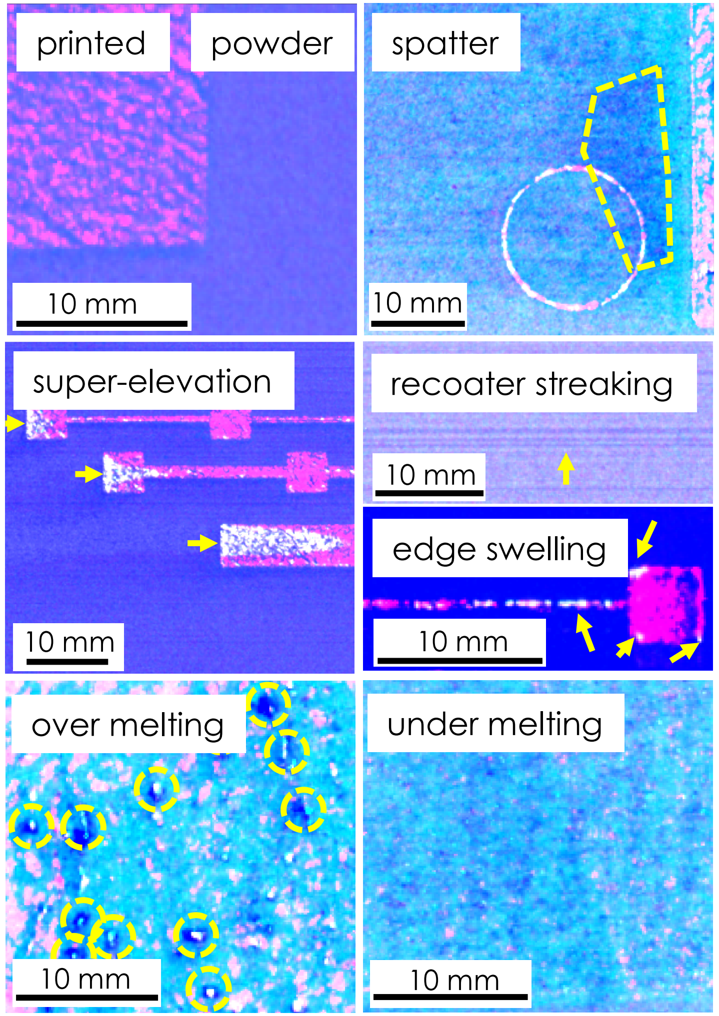


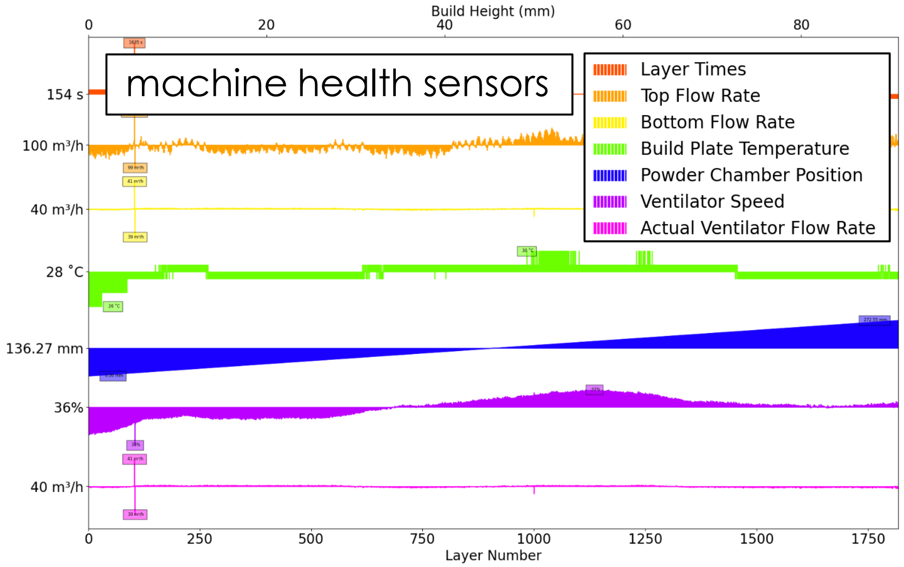
pixel-wise heuristics

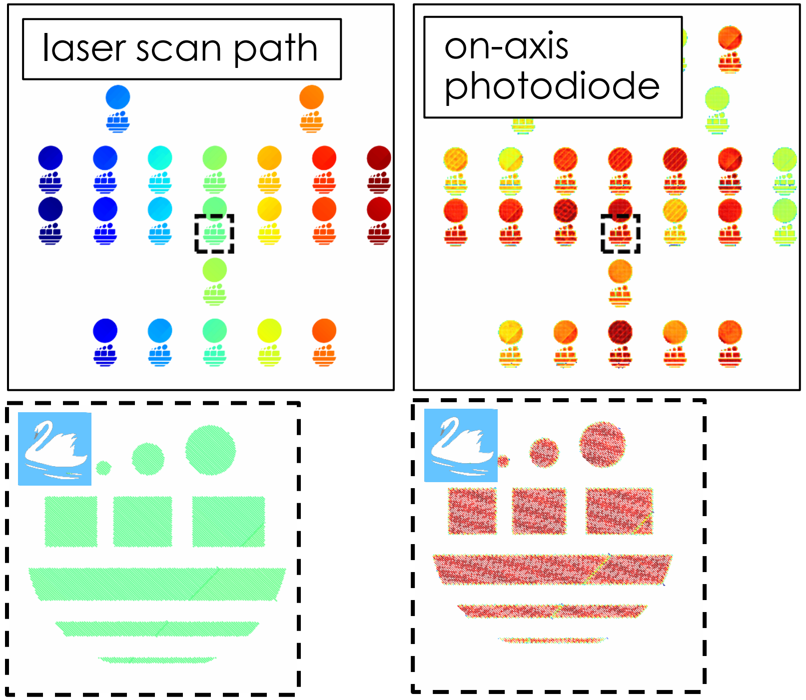
- compare to STL
- threshold camera data
- filter based on object size
- filter based on object morphology

Example In-Situ L-PBF Data





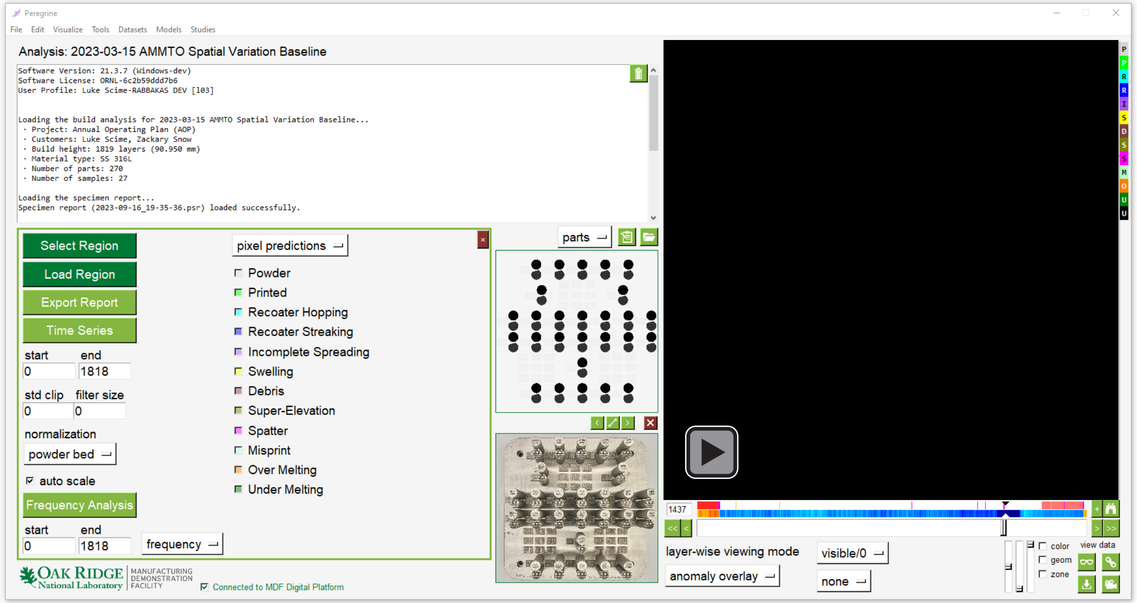




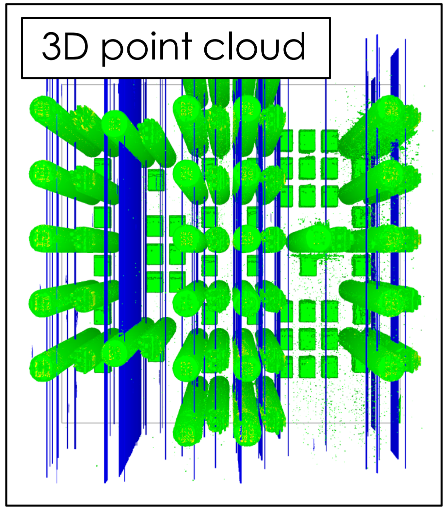
- **Concept Laser M2** L-PBF printer
- OEM **5 MP visible-light** camera
- Printed in stainless steel 316L
- Build designed to test spatial variations

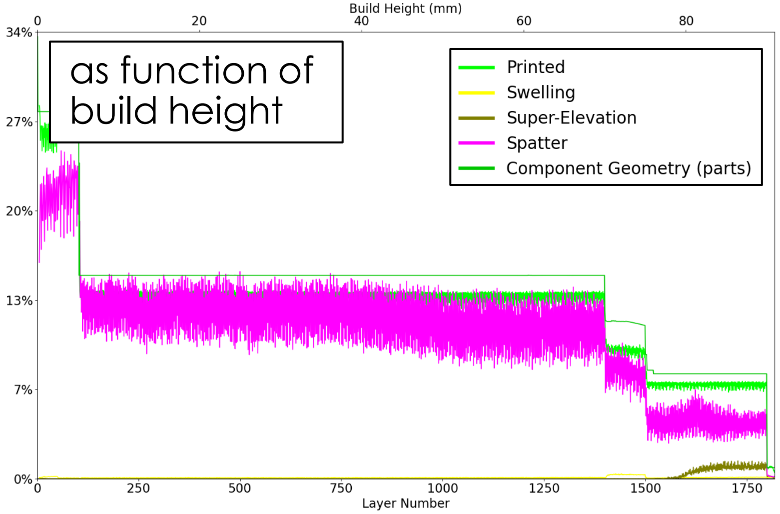
- Different anomalies are visible in the post-fusion versus the post-spreading images
- Shown as false-color composites to highlight the anomalies

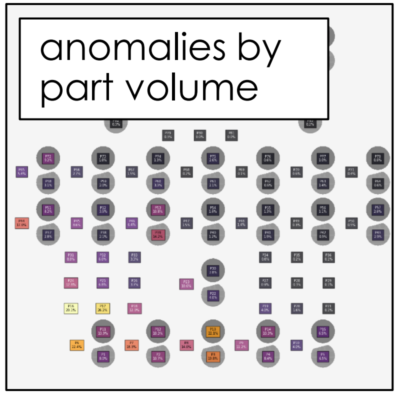
Visualization of DMSCNN Anomaly Detections

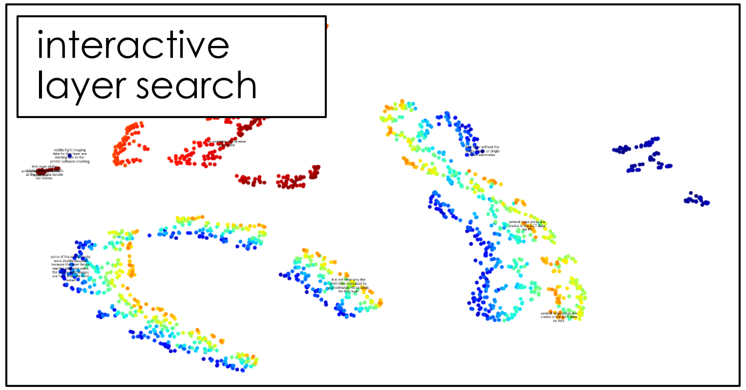


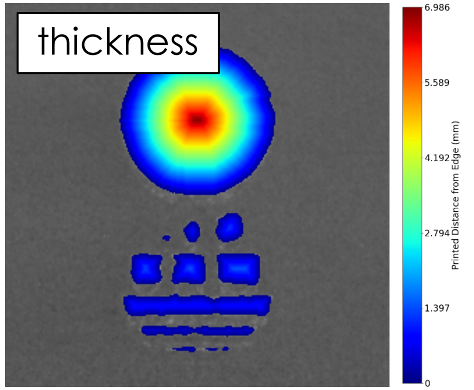
- All the meta, in-situ, and ex-situ data for a build is packaged into a **build analysis** with a set format
- Different visualizations help the user answer questions about both the whole build and individual specimens
- Most visualizations focus on either **spatial distribution** anomaly indications or **evolution** through the build height
- "**Reverse layer search**" and other search tools allow for the rapid identification of layers of interest
- As-printed geometries can be measured from in-situ data











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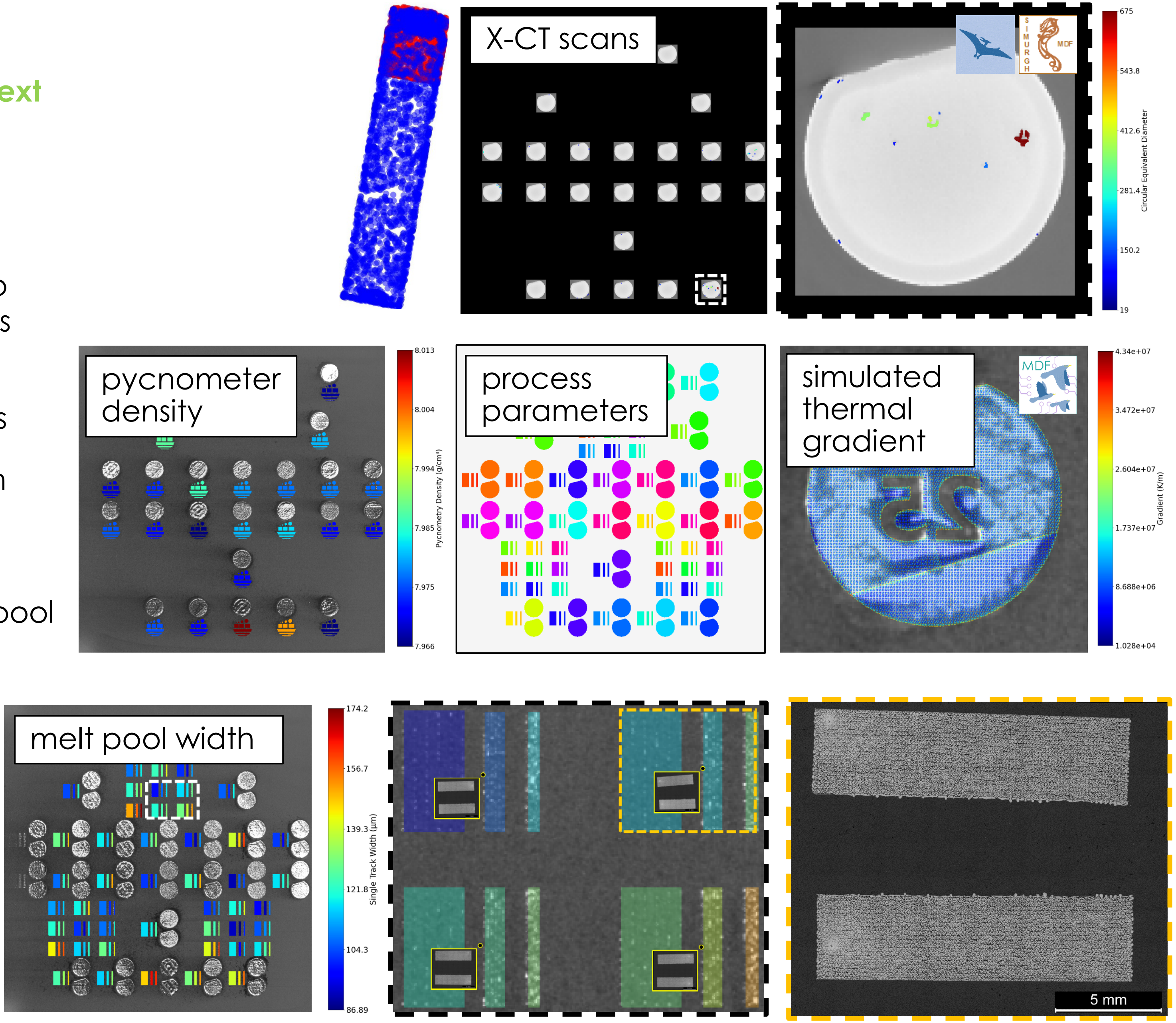
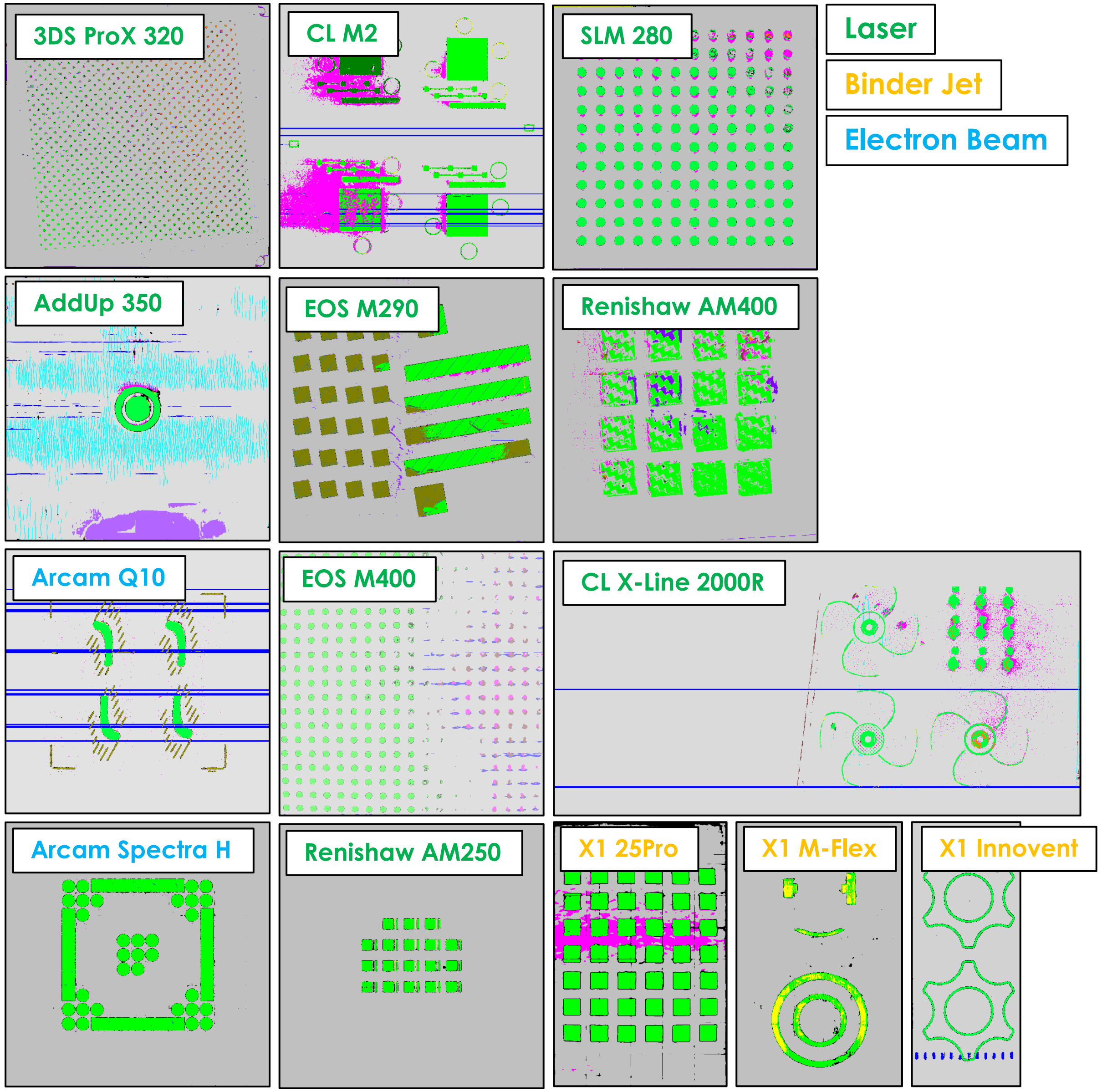
Co-Registration of Ex-Situ Data

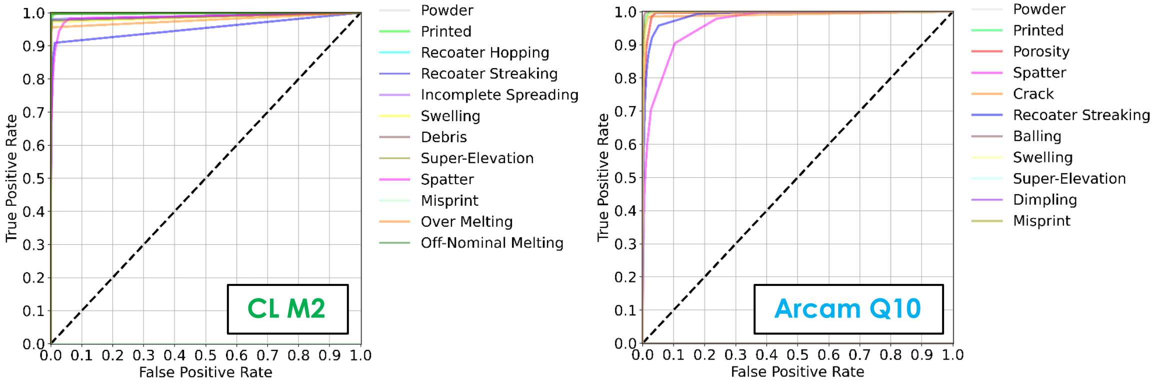
- The build analysis enables ex-situ data to be organized and visualized within the **full build context**
- X-ray computed tomography (X-CT) scans are **automatically registered** to individual specimens and then placed in the global coordinate system
- Flaws observed in the X-CT scans are then used to **train the DMSCNN** to detect in-situ flaw indications
- Volumetric measurements such as tensile tests or **density measurements** are assigned to specimens
- The registered process parameters and laser scan paths are used to instantiate **thermal simulations**
- Co-registration and consistent formatting ensure **provenance** – if there is a question about a melt pool cross-section measurement, the corresponding **micrograph** is immediately accessible

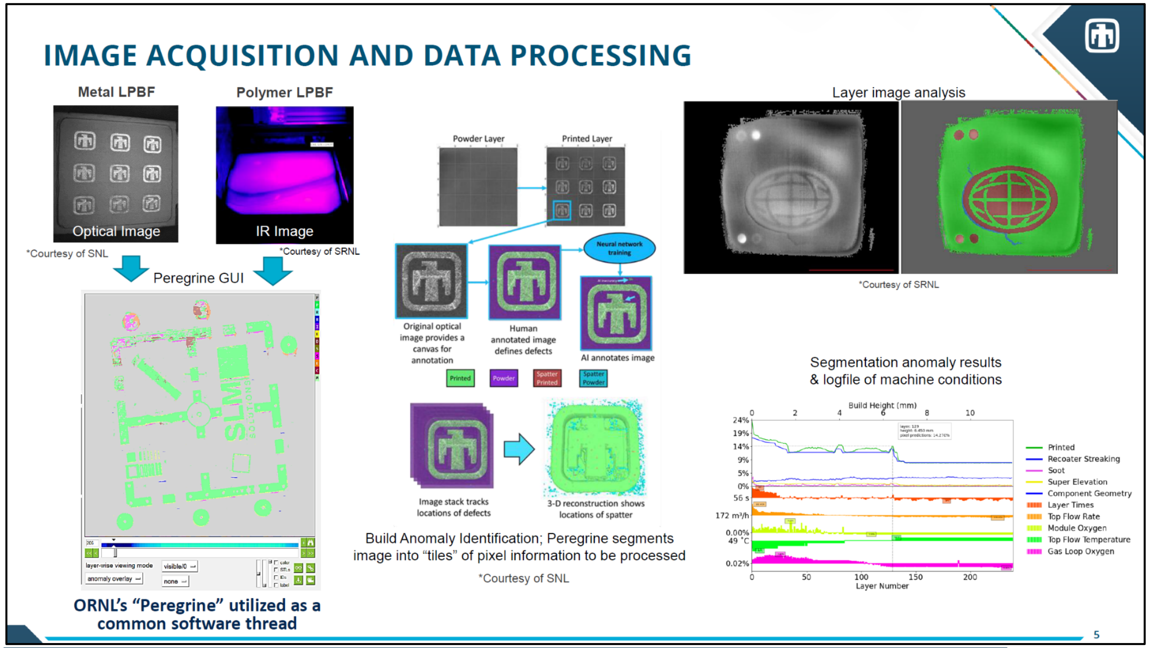


Scaling Data Collection, Performance Metrics, and Analytics Capabilities



validation receiver operating characteristics (ROC) curves for different technologies

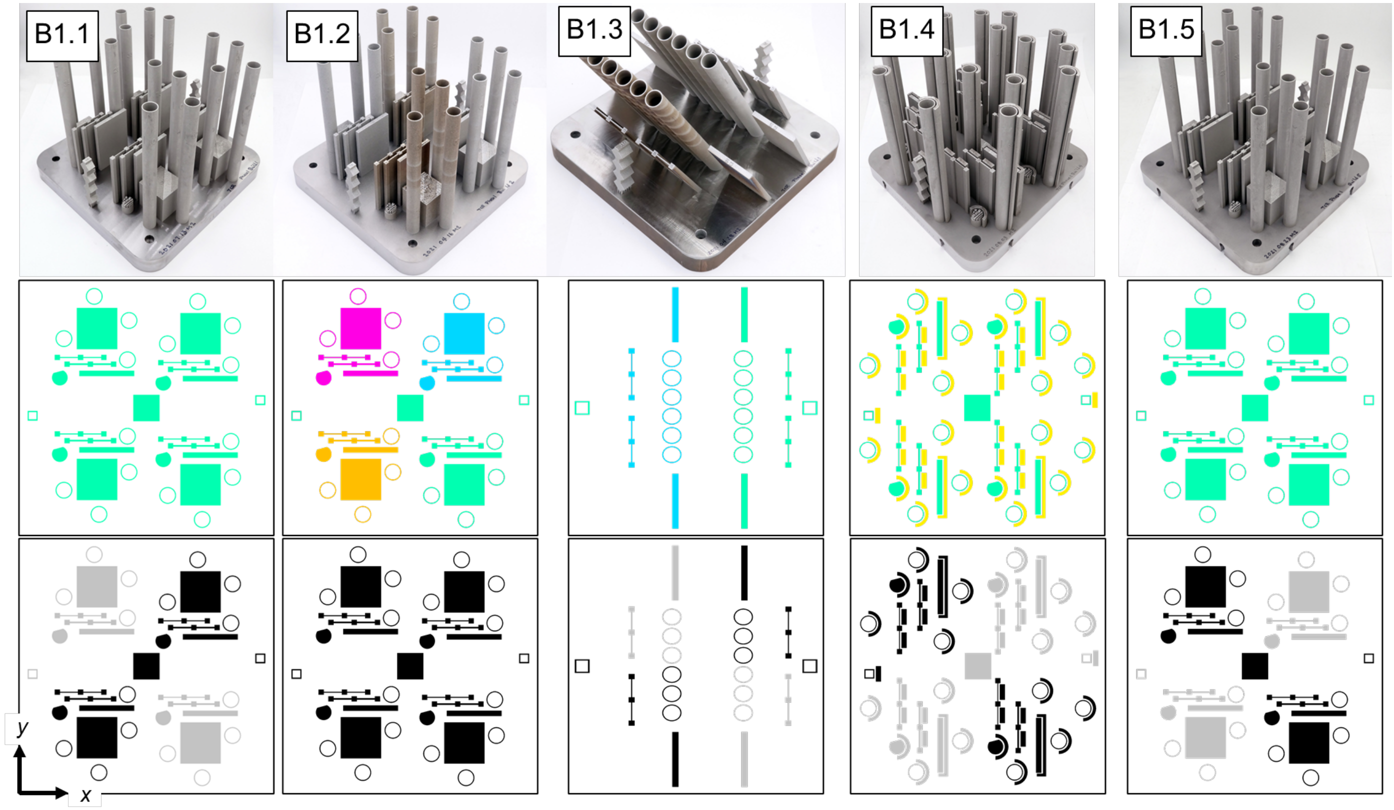


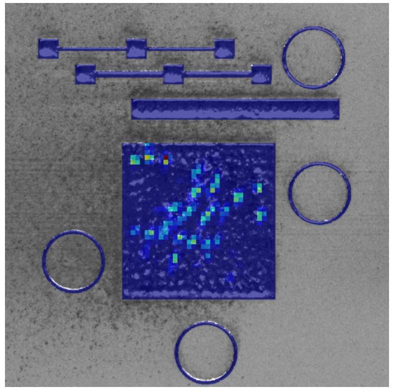


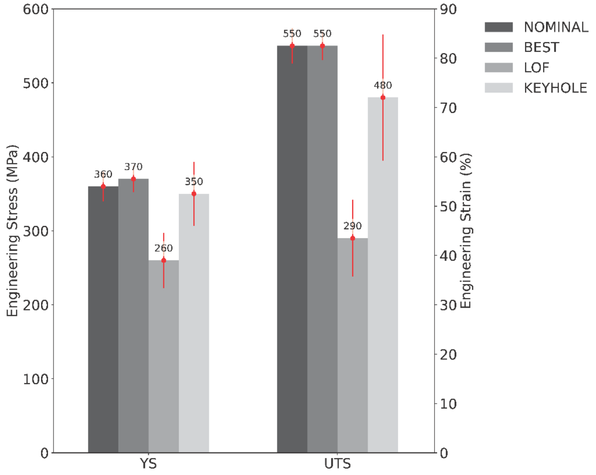
*Courtesy of Michael Heiden and Sandia National Laboratory

AMMT/TCR Tensile Testing Campaign

- Printed **5** Concept Laser M2 builds with varying process **parameters**, printing **conditions**, and local part **geometry**
- Collected visible-light layer-wise images, machine health data, and scan path information
- In-situ data and local part geometry are packaged into **~1 mm³ super-voxels**
- Thousands of individually tracked **SS-J3** coupons were extracted from printed **SS 316L** using wire EDM
- Performed **6,299** room-temperature static tensile tests and measured UTS, YS, UE, and TE







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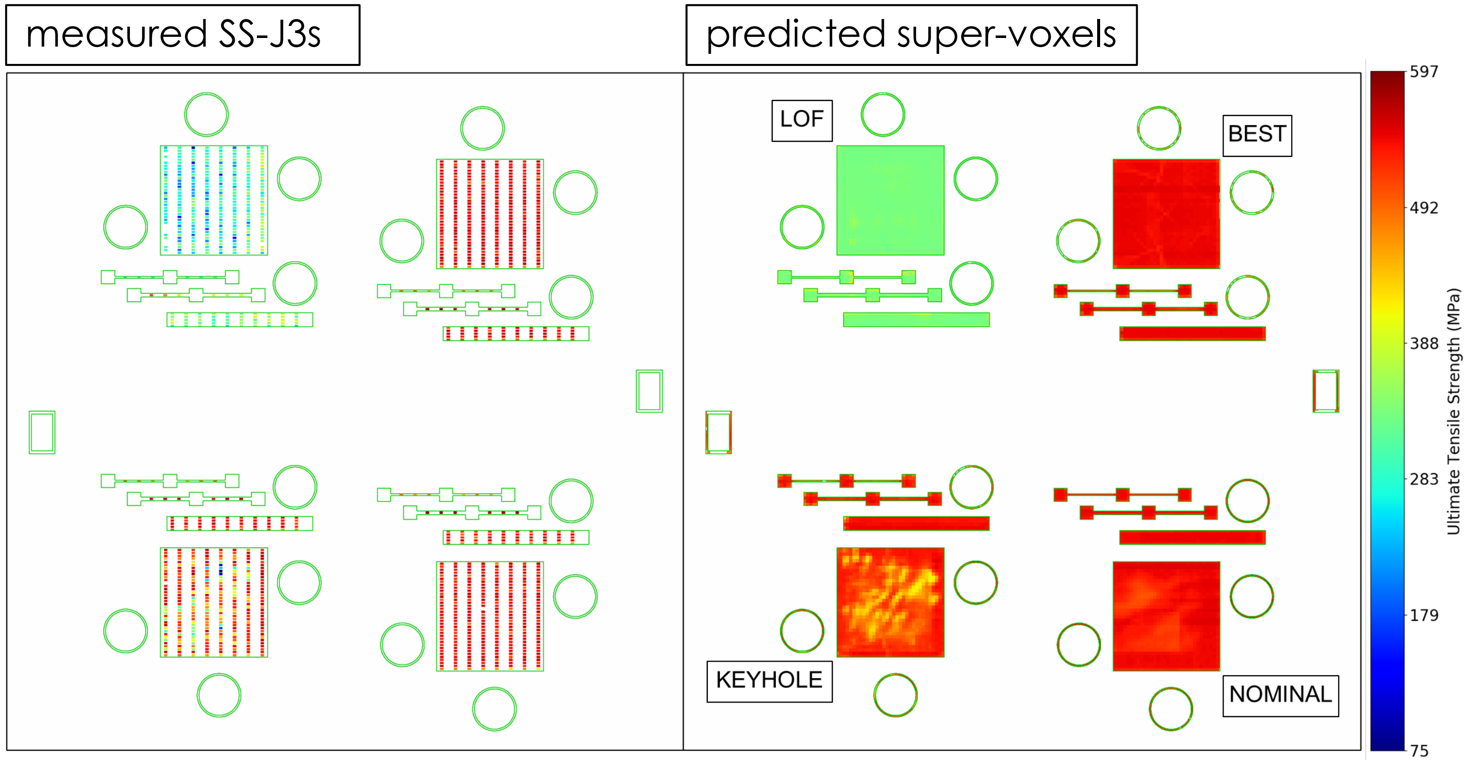
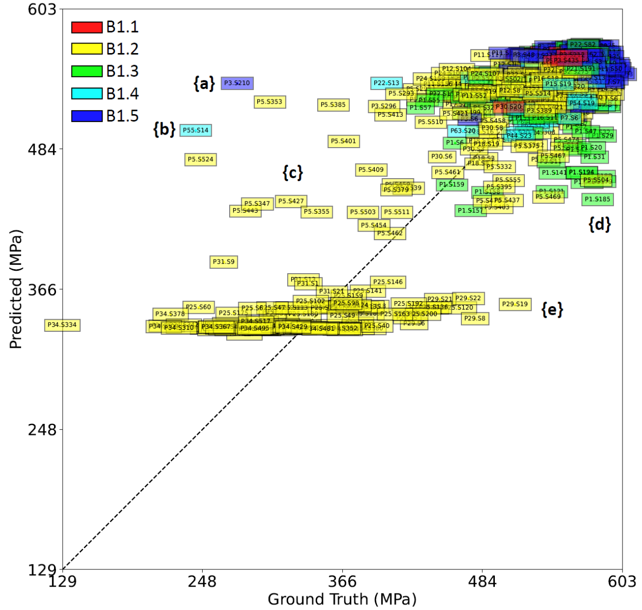
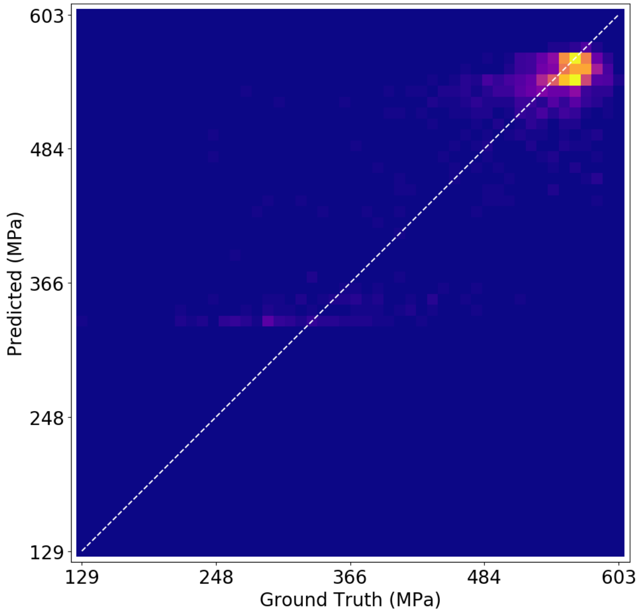
Tensile Property Prediction Results

- Each 1 mm^3 super-voxel is represented by a single **feature vector**
- A multi-layer perceptron (shallow neural network) is trained to predict the **UTS**, YS, UE, and TE at each super-voxel
- Trends correlated to process parameters and local part geometry are correctly predicted
- The final **AI Relay** demonstrates a **61%** error reduction in UTS predictions relative to estimates made without any in-situ information







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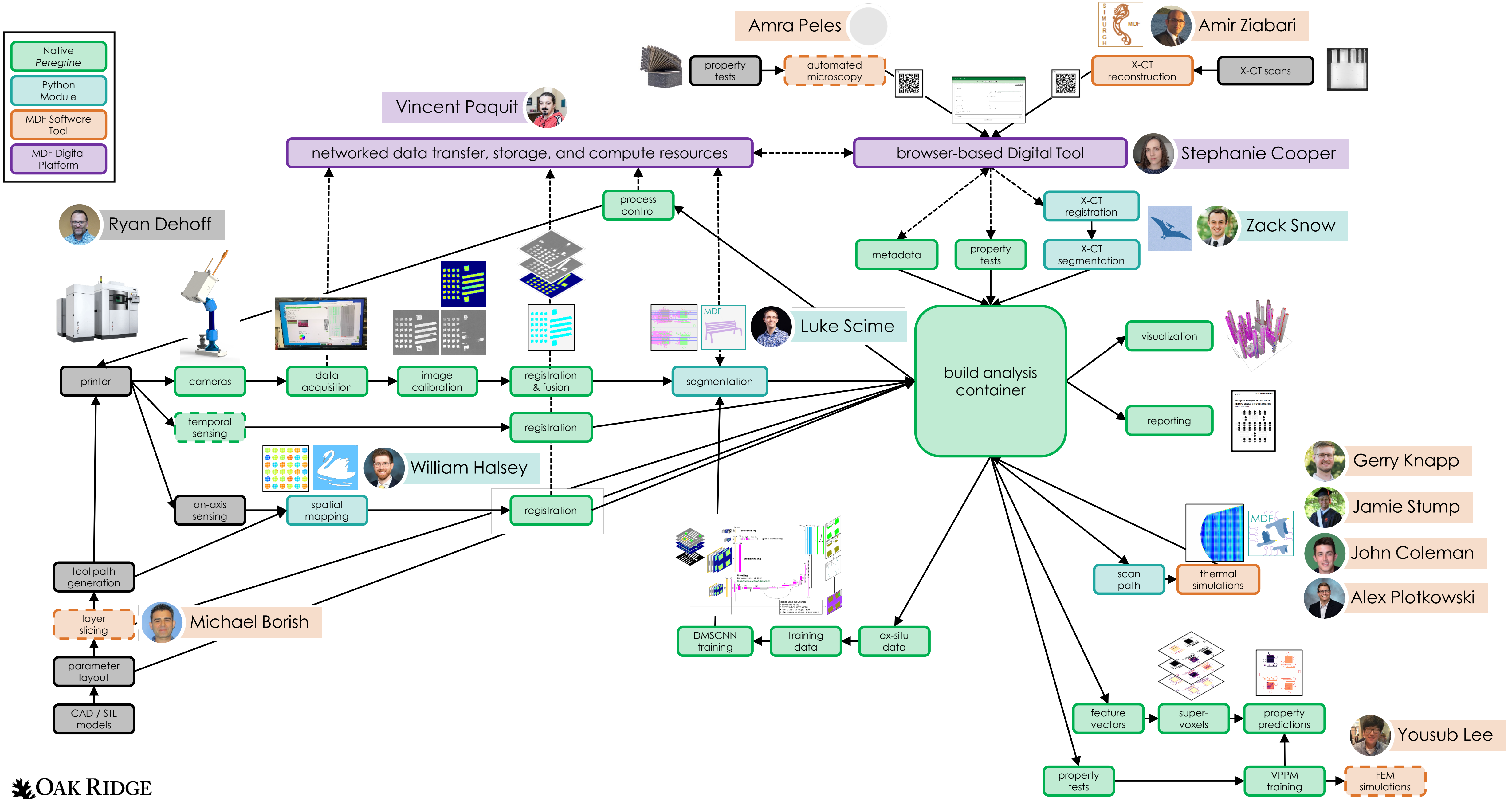
Interfaces with the MDF Digital Platform



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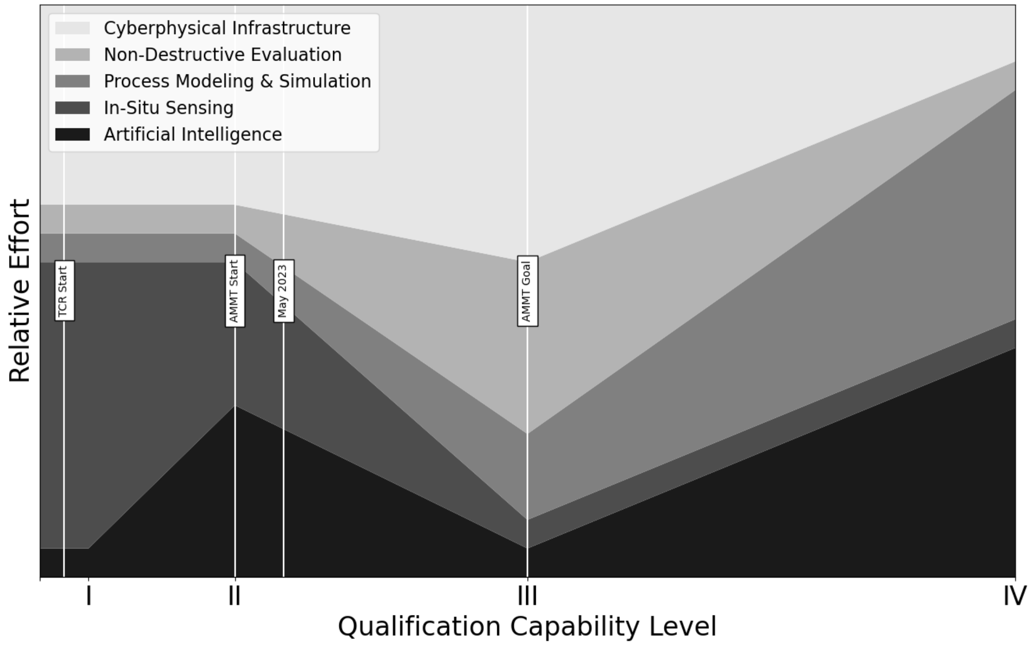
Conclusions

- The capabilities needed for data to support **part qualification** are developed along a **continuum** and our focus will shift across multiple technical areas over time
- The *Peregrine* development team maintains a **multi-year backlog** for tracking bugs, new features, and fundamentally new capabilities
- Being able to release new capabilities across the U.S. Government every **1 – 2 weeks** has significant implications for accelerating in-situ sensing research and data-driven part qualification
- Our goal for 2024 is to begin incorporating software features developed at other DOE Laboratories back into the *Peregrine* code base
- Specific areas of focus for 2024 include:
  - A generalized interface for loading in **tool path vectors**
  - An integrated visualization and analysis **tool suite for X-CT** data
  - Integration with **fracture mechanics** models for predicting fatigue life
  - Increased integration with thermal and microstructure **simulation** tools
  - Improved integration with the **MDF Digital Platform** and web interface



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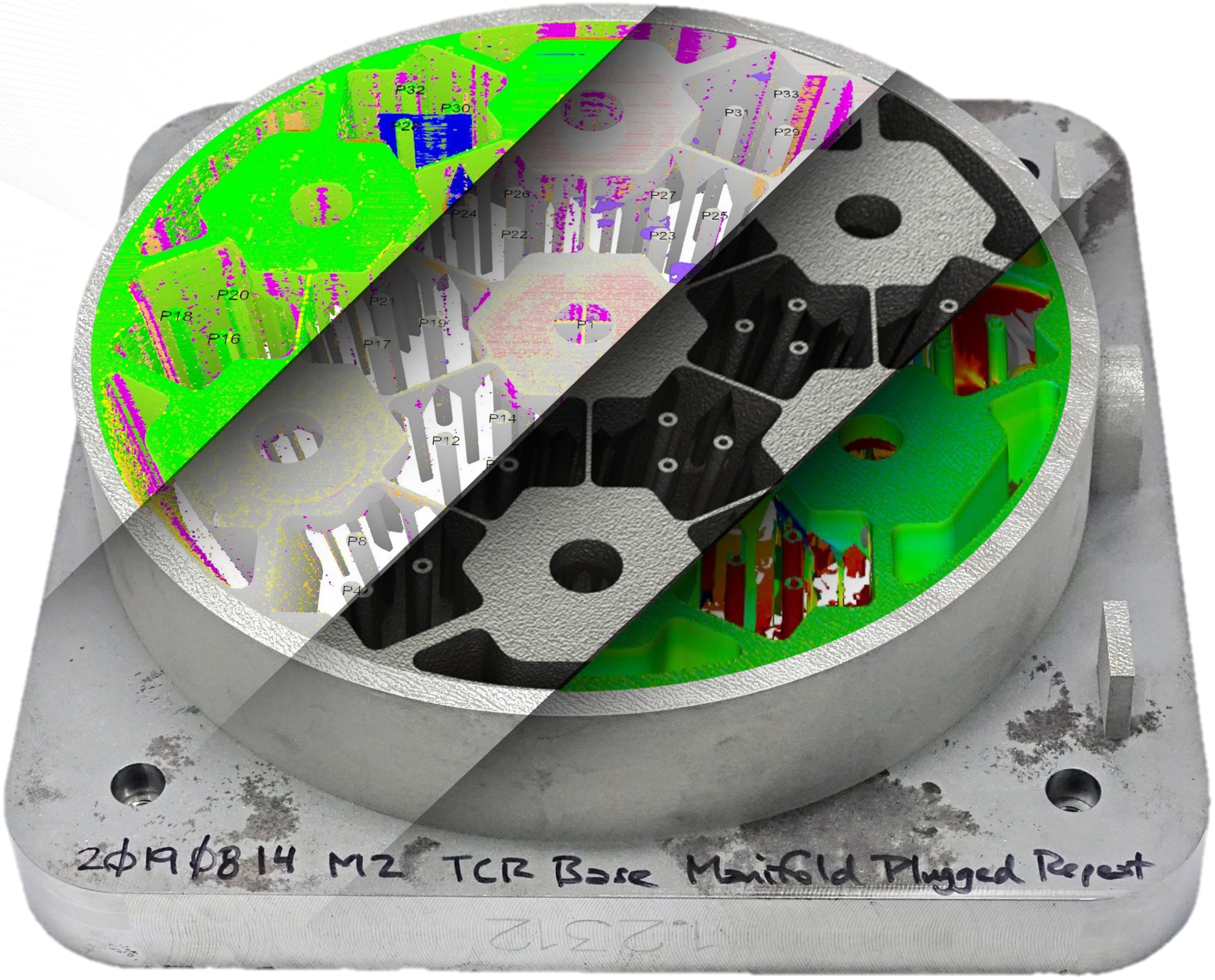
Questions?



This work was performed by UT-Battelle, LLC under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy. Research was sponsored by the DOE Advanced Materials and Manufacturing Technologies Office (AMMTO) and the Office of Nuclear Energy.

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