

# Optical and Thermal Sensing for Additive Manufacturing

**Albert C. To, Ph.D.**

William Kepler Whiteford Professor

with contributions from Shawn Hinnebusch, Berkay Bostan, David Anderson, Alaa Olleak, Xuan Liang, Ran Zou (ECE Dept.), Prof. Kevin Chen (ECE Dept.)

Department of Mechanical Engineering and Materials Science

University of Pittsburgh

Virtual Workshop on Optical Sensors for Energy Applications

March 2, 2023

# Ansys Additive Manufacturing Research Lab (AMRL)

**Optomec LENS 450**



**EOS M290 DMLS**



- **Established in 2015**
- **2,000 sq ft lab space**

**GEFERTEC arc605**

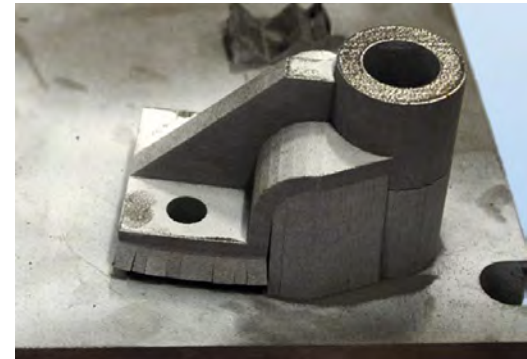
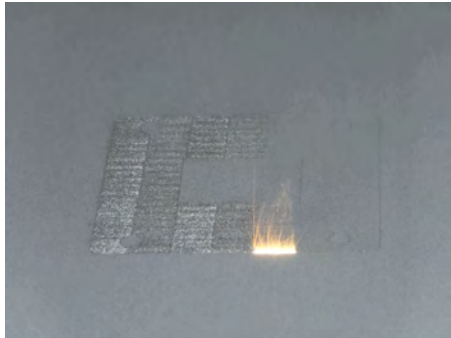
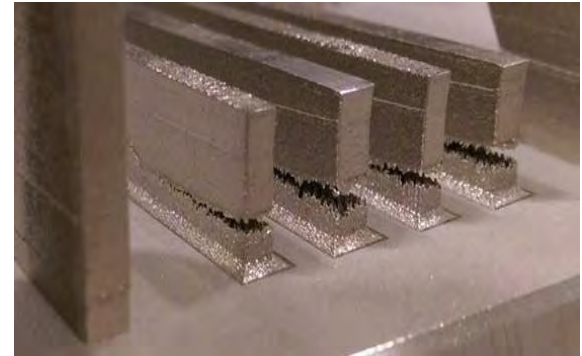
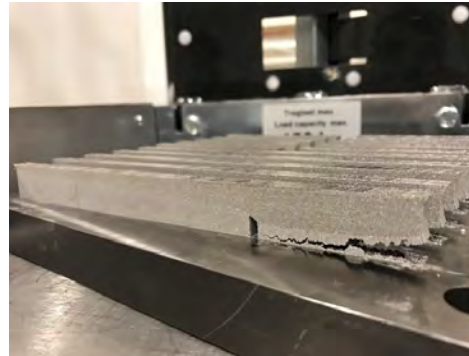


**ExOne Innovent**



# AM Build Failures

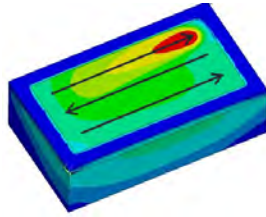
EOS M290 DMLS



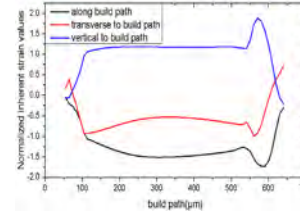
# Efficient Residual Stress Modeling

## Detailed model

- Meso-scale (~0.1mm)
- Sequentially coupled thermomechanical analysis



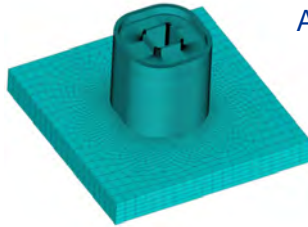
Extract inherent strains  
(element-by-element)



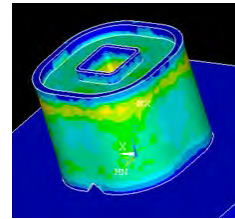
$$\varepsilon^{In} = \varepsilon_{t_i}^{Plastic} + (\varepsilon_{t_i}^{Elastic} - \varepsilon_{t_s}^{Elastic})$$

## Inherent strain model

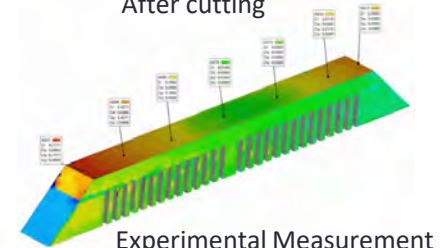
- Macro-scale (~100mm)
- Quasi-static mechanical analysis



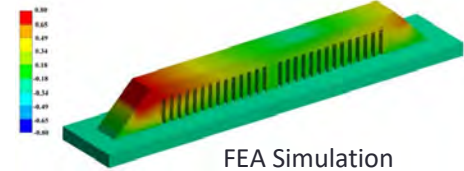
Apply inherent strains  
(layer-by-layer)



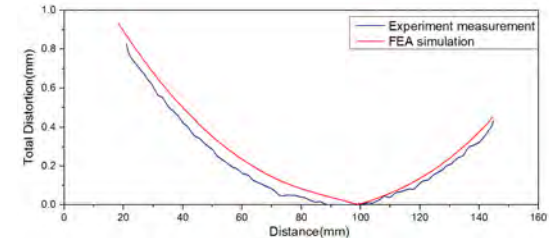
After cutting



Experimental Measurement



FEA Simulation



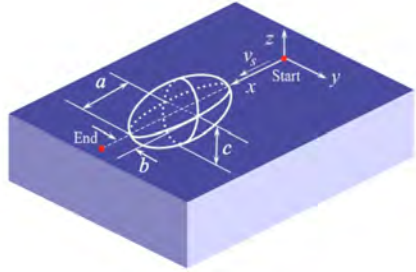
➤ **Reduce error in deformation from 40% to 10% compared to original inherent strain model**

Q. Chen, **A. C. To**, et al., "An inherent strain based multiscale modeling framework for simulating part-scale residual deformation for direct metal laser sintering," *Additive Manufacturing*, vol. 28, 406-418, 2019.

X. Liang, **A. C. To**, et al., "Modified inherent strain method for fast prediction of residual deformation in direct metal laser sintered components," *Computational Mechanics*, vol. 64, 1719-1733, 2019.

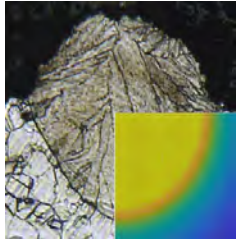
# Thermal Model Calibration

Goldak heat source model: 
$$Q = \frac{6\sqrt{3}P\eta}{abc\pi\sqrt{\pi}} \exp\left(-\frac{3(x_0 + vst - x')^2}{a^2} - \frac{3(y' - y_0)^2}{b^2} - \frac{3(z' - z_0)^2}{c^2}\right)$$

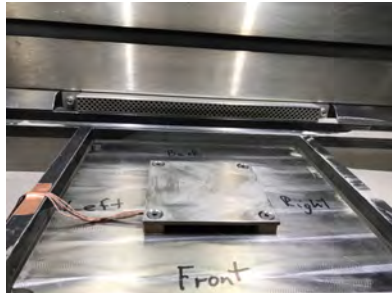


laser power:  $P$   
 laser absorptivity:  $\eta$   
 local coordinates :  $x', y', z'$   
 Geometric factors:  $a, b, c$

J. Goldak, A. Chakravarti, M. Bibby, Metall. Trans. B 15B (1984) 299-305



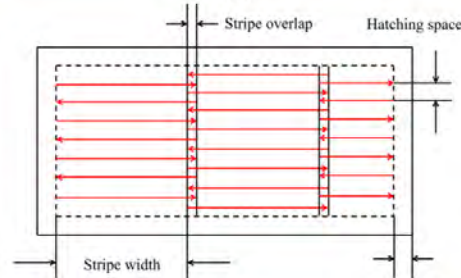
Melt pool cross section



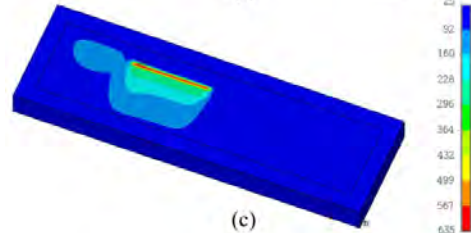
In-situ thermocouples



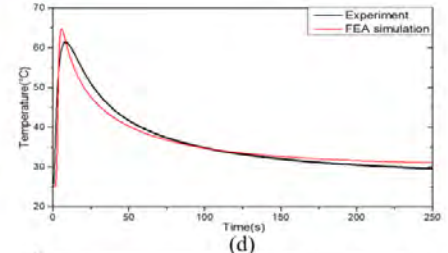
(a)



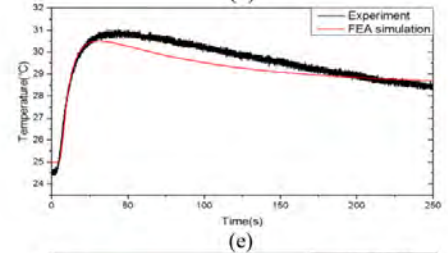
(b)



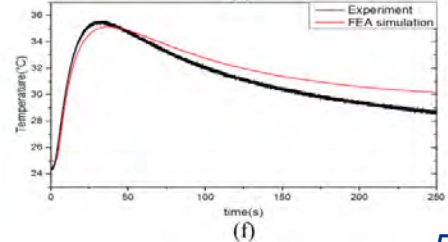
(c)



(d)

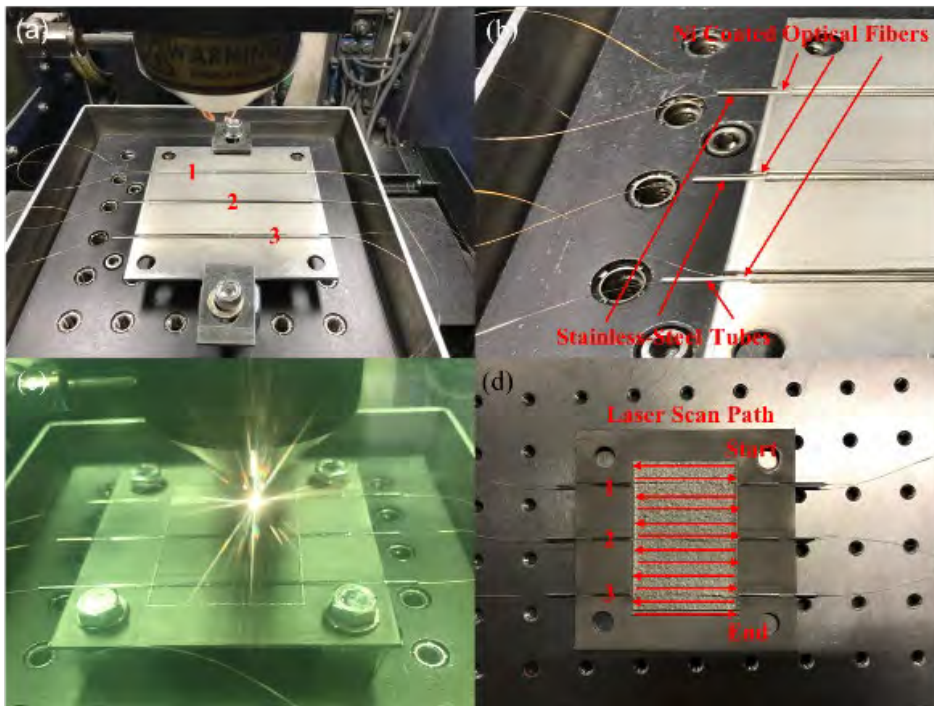


(e)



(f)

# Sensor-Fused AM Process

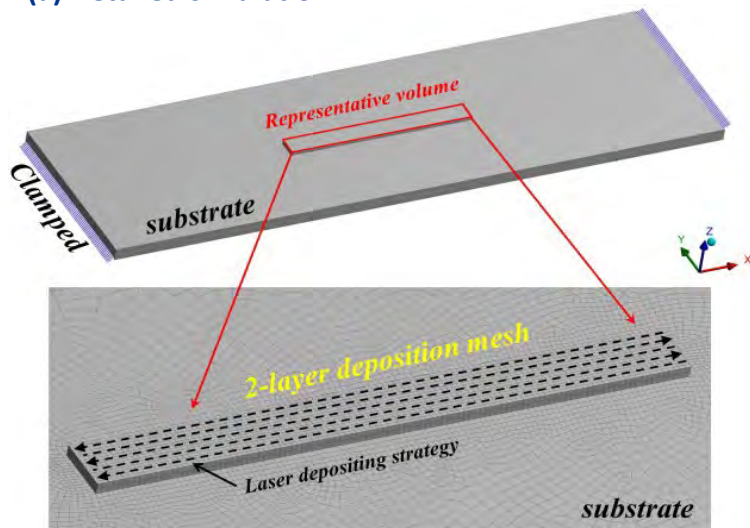


## Sensor Fused AM Process

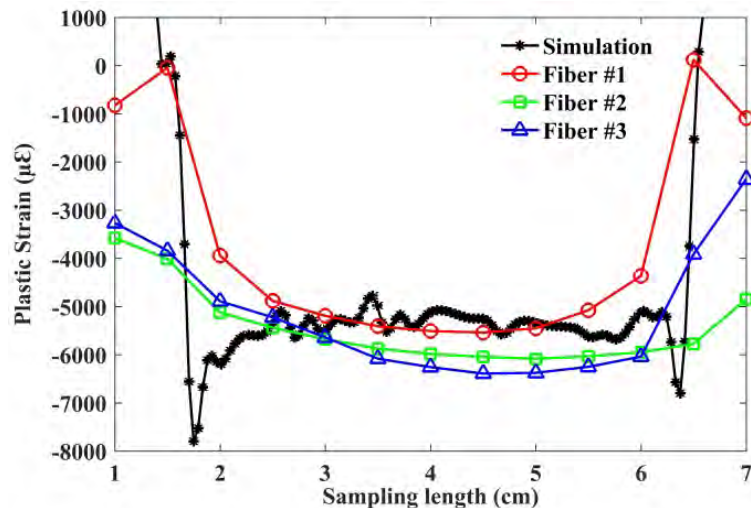
- **High resolution real-time T &  $\mu\epsilon$  measurements**
- **Design proper structures to embed sensors without disturbing AM process and part itself**
- **Real-time measurements to study AM process itself**
- **Post-process monitoring to study residual strain formation and relaxation.**
- **Compare, correct, and validate DT**

# Sensor-Fused AM Process

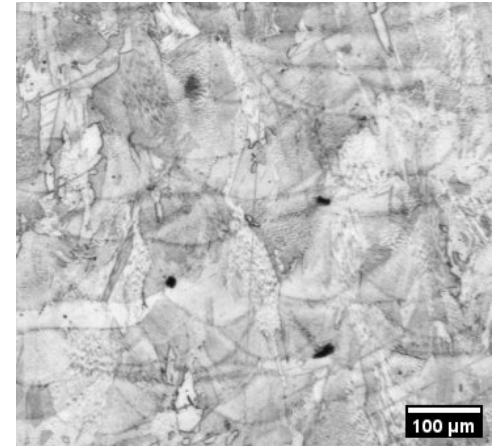
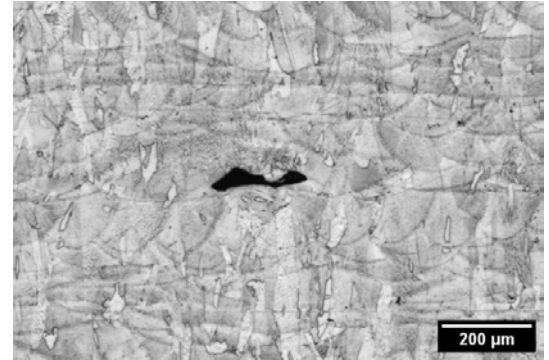
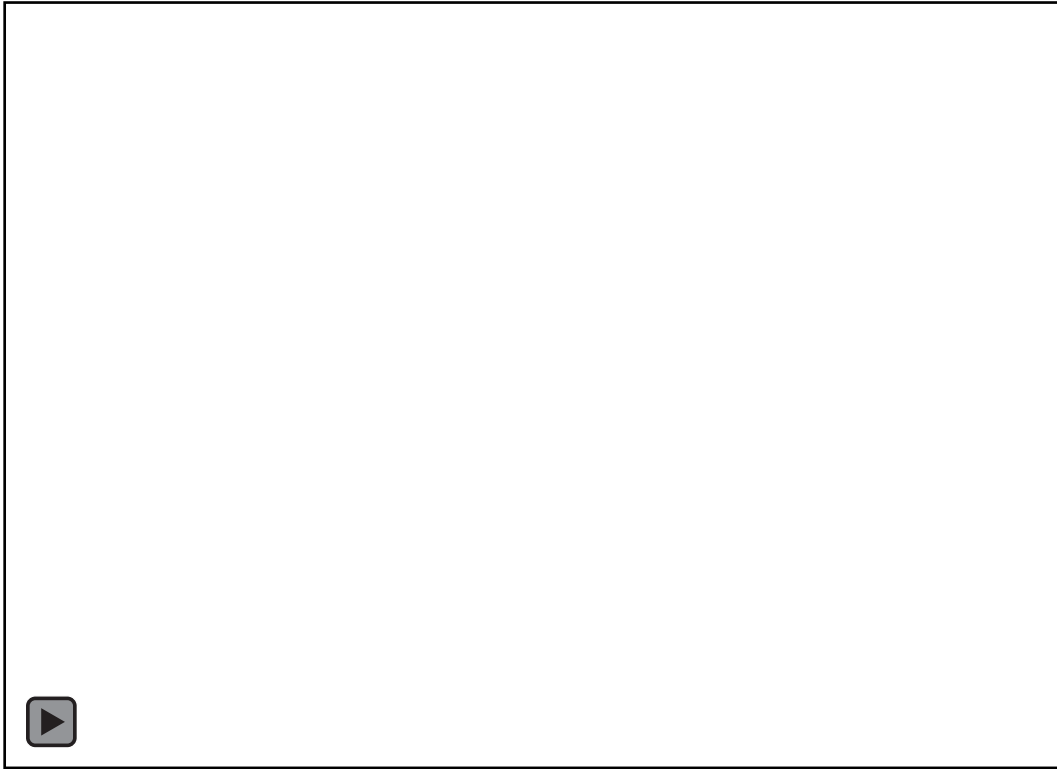
(a) Detailed simulation



(b) Strain from simulation and experimental results



# Defects in Laser Powder Bed AM

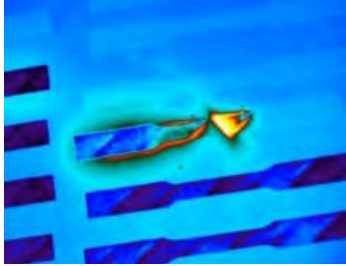




# In-Situ Defect Detection Using IR Imaging and ML

## Inputs

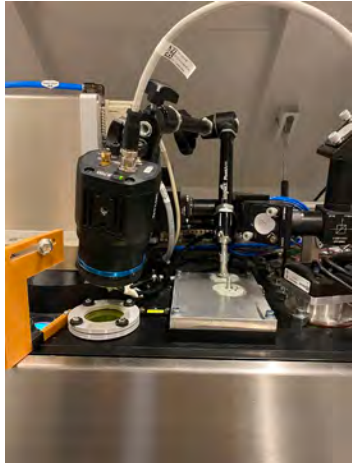
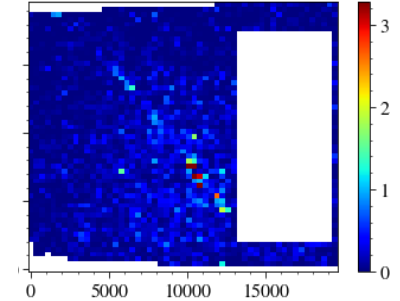
- Heat intensity
- Cooling rate
- Interpass temperature
- Local spatter counts



Deep  
Neural  
Networks

## Outputs

- Local porosity
- Defect type
- Maximum defect size

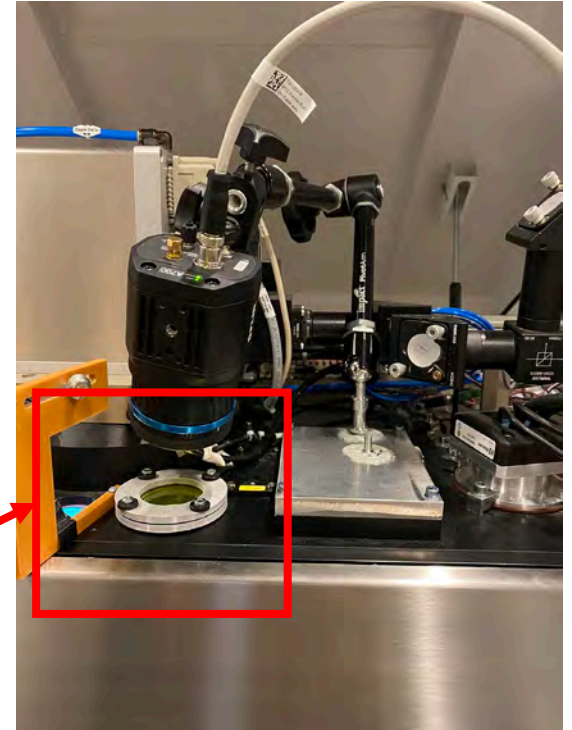
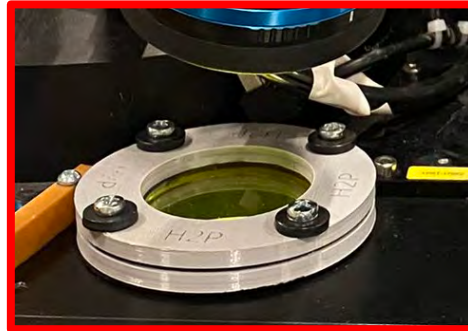


**Infrared (IR)  
camera**

Aims to estimate the defects in LBPF-manufactured parts from in-situ IR monitoring data using deep learning

# In-Situ IR Camera

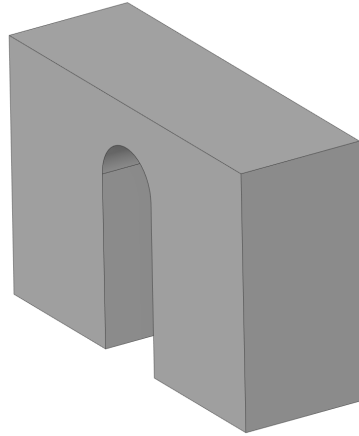
- The camera is mounted on an EOS M290 DMLS machine
- 640x480 Pixel detector
  - 360  $\mu\text{m}$  pixel size
- Frame Rate: 30 (FPS)
- Ranges:
  - -20 – 120 °C
  - 0 – 650 °C
  - 300 – 2,000 °C



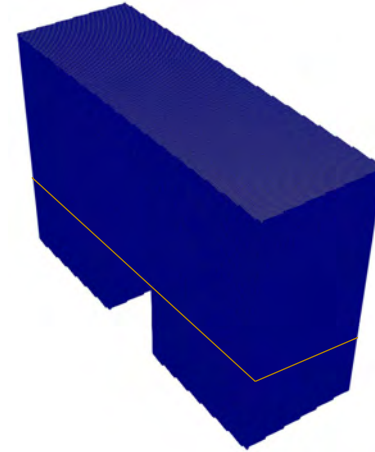


# In-Situ IR Signature Extraction

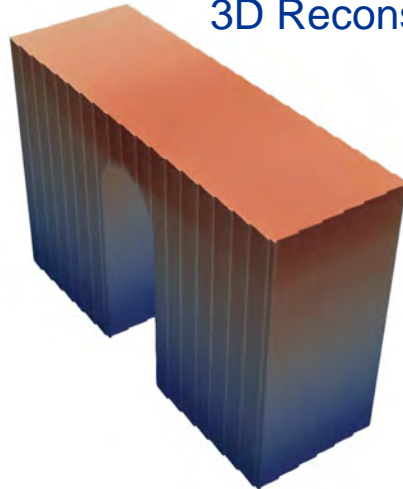
CAD Geometry



Voxel Mesh



3D Reconstruction

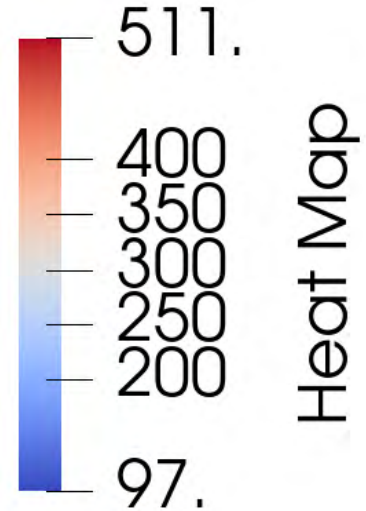
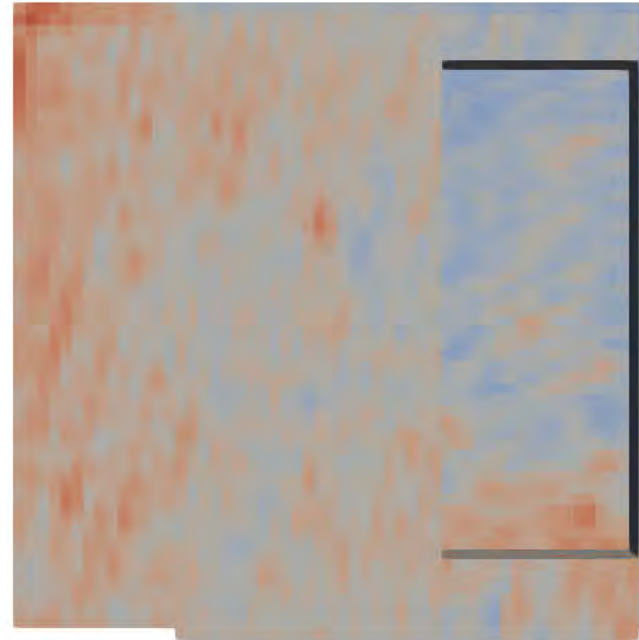
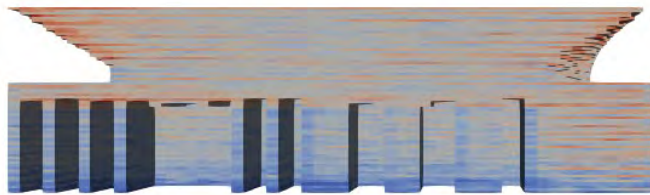
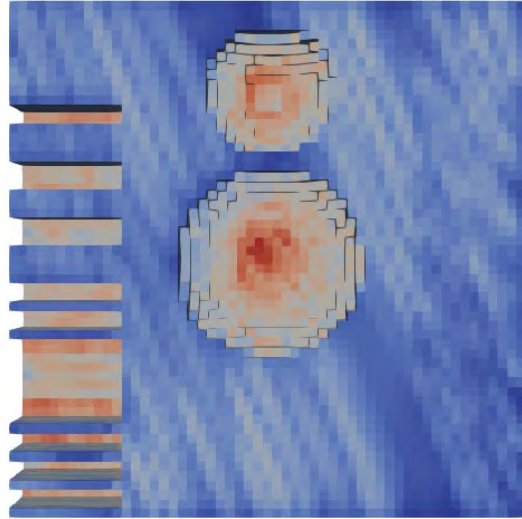
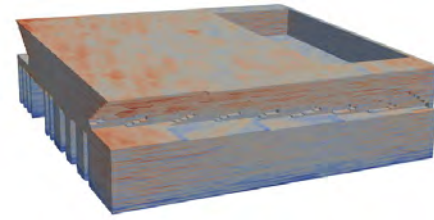


IR Image

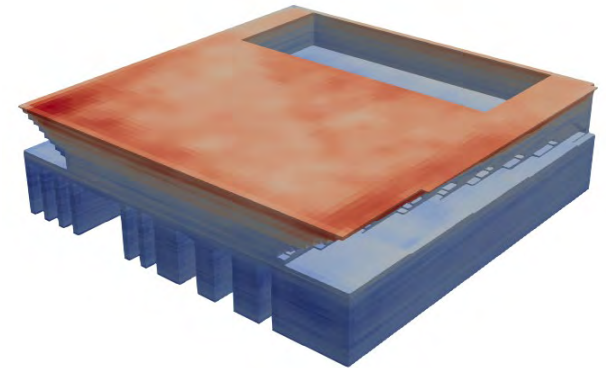
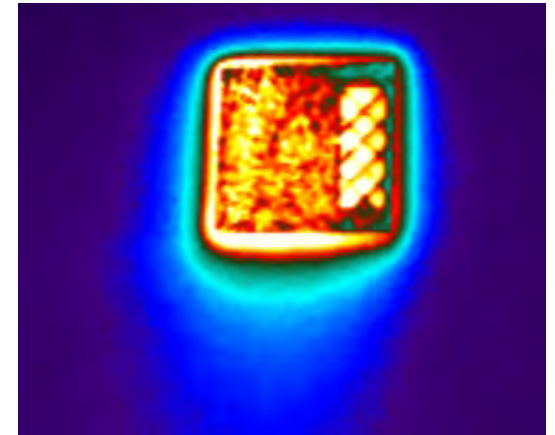
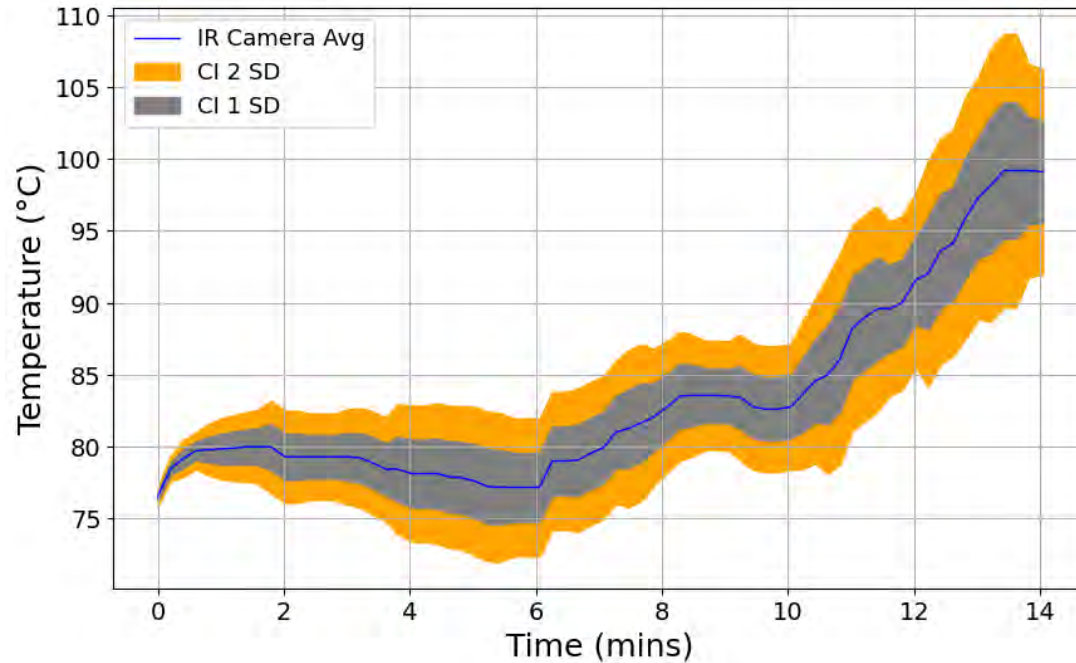


- Understand causal relationship with porosity
- Reduce data storage and enable real-time processing

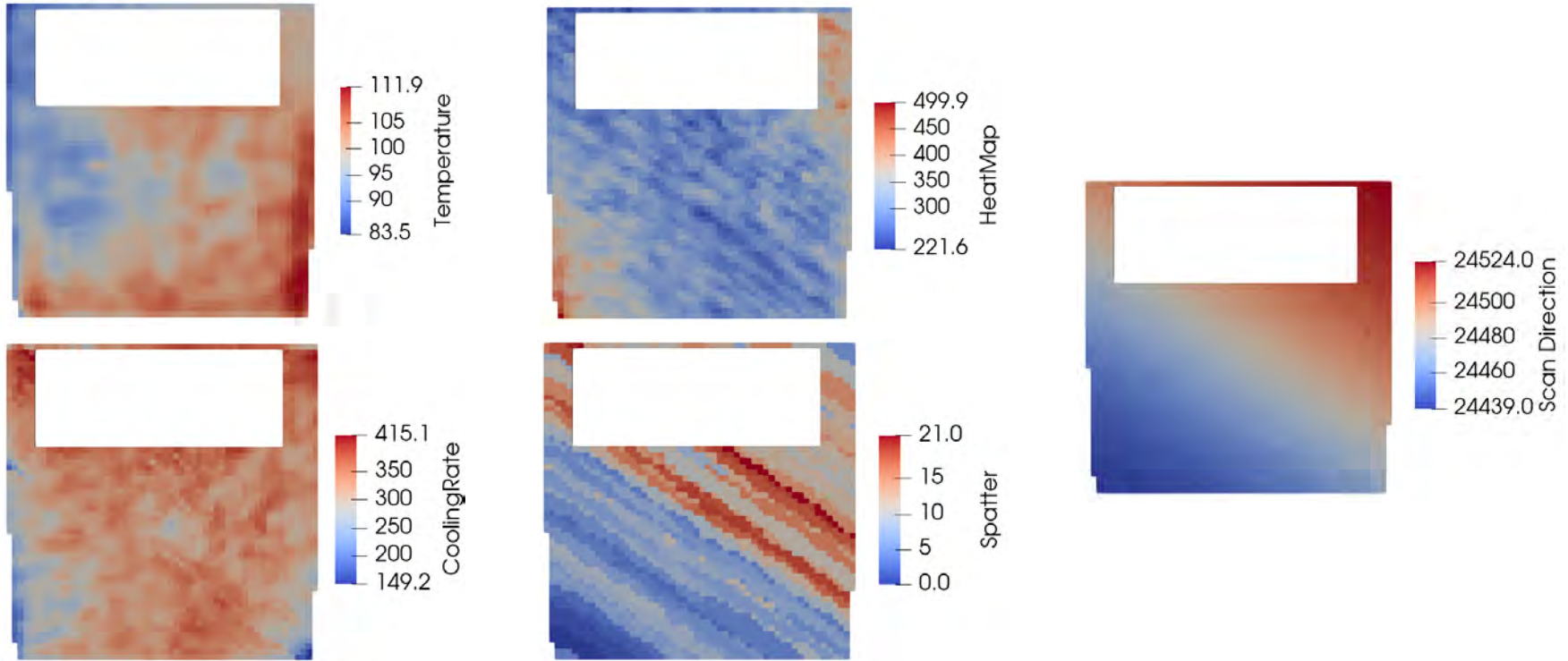
# Complex Part: Heat Map



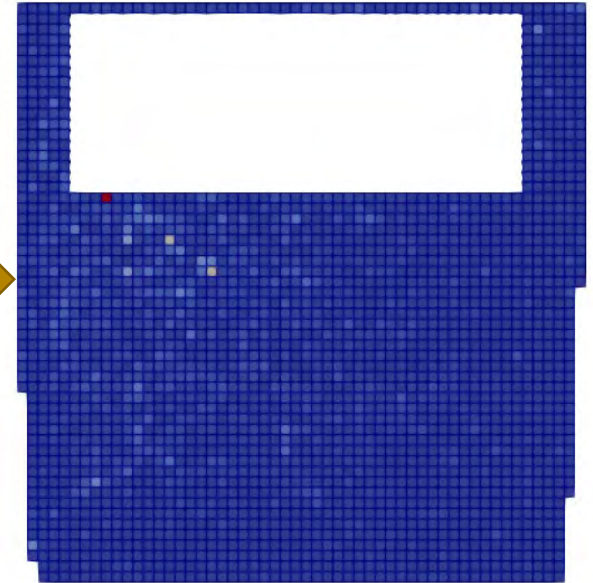
# Complex Part: Interpass Temperature



# In-Situ IR Signatures

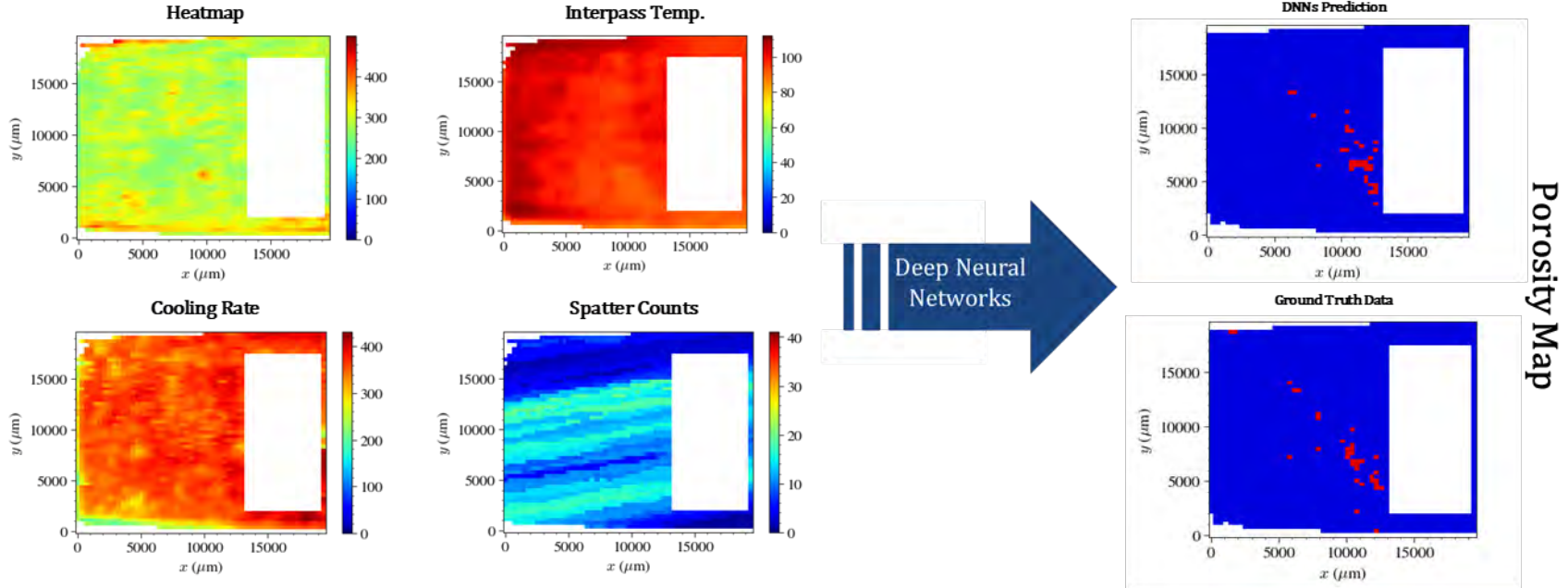


# Porosity Analysis



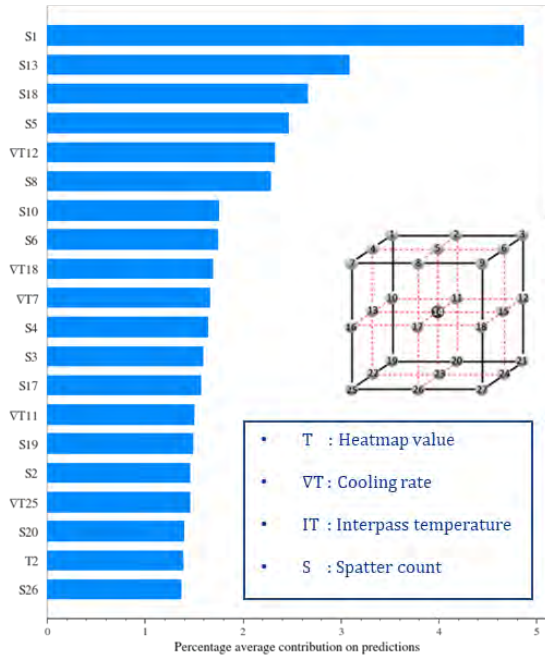


# DNNs Porosity Prediction



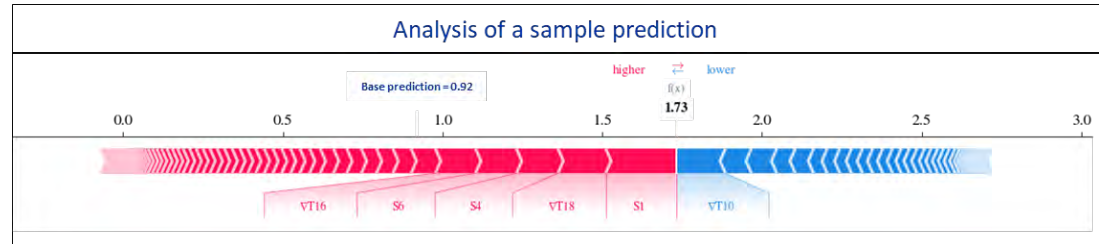
Prediction accuracy over 90% for porosity over 0.8% (~50  $\mu\text{m}$ )

# Feature Importance Analysis by SHAP (SHapley Additive exPlanations) Method

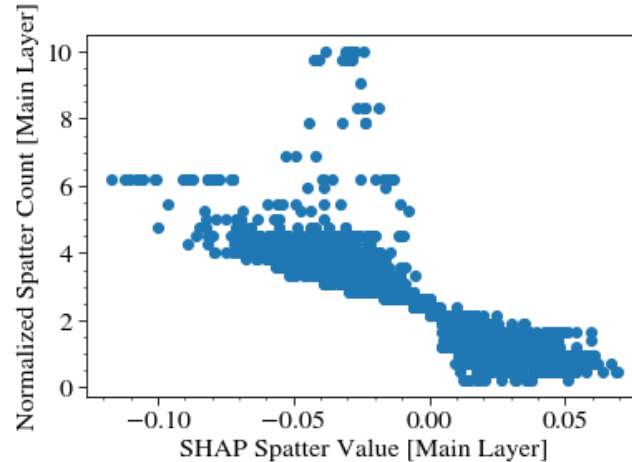
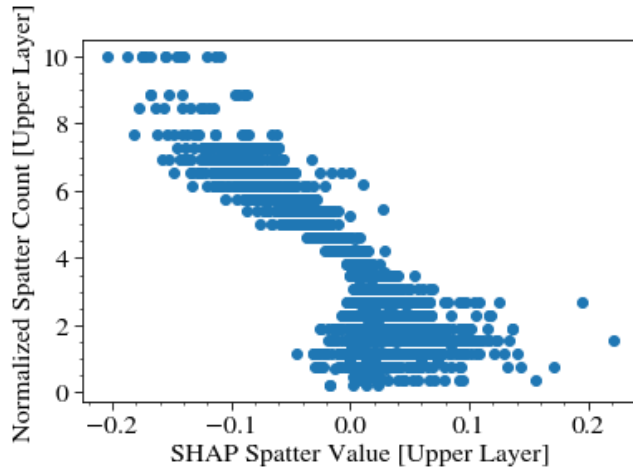


$$g(z') = \phi_0 + \sum_{j=1}^M \phi_j z'_j$$

Model Prediction:  $g(z')$   
 Base Prediction:  $\phi_0$   
 Feature Attribution:  $\phi_j z'_j$   
 Number of features:  $M$   
 Coalition Vector ( $z'_j \in \{0, 1\}^M$ )

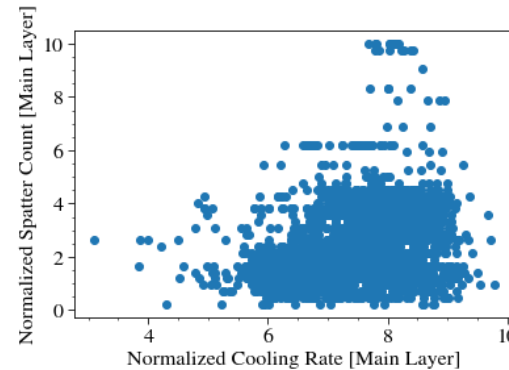
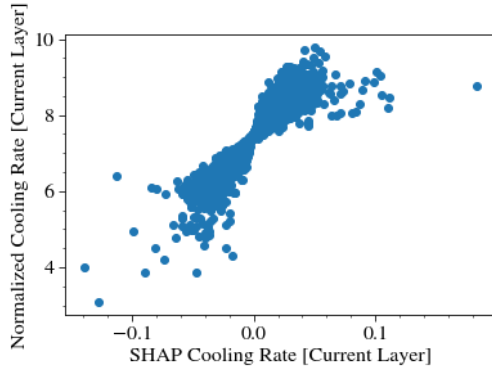


# Inverse Correlation between Spatter Counts and Porosity

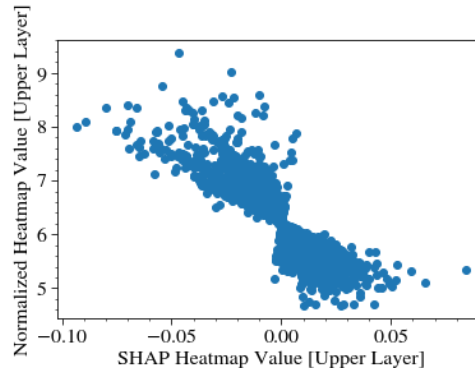


# What About the Cooling Rate and Heatmap?

- Higher cooling rates cause more porosity



- correlation between spatter count and cooling rate not clear



- Inverse correlation between maximum heat intensity and porosity

# Conclusions

- Optical fiber successfully embedded using AM and deformation measurement validated
- Various key signatures can be extracted from a single IR camera for detecting defects
- Porosity predictor DNNs developed have more than 90% prediction accuracy for porosity greater than 0.8% (~50  $\mu\text{m}$ )
- Possible defect generation mechanisms found:
  - Spatter generation is the most dominant feature of lof-pore generation
  - High cooling rates and low heat intensity cause lof-pore generation

## Future Work

- Develop algorithms to obtain other key defect signatures
- Use simulation data to improve ML predictions
- Integrate optical fiber sensing into in-situ AM monitoring

# Thank You!

- Prof. Albert C. To
- [albertto@pitt.edu](mailto:albertto@pitt.edu)
- Department of Mechanical Engineering & Material Science
- University of Pittsburgh

