Solid Freeform Fabrication Symposium, 2019

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Time: 9:15 AM

Heterogeneous Sensing-based In-process Quality Monitoring of Single-tracks Built using Laser Powder Bed Fusion Additive Manufacturing Process

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Yuan, Bodi, Gabriel M. Guss, Aaron C. Wilson, Stefan P. Hau-Riege, Phillip J. DePond, Sara McMains, Manyalibo J. Matthews, and **Brian Giera**. "Machine-Learning-Based Monitoring of Laser Powder Bed Fusion." *Advanced Materials Technologies* (2018): 1800136.

Lawrence Livermore National Laboratory

Detect AM part flaws using data from in-situ heterogeneous sensors

Outline

- Introduction
- Objective and Hypothesis
- Experimental Studies
- Methodology and Results
- Conclusions and Future Work

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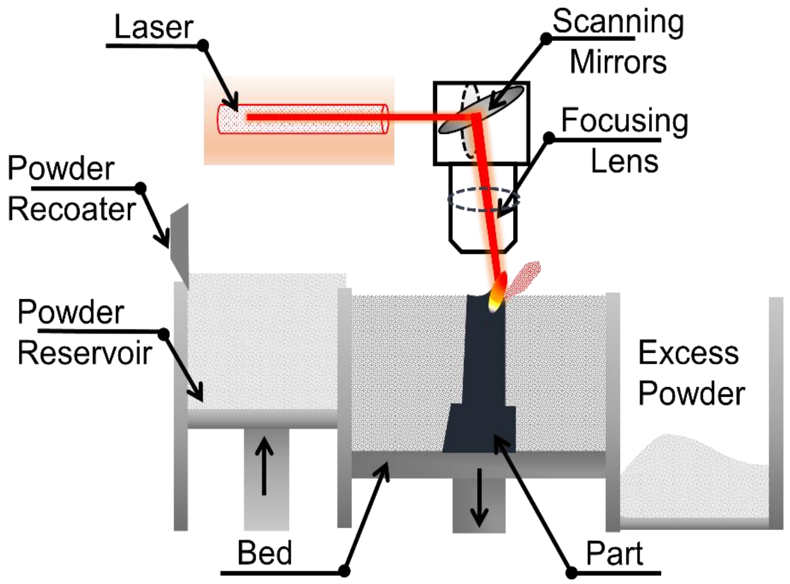
- Introduction
  - Background
  - Motivation
- Objective and Hypothesis
- Thermal Modeling using Graph Theory
- Experimental Studies and Results
- Conclusion and Future Work

Background

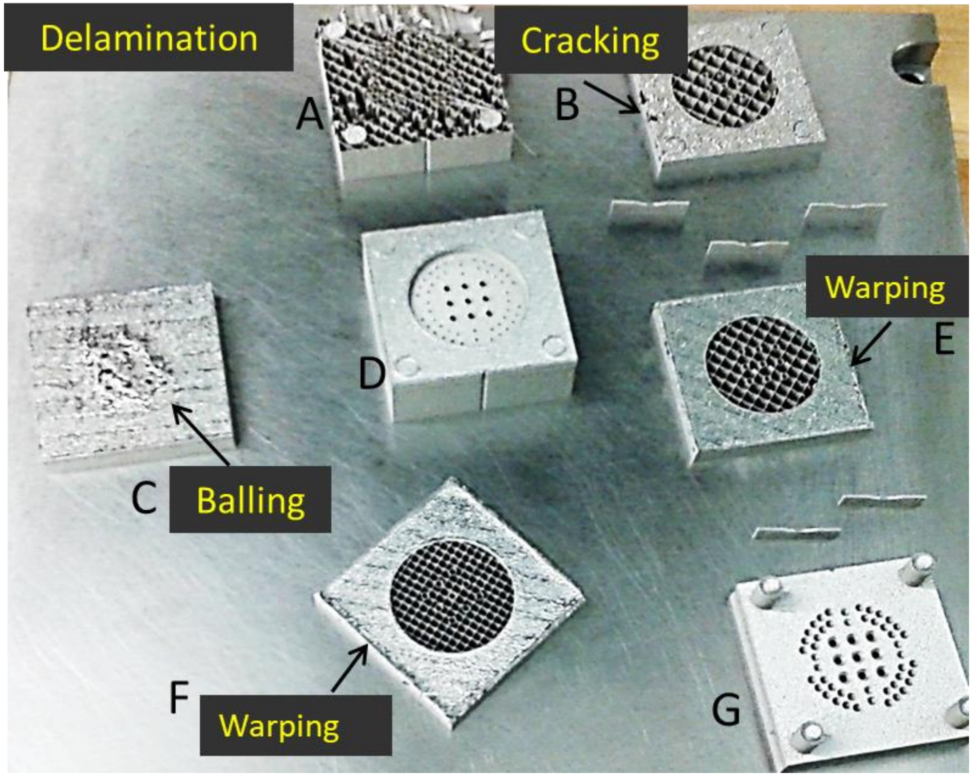
Laser powder bed fusion (LPBF) additive manufacturing (AM) process



Motivation

Part quality inconsistency is major impediment in AM

Only 2 out of 7 parts were built defect free



Can we build parts without having to print-and-pray?

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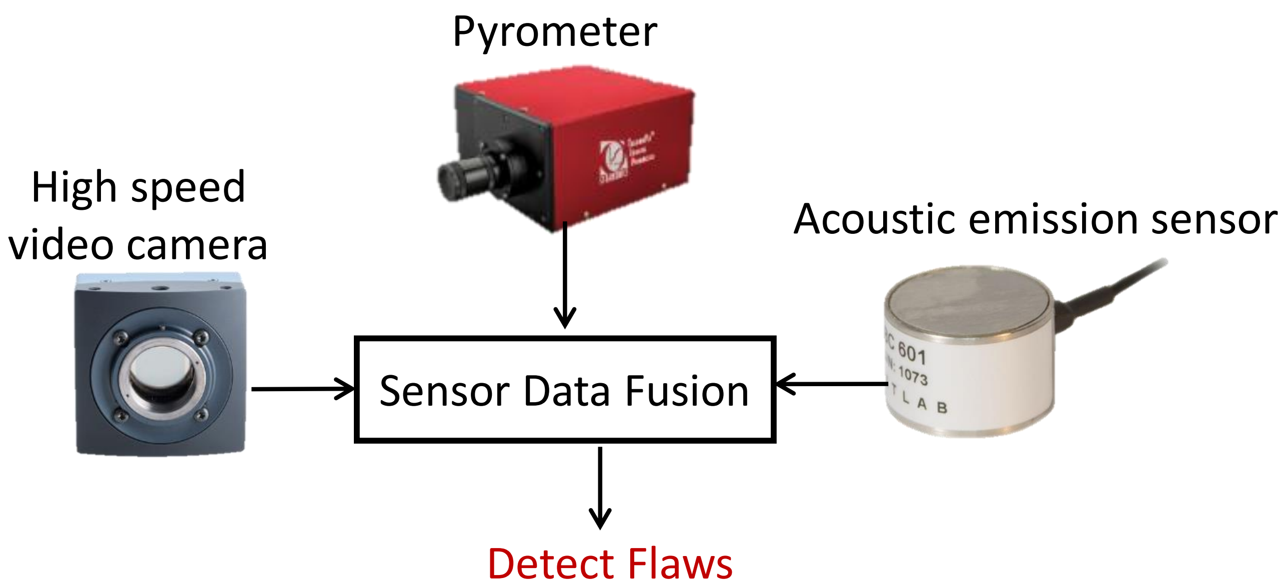
Objective and Hypothesis

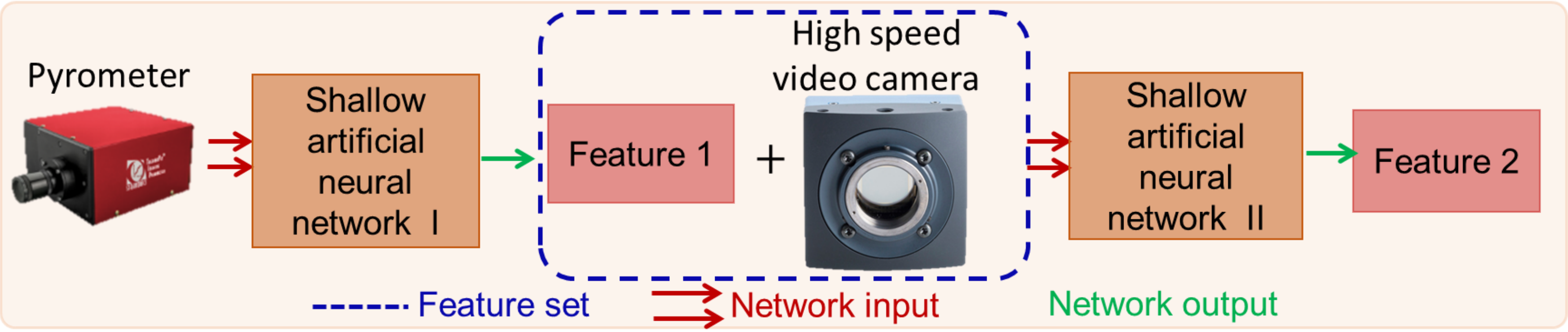
Develop a cascading artificial neural network (C-ANN) to fuse process signatures acquired from heterogeneous in-situ sensors, and subsequently identify defects



Rationale

Chain a series of neural networks to make step-wise multiple predictions.

- Computationally sparse
- Can accommodate multiple types of data (image, time series)
- Physically interpretable
- Multiple Input – Multiple Output



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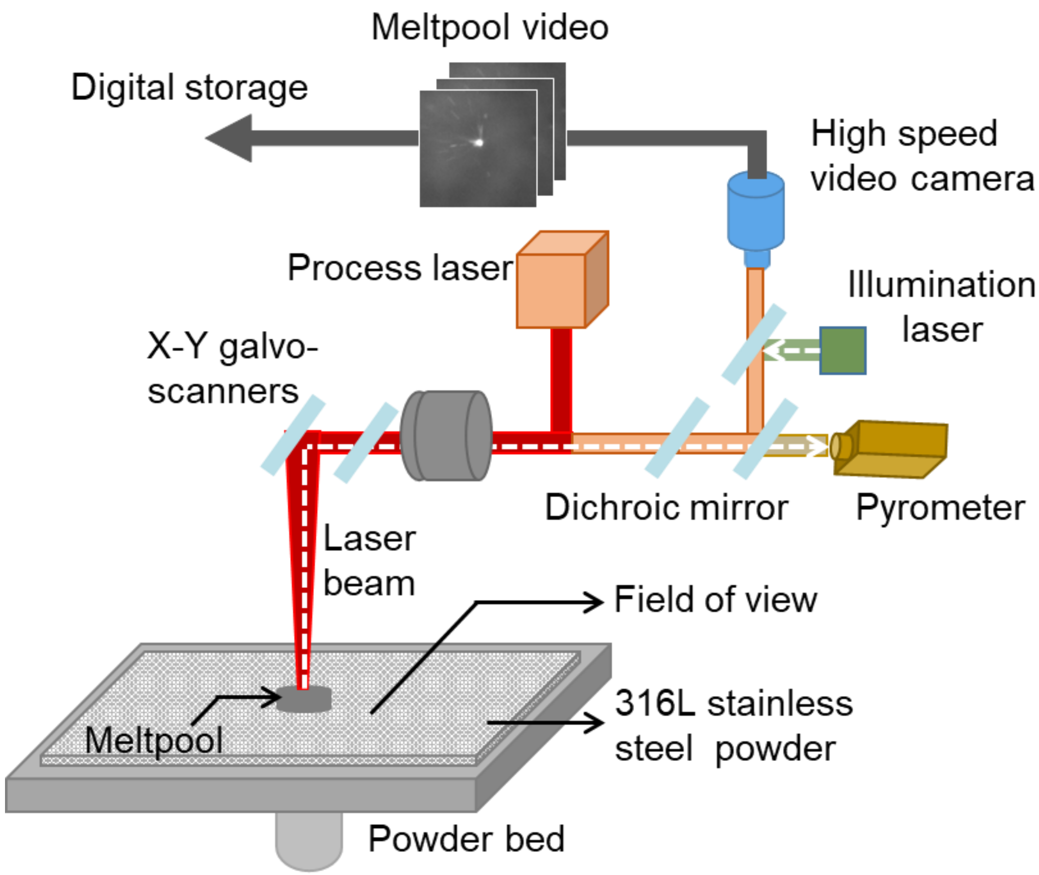
Experimental Setup

Heterogeneous in-process sensors coaxial to the laser: video camera and pyrometer



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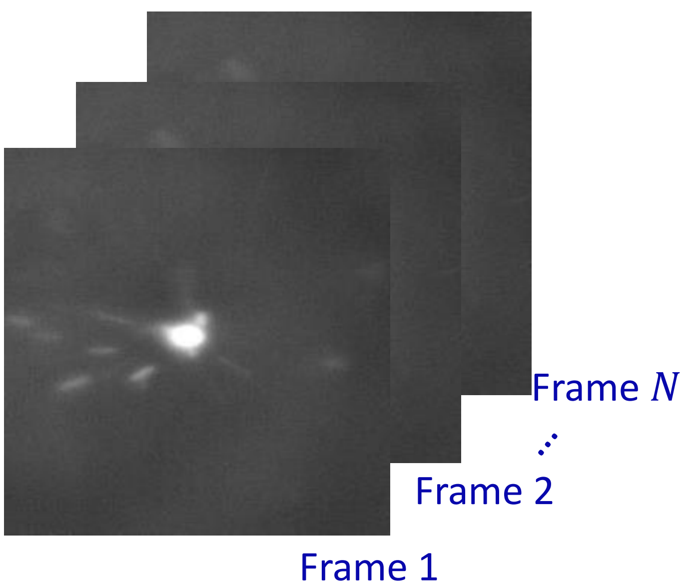
Experimental Data

Video camera frame rate: 20 kHz

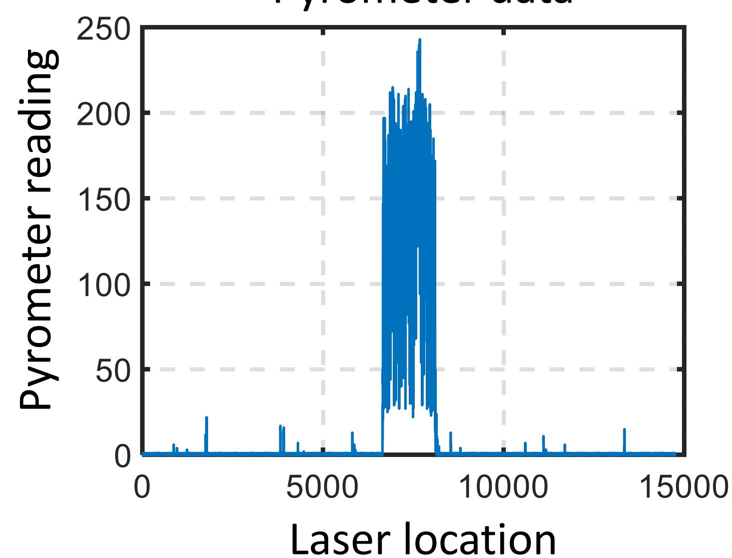
- Frame size: 256 × 256 pixels
- Video camera is co-aligned with the laser.
- Number of frames per video (N): 12 to 50 frames (depends on laser velocity)

Pyrometer sampling rate is 100 kHz (5 times faster than video camera frame rate)

High speed video camera frames



Pyrometer data



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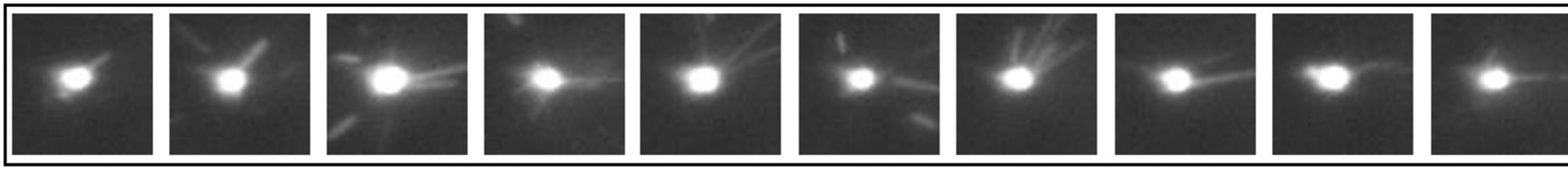
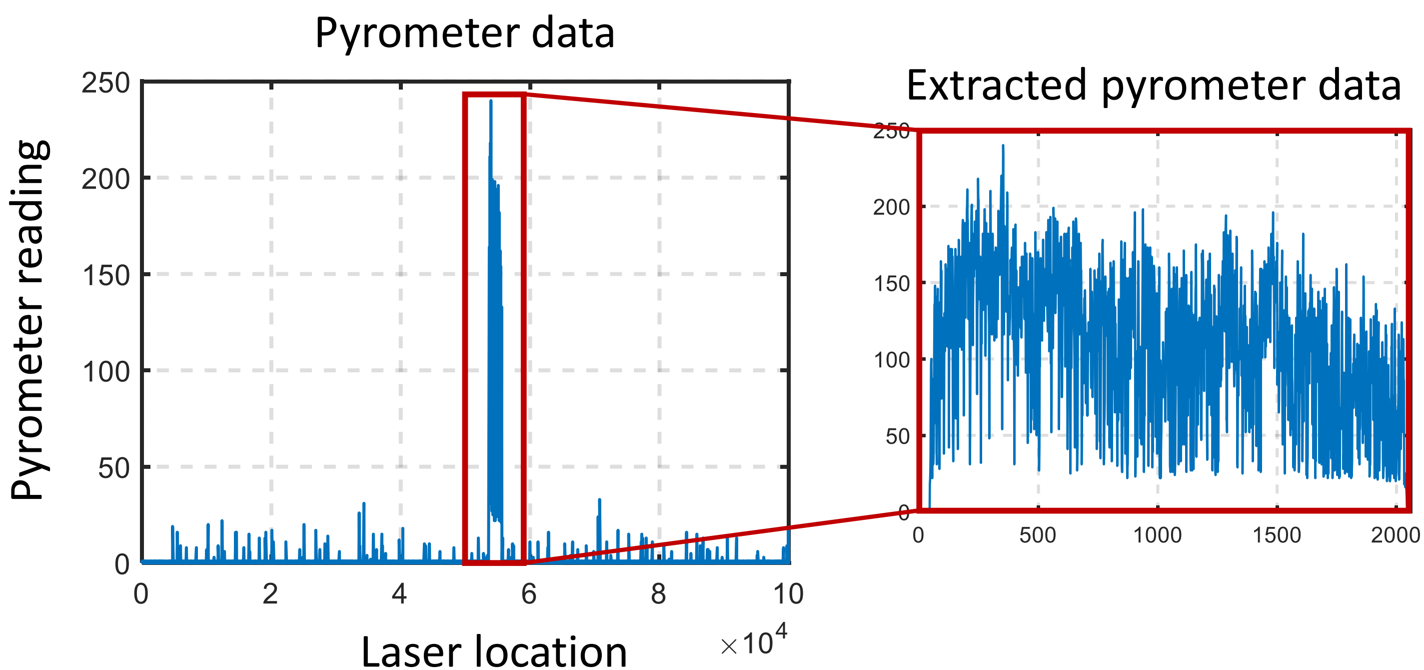
Experimental Data Used in this Work

Below shown is an example of the data used from the sensors

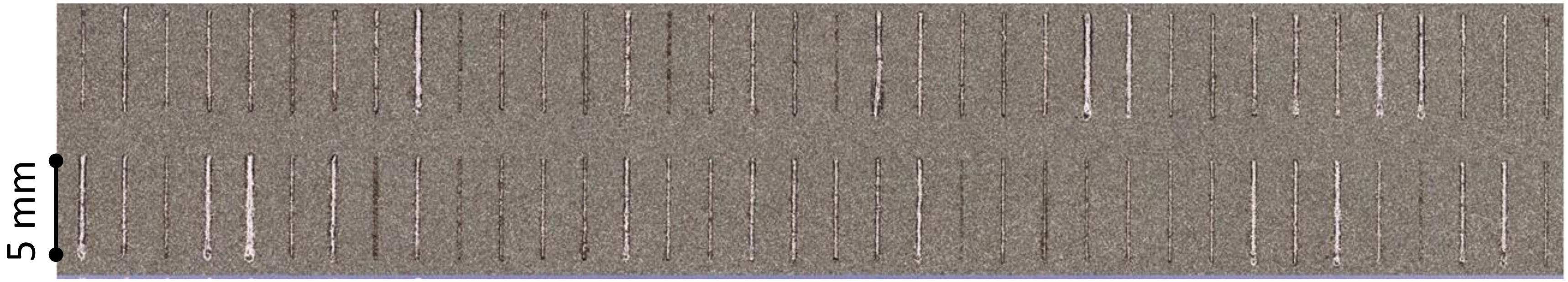
10 video camera frames used per single track





Experimental Conditions

- Laser power: 50 W to 375 W
  - Equal increments of 32.5 W (11 different laser power settings)
- Laser velocity: 100 mm/s to 400 mm/s
  - Equal increments of 30 mm/s (11 different laser velocity settings)
- Layer thickness: ≈50 μm
- Length of single track is 5 mm



Develop and apply an algorithm to analyze heterogeneous sensor data fusion to monitor quality of single-tracks

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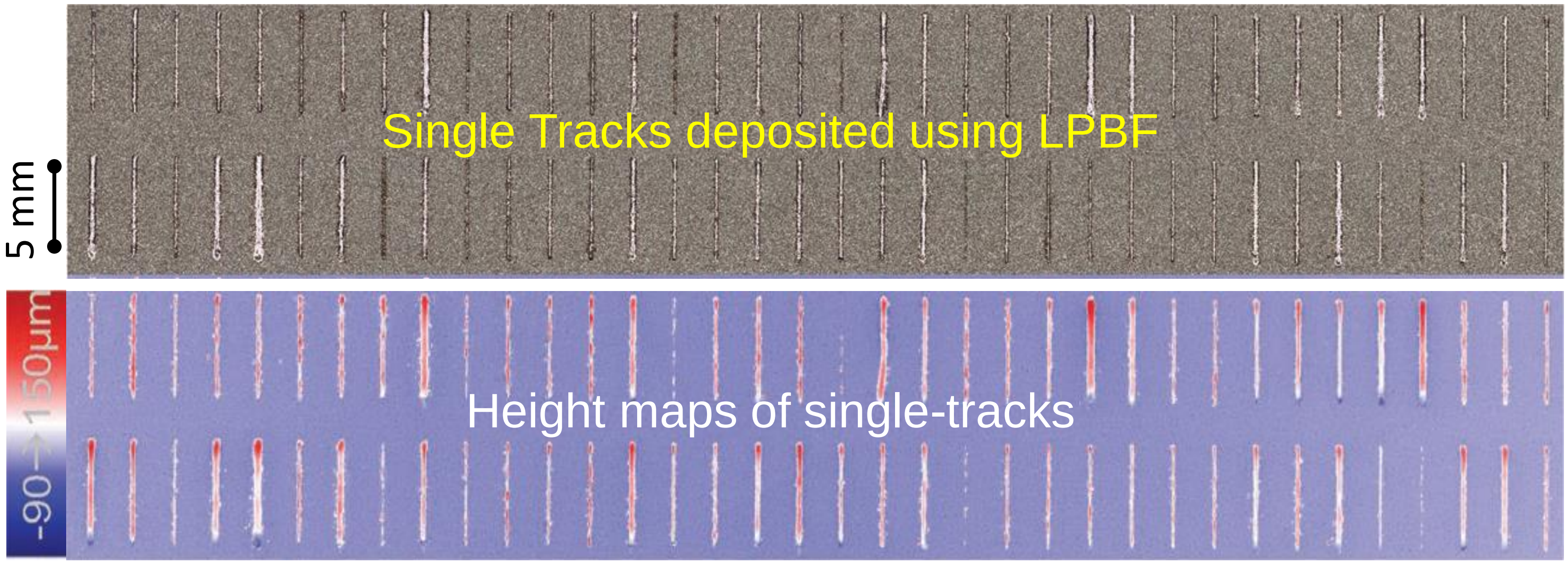
Characterizing Single-Track Quality

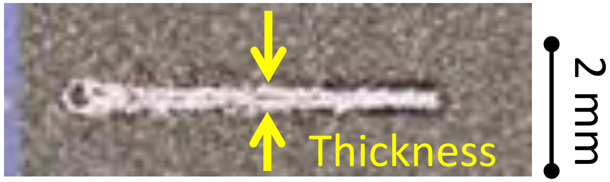
Quality related features are estimated from height maps



Characterizing Single-Track Quality

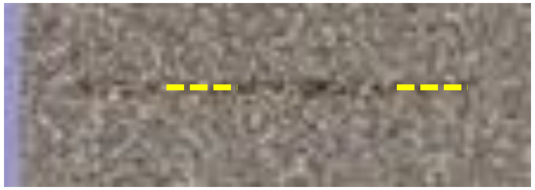
The following single-track quality related features are estimated from the height maps

Mean of width of single track (μ)



Standard deviation of width of single track (σ)

Continuity of single track (δ)



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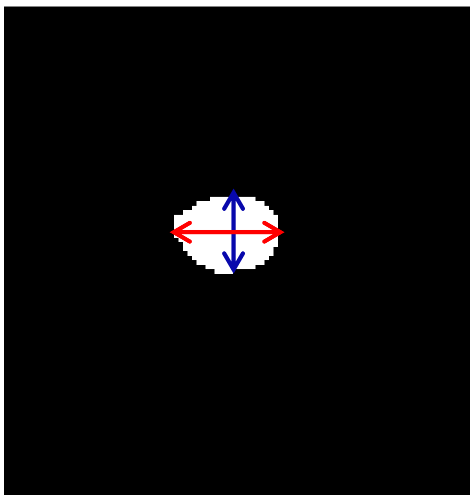
  - Statistical Feature Extraction from Sensor Data
  - Cascading Artificial Neural Network
  - Results
- Conclusions and Future Work

Statistical Feature Extraction from Sensor Data

Pyrometer signal $\longrightarrow$ mean, standard deviation, skewness, kurtosis

High speed video camera frames

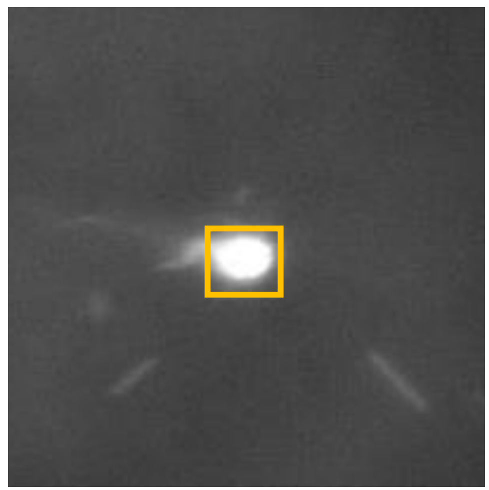
Meltpool area



$$A_a^i = \pi \times L_{major} \times L_{minor}$$

A_a^i= Area of meltpool
L_{major}= Major axis length
L_{minor}= Minor axis length

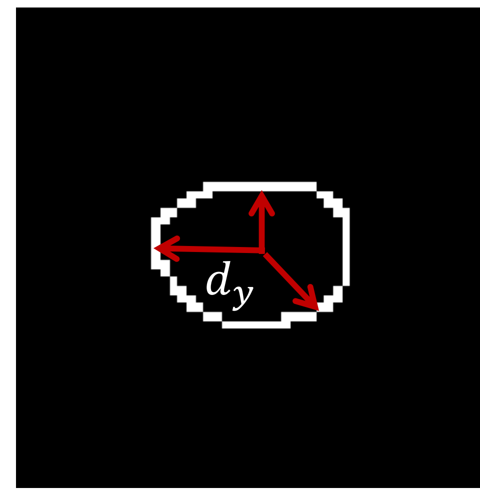
Meltpool intensity



$$I_a^i = \sum_{x=1}^{M} I_x$$

I_a^i= Intensity of meltpool
I_x= Intensity of a pixel in the meltpool
M= number of pixels in the meltpool

Meltpool circularity

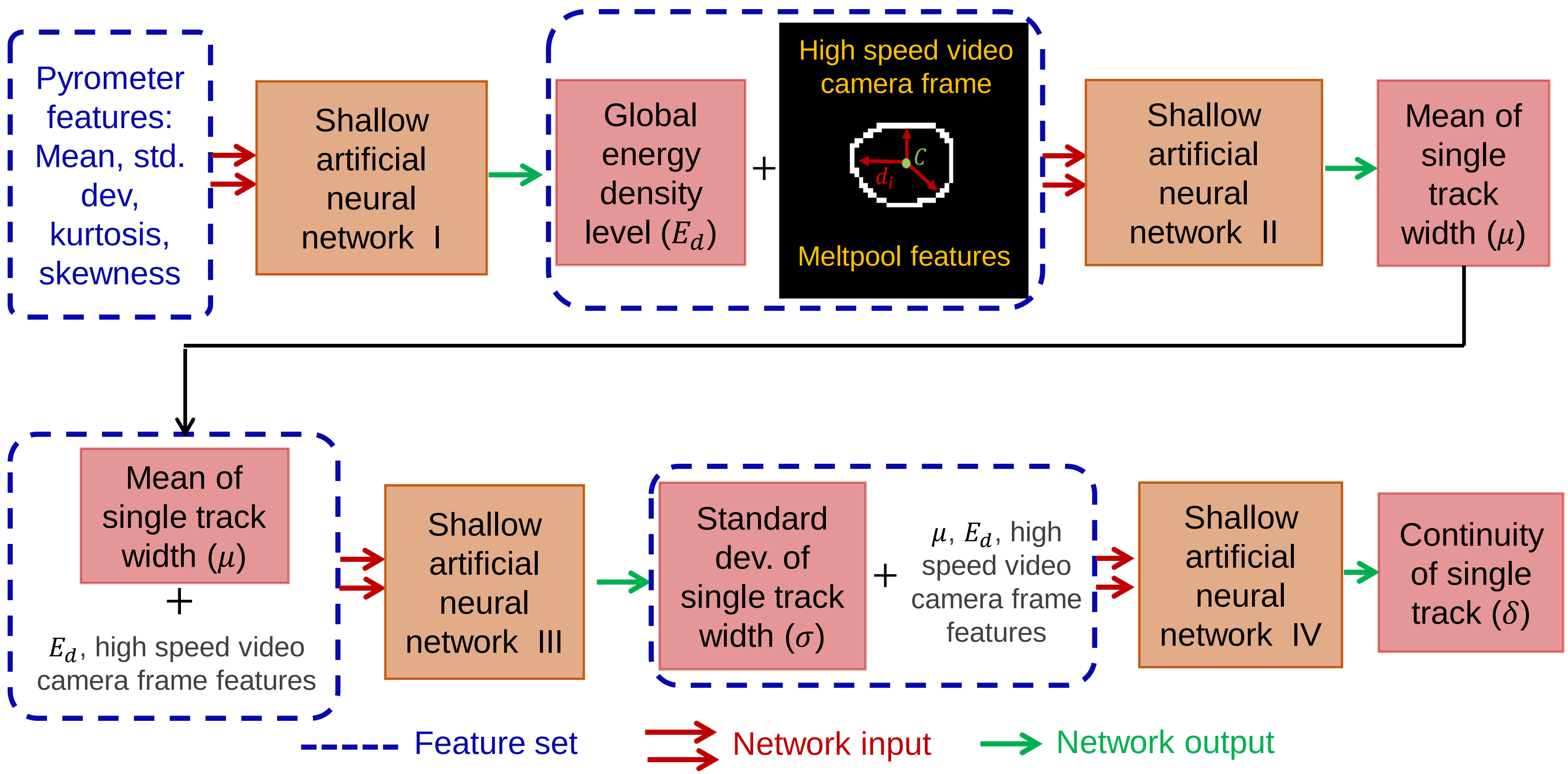


$$circ(\mu)_a^i = \frac{\sum_{y=1}^{E} d_y}{E}$$

$$circ(\sigma)_a^i = \sqrt{\frac{\sum_{y=1}^{E} d_y - circ(\mu)_a^i}{E}}$$

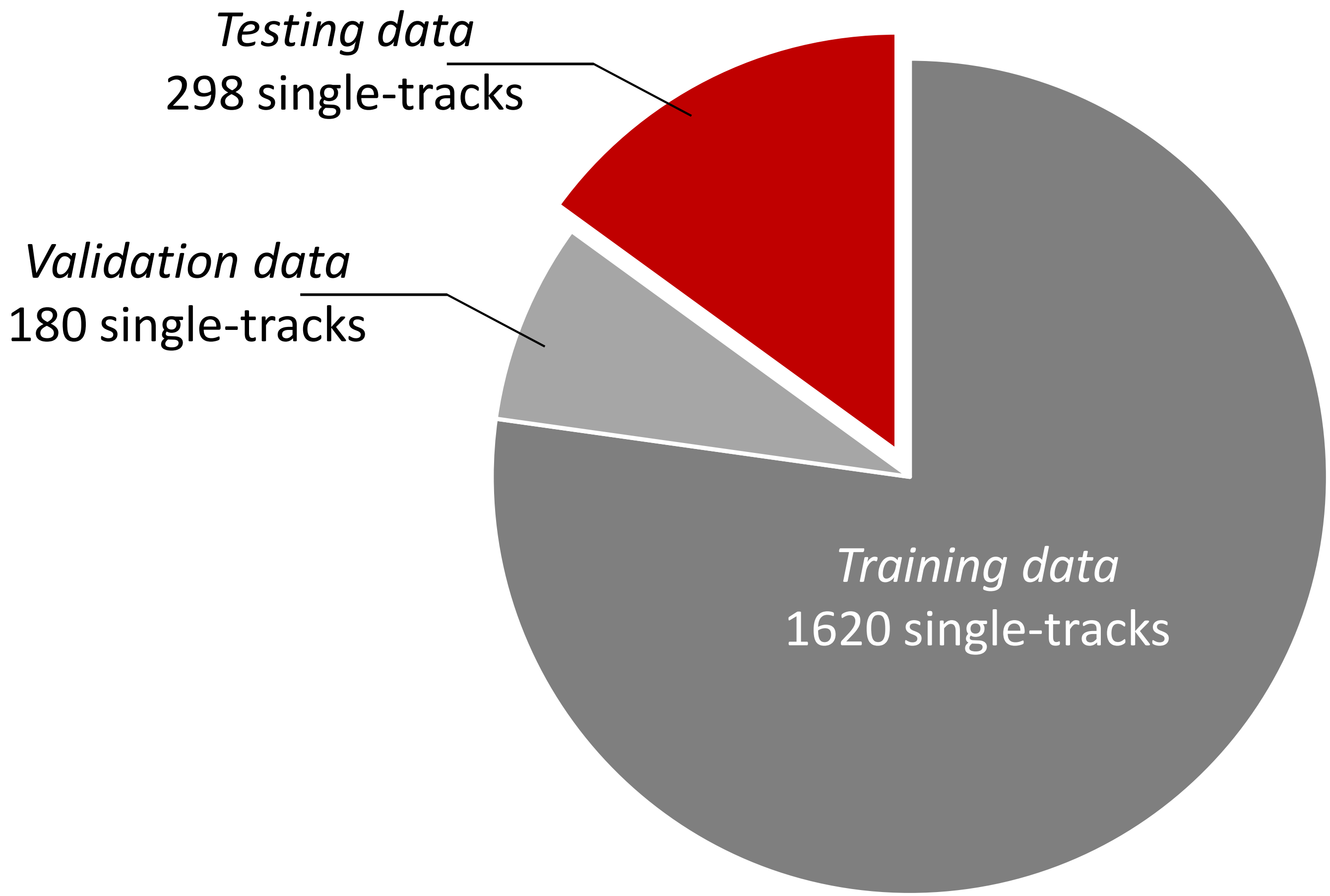
Cascading Artificial Neural Network (C-ANN)

Below shown is the architecture of the cascading artificial neural network (C-ANN)



Cascading Artificial Neural Network (C-ANN)

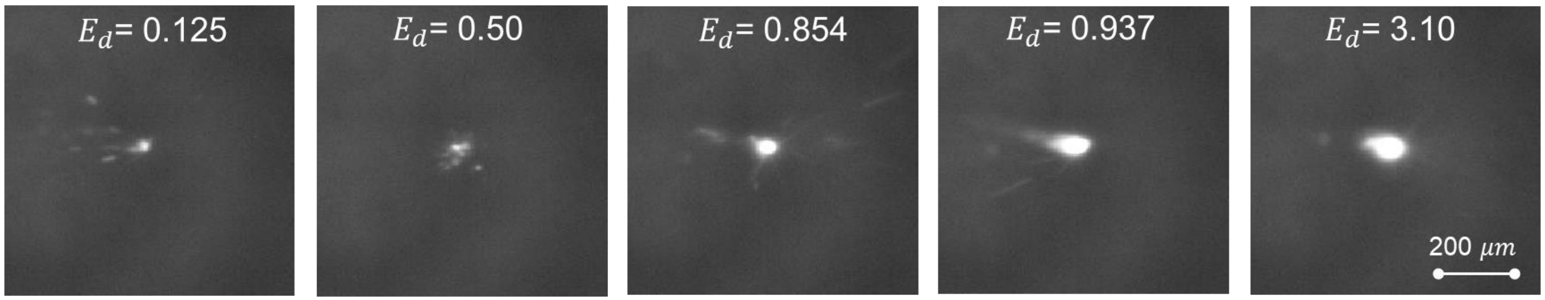
Ten-fold cross-validation is performed on the Training/Validation data set
Testing data is not seen by the trained network

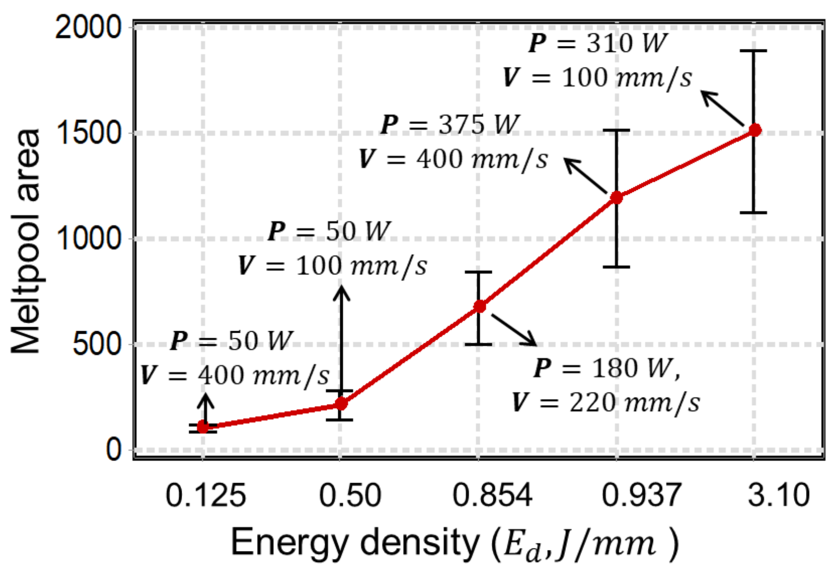


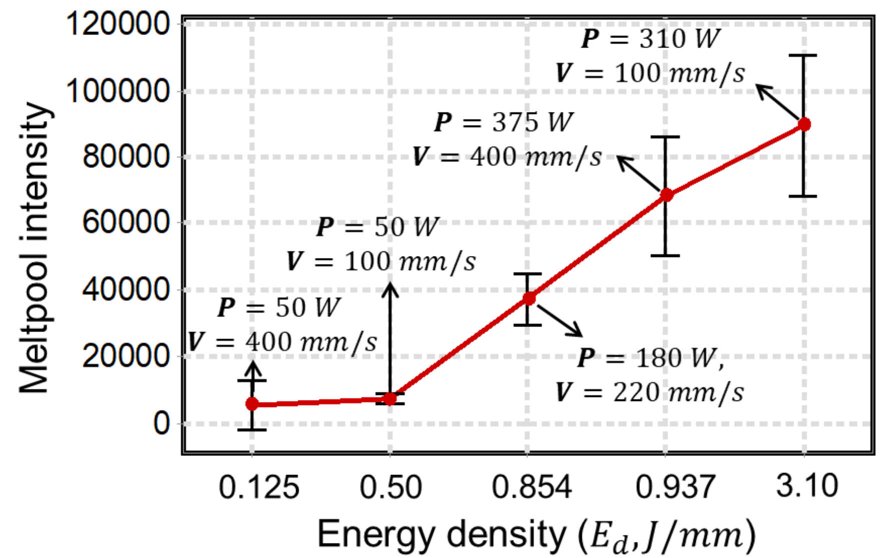
Each printing condition has approximately 17 single-tracks

High Speed Video Camera Features

Effect of energy density ($E_d, J/mm$) applied to deposit single-tracks on meltpool area and meltpool intensity



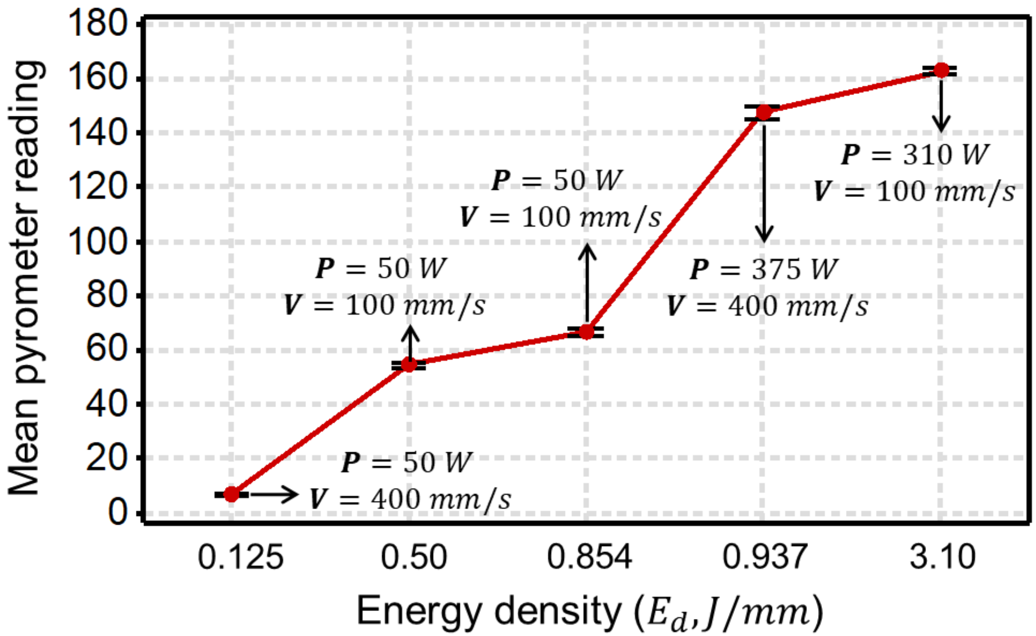




Meltpool area and meltpool intensity increase with increasing E_d

Pyrometer Features

Below shown is the effect of change in energy density applied to deposit single-tracks on meltpool intensity captured by pyrometer



Meltpool intensity captured by pyrometer increases with increasing E_d

Result: Cascading Artificial Neural Network

C-ANN performs better than algorithms with single sensor data

Methodology (*sensor*)	**Global energy density (E_d)**	**Single-track width (μ)**	**Consistency of single-track width (σ)**	**Continuity of single-track**
C-ANN (*high speed video camera + pyrometer*)	**0.9657**	**0.8845**	**0.7726**	**0.7256**
ANN (*high speed video camera*)	*NA*	0.7727	0.6571	0.6952
ANN (*pyrometer*)	*NA*	0.8165	0.7154	0.6525
ANN (*high speed video camera + pyrometer*)	*NA*	0.8565	0.7423	0.6884
Deep learning CNN (*high speed video camera*) [1]	*NA*	0.93	0.73	*NA*

[1] Yuan, Bodi, Gabriel M. Guss, Aaron C. Wilson, Stefan P. Hau-Riege, Phillip J. DePond, Sara McMains, Manyalibo J. Matthews, and Brian Giera. "Machine-Learning-Based Monitoring of Laser Powder Bed Fusion." *Advanced Materials Technologies* (2018): 1800136.

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Conclusion and Future Work

- Cascading-artificial neural network (C-ANN) is an approach for sensor data fusion
  - Predicts single track quality aspects with statistical fidelity exceeding data from a single sensor.
  - Computationally tractable and interpretable compared to deep learning.
- Implement C-ANN for flaw detection, such as porosity and delamination.