

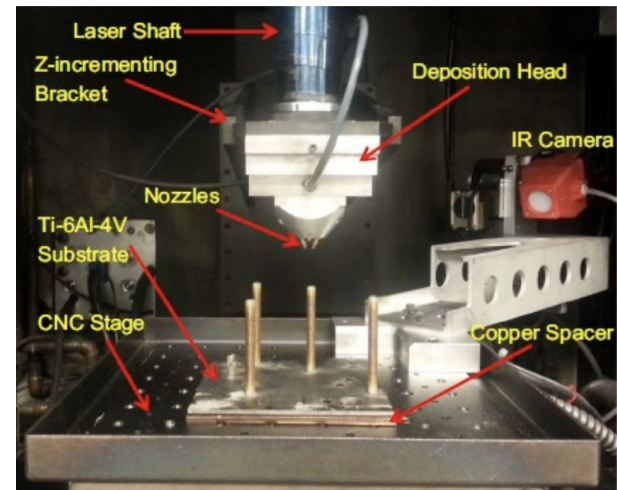
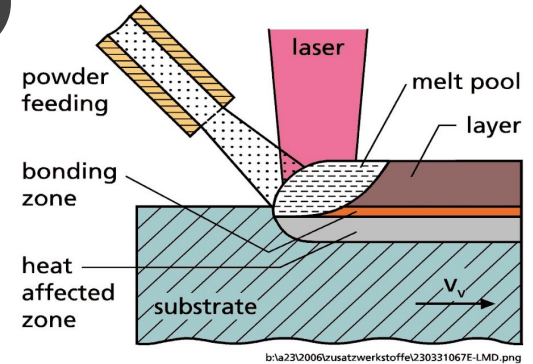
Deep Learning for Quality Prediction in Metal Additive Manufacturing

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Laser Metal Deposition (LMD)

- Additive manufacturing (AM) technique in which a laser beam is used to fuse metal powder by melting it as it is deposited, layer by layer
- Used to build commercial aircraft, other vehicles, and medical implants
- Benefits:
 - High build-up rate and density
 - Very customizable
 - Reduces waste
 - Works for large components
 - Suitable for manufacturing and repair



Porosity

- Occurs when tiny cavities form in the metal as it is printed
- Can never be completely eliminated
- Considered to be one of the most destructive defects in metal AM
 - Reduces static mechanical properties
 - Causes significant scatter of fatigue
- **Our goal:** predict whether parts printed via LMD will have a good (<0.05mm diameter) or bad level of porosity, and how large the pores will be if classified as bad

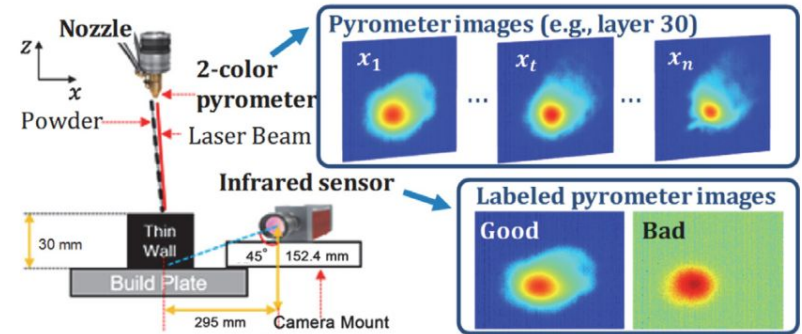
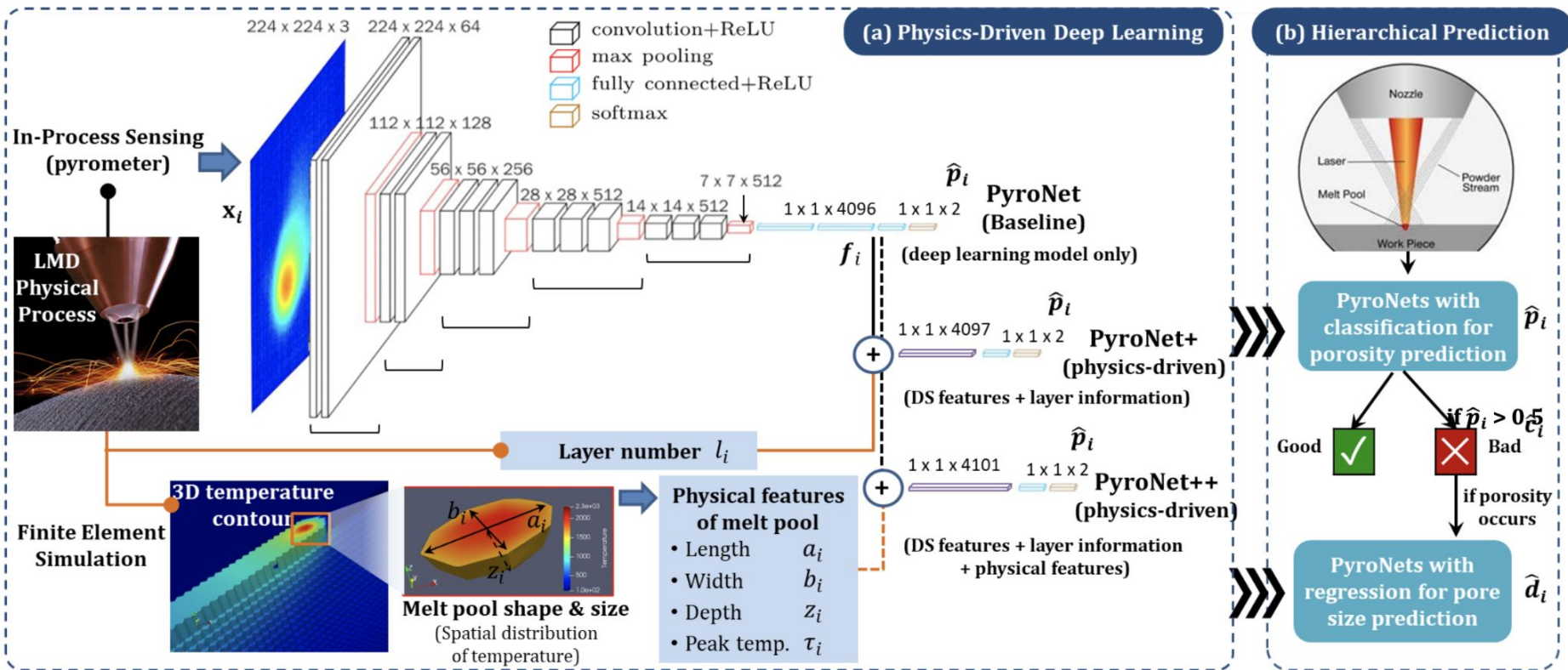


Fig. 1. In-process sensing in LMD [7] and examples of pyrometer data.

	<h2 style="text-align: center;">Physics-Driven Approach</h2> <p style="text-align: center;">Analytical and numerical models based on process mechanics</p>	<h2 style="text-align: center;">Data Science Approach</h2> <p style="text-align: center;">Supervised learning methods that take in high-speed thermal images melt pools and put out a binary indicator of porosity</p>
Advantages	<ul style="list-style-type: none"> ● Useful for understanding the nature of pore formation and its characteristics 	<ul style="list-style-type: none"> ● Can predict porosity during LMD ● Can handle complex data (high dimensionality, heterogeneity, large volume) ● Efficient and accurate
Disadvantages	<ul style="list-style-type: none"> ● Can have incomplete or missing physics ● Requires calibration of model parameters ● Computationally expensive ● Lacks the ability of real-time prediction 	<ul style="list-style-type: none"> ● Black-box methods don't incorporate physics knowledge ● Must be carefully trained with available experimental data ● Difficult to interpret, apply, or generalize for a wider set of process conditions

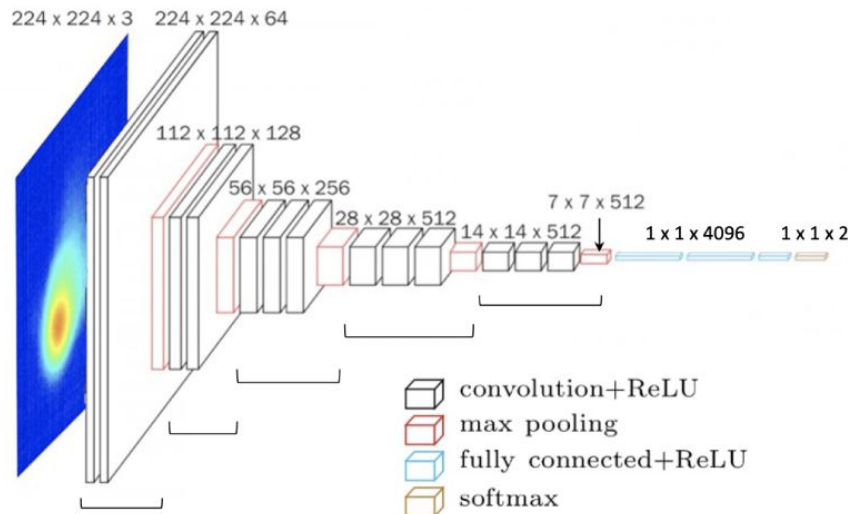
Physics-Driven Deep Learning Model



$$\hat{d}_i = \min(\hat{d}_i^{DL}, 1) \cdot \mathbb{I}(0.05 \leq \min(\hat{d}_i^{DL}, 1) \leq 1)$$

VGG16 Deep Learning Model

- VGG16 is a convolutional neural network (CNN), a type of neural network typically used to analyze images
- Proposed by K. Simonyan and A. Zisserman (University of Oxford) in 2014
- 92.7% accurate when completing a top-5 test in ImageNet, a dataset of over 14 million images that can be sorted into 1000 classes





Next Step: VGG16 + Finite Element Simulation + Empirical Physical Data

- This summer I will build the next iteration of this model that
 - Incorporates empirical data
 - Incorporates more simulated variables
 - Will potentially incorporate the physical data earlier in the model
- I intend to accomplish this using transfer learning on the pre-trained VGG16 from the Keras (Python deep learning API) library

Table 1: Full set of features extracted and transformed.

Feature type	Description and Notation in Figure 5	Total number
Pyrometer	Smoothed radians from cubic spline interpolation	63
Pyrometer	Principal Components from FPCA	63
Pyrometer	Principal Components from PCA	63
Pyrometer	Maximum Temperature	1
FEA; geometric	Dimensions: length (a), width (b), height (c)	3
FEA; geometric	Rectangular prism volume = length \times width \times height (d)	1
FEA; geometric	Hemisphere volume = $2/3 \times \pi \times r^3$ where r is average of length and width (e)	1
FEA; thermal cooling	Maximum Temperature	1
FEA; thermal cooling	Area under curve of plot of line through center of bounds for x , y , and z directions ($h1, h2, h3$)	3
FEA; thermal cooling	Slope of line formed by peak of graph and bottom leftmost point for x , y , and z directions ($f1, f2, f3$)	3
FEA; thermal cooling	Slope of line formed by peak of graph and bottom rightmost point for x and y directions ($g1, g2$)	2
Hybrid	Residual by Eq. (4)	1
Hybrid	Layer number	1



References

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