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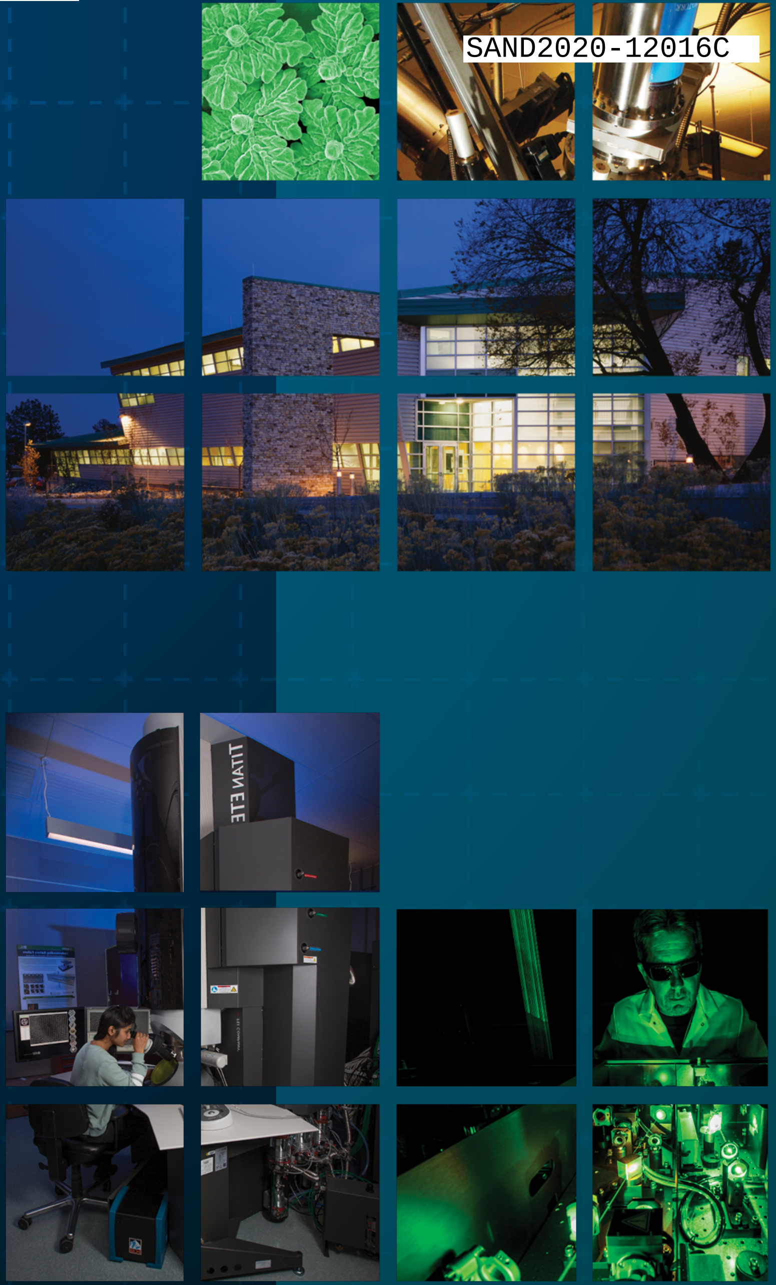
SAND2020-12016C

Deep Convolutional Neural Networks as a Rapid Screening Tool for Complex Additively Manufactured Structures

PRESENTED BY

Anthony Garland, Benjamin C. White, Bradley H. Jared, Michael Heiden, Emily Donahue, **Brad L. Boyce**



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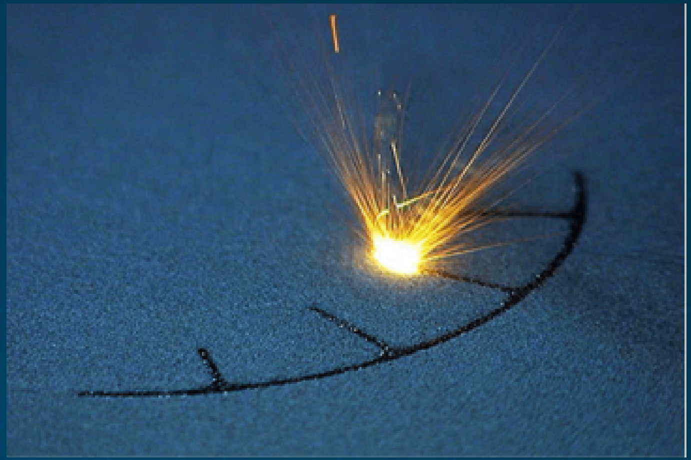
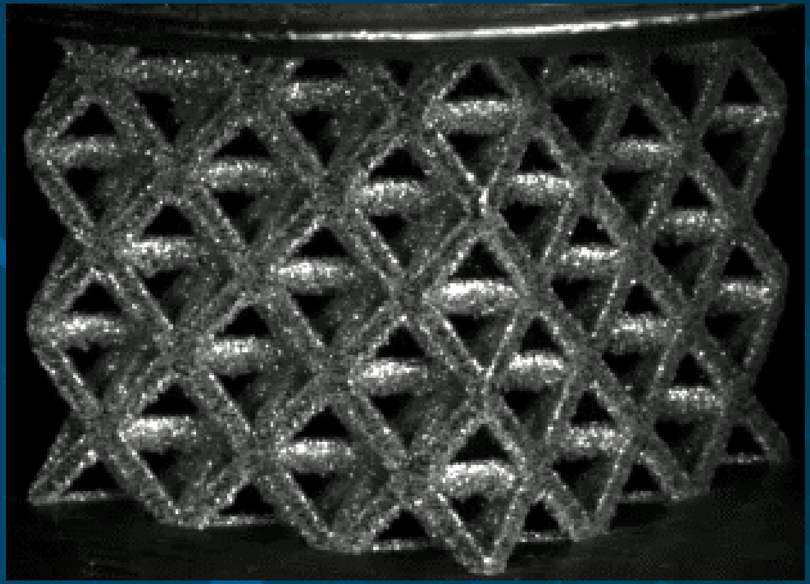
Background: Additive Manufactured Metal Lattices

Additive Manufacturing enables producing lattice meta-materials

1. Laser powder bed fusion enables making 316SS lattices
   - Start with a 3D model
   - Printer melts powder together 1 layer at a time.
   - Slowly build up the part





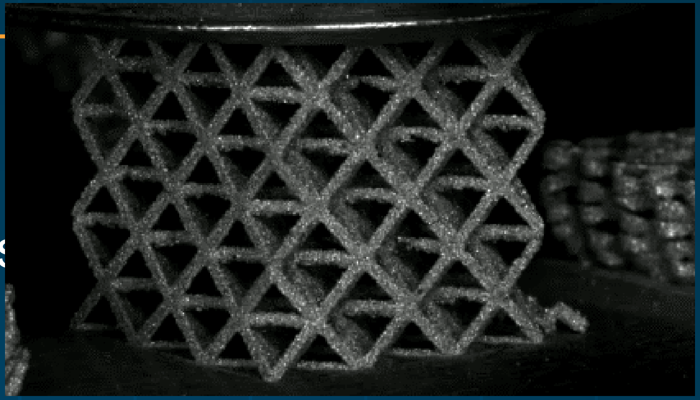
2. Lattice metamaterials can have unique properties
   a) High strength to weight ratio (i.e. light weight)
   b) High energy absorption during crush.
   c) Shock mitigation
   d) Vibration attenuation

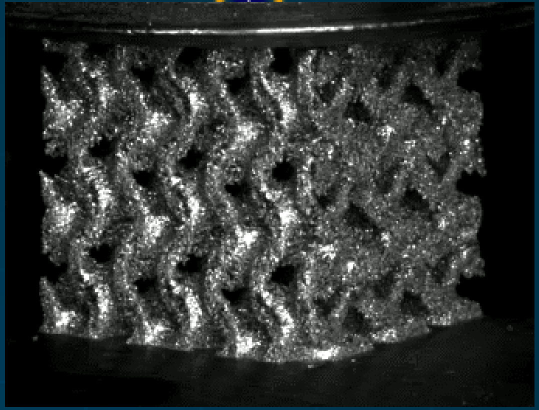
A Process-Structure-Property Dataset for Lattices

Printed 98 Lattice

- 48 gyroids and 48 octets (FCC)
- Purposefully varied the laser power and scan s

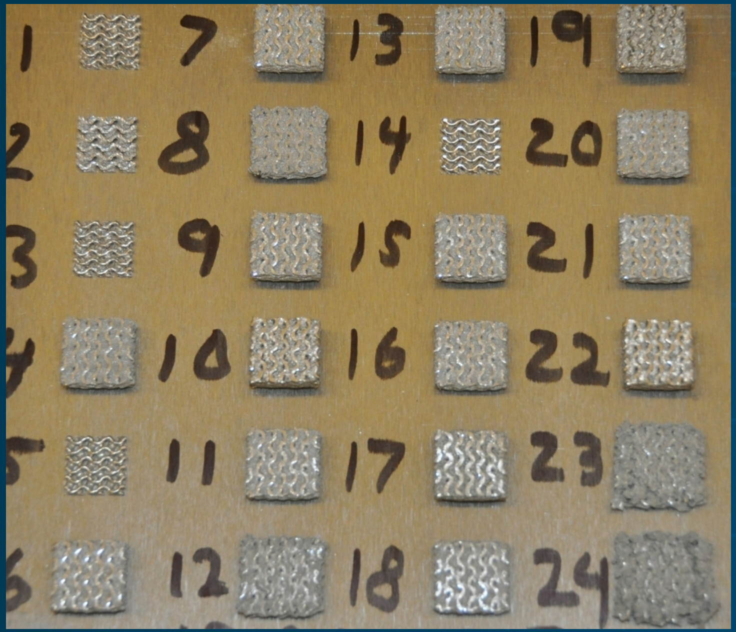
1. Changes the physical process of melting
2. Changes the lattice properties.



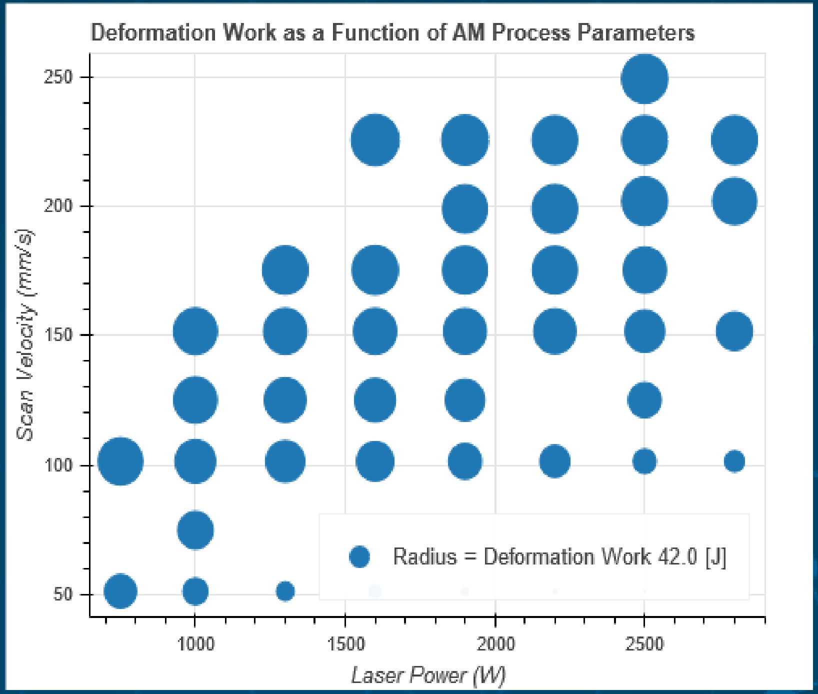


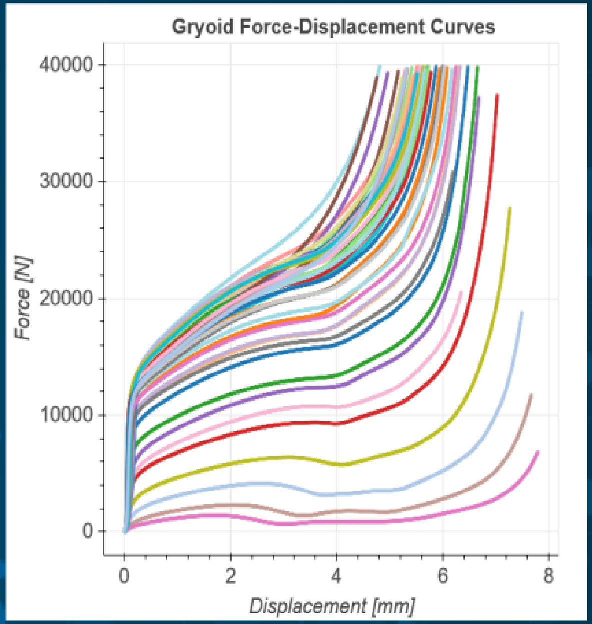
Crush Energy as a function of process parameters.

24 crushed lattices



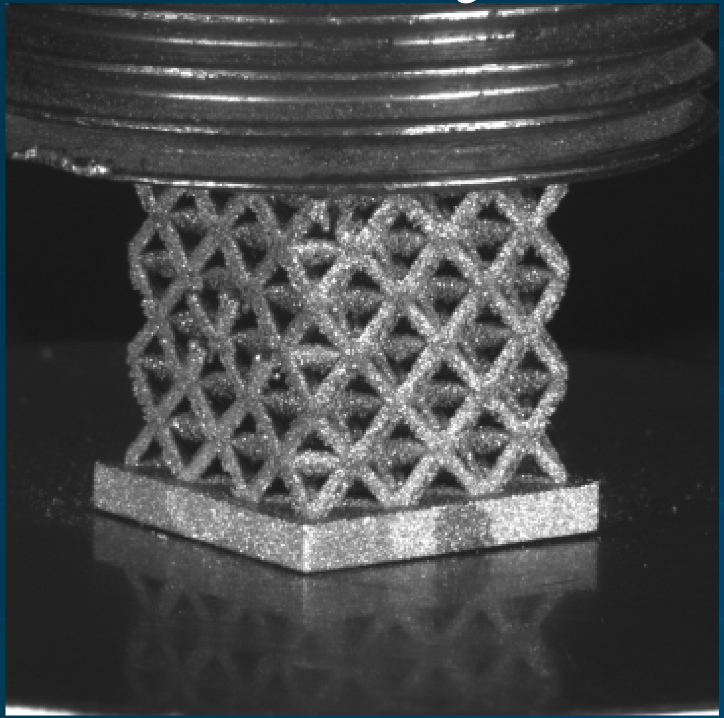
10 mm





The ridiculous proposition

Initial image



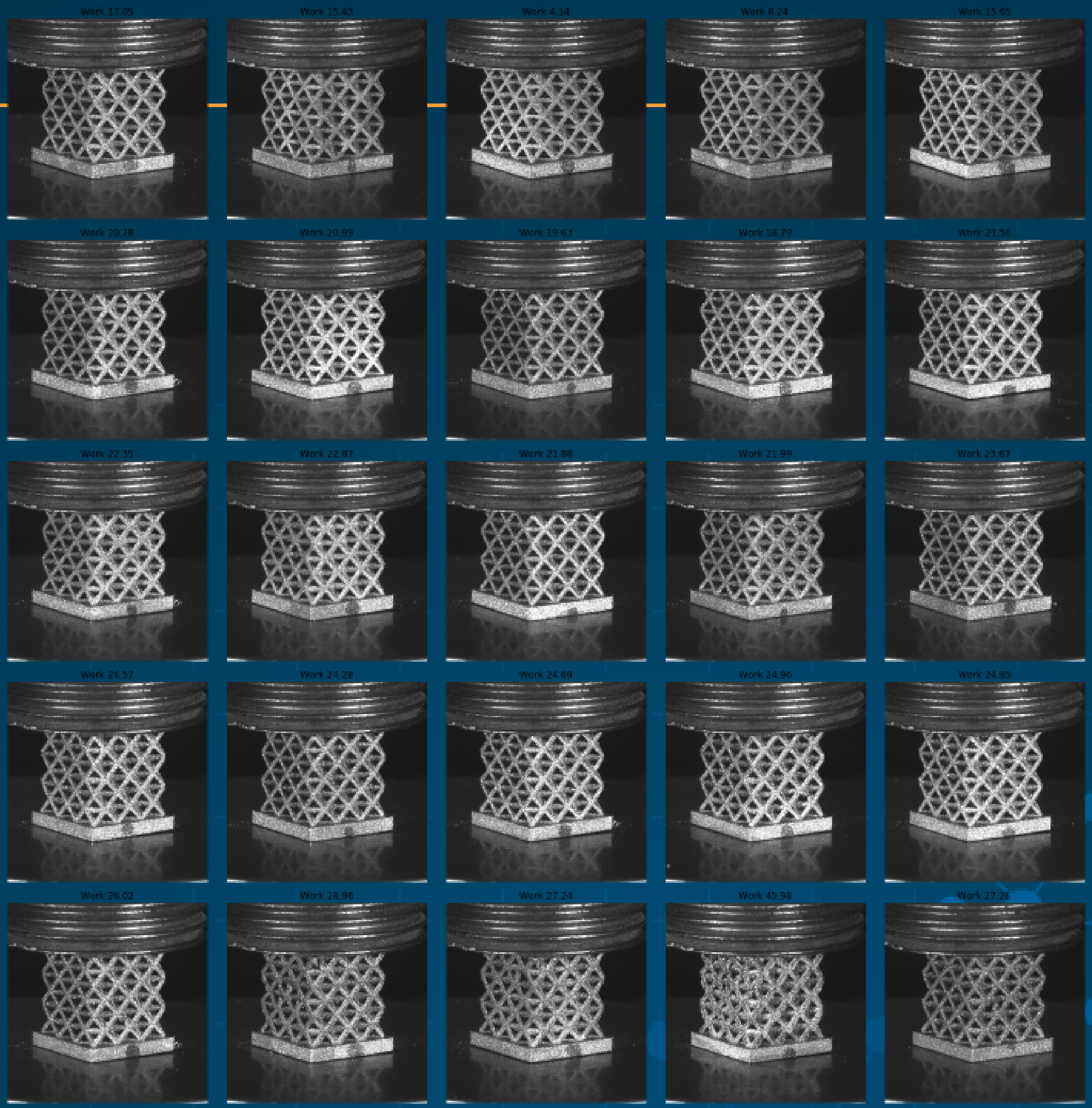
prediction

How much energy will it absorb when crushed?

Method 1: Traditional expert-guided structure-property correlations

Method 2: Automated machine learning algorithm

The ridiculous proposition



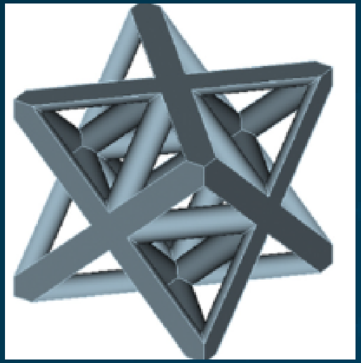
Laser Scan Speed

Laser Power

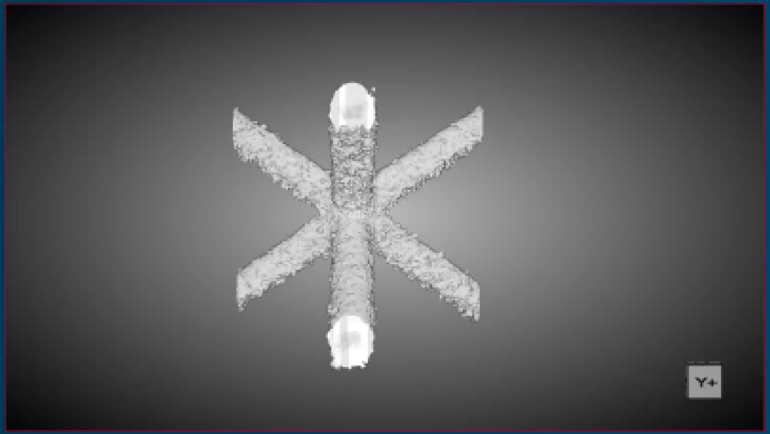
Method 1: Structure-Property relationships guided by human experts

Method 1: The traditional **expert-guided** method to predict mechanical properties

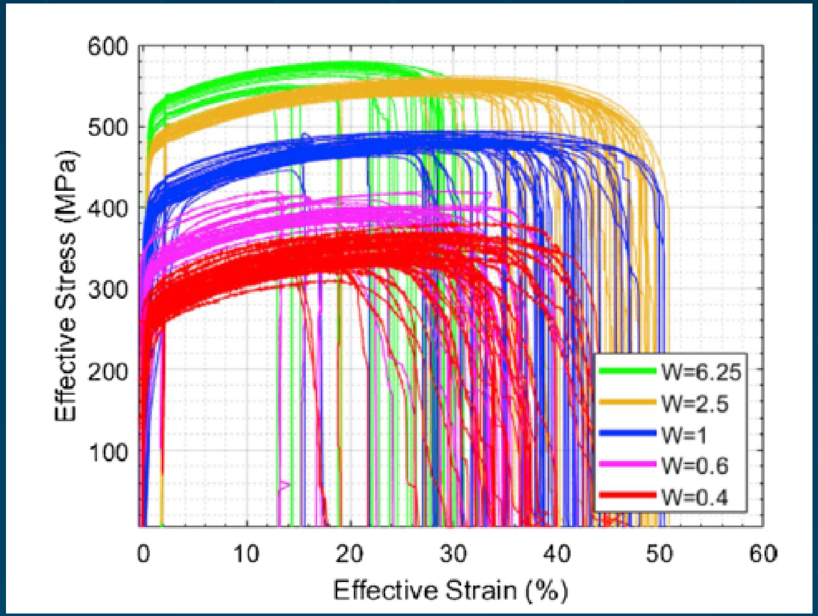
Shape & topology



Hierarchical representations of shape



Base Material Constitutive Properties



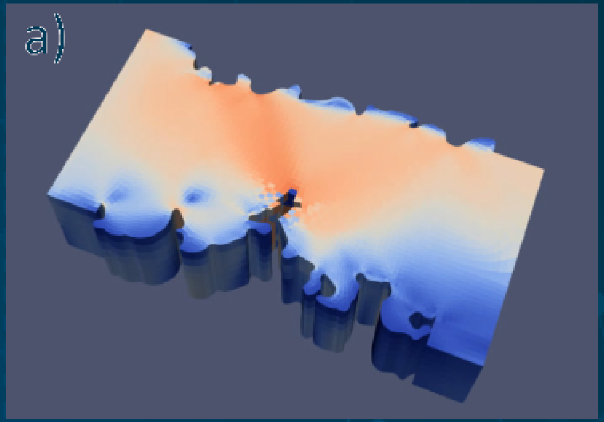
Constitutive model:

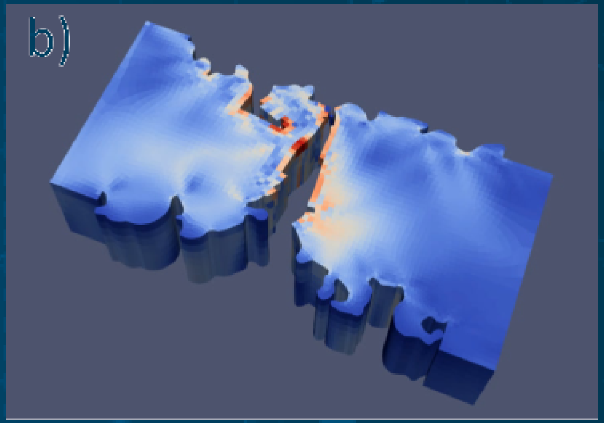
Yield criterion; flow rule; hardening law

$$\varepsilon = \frac{\sigma}{E}\left\{1+\alpha\left(\frac{\sigma}{Y}\right)^{n-1}\right\}$$

Ramberg-Osgood

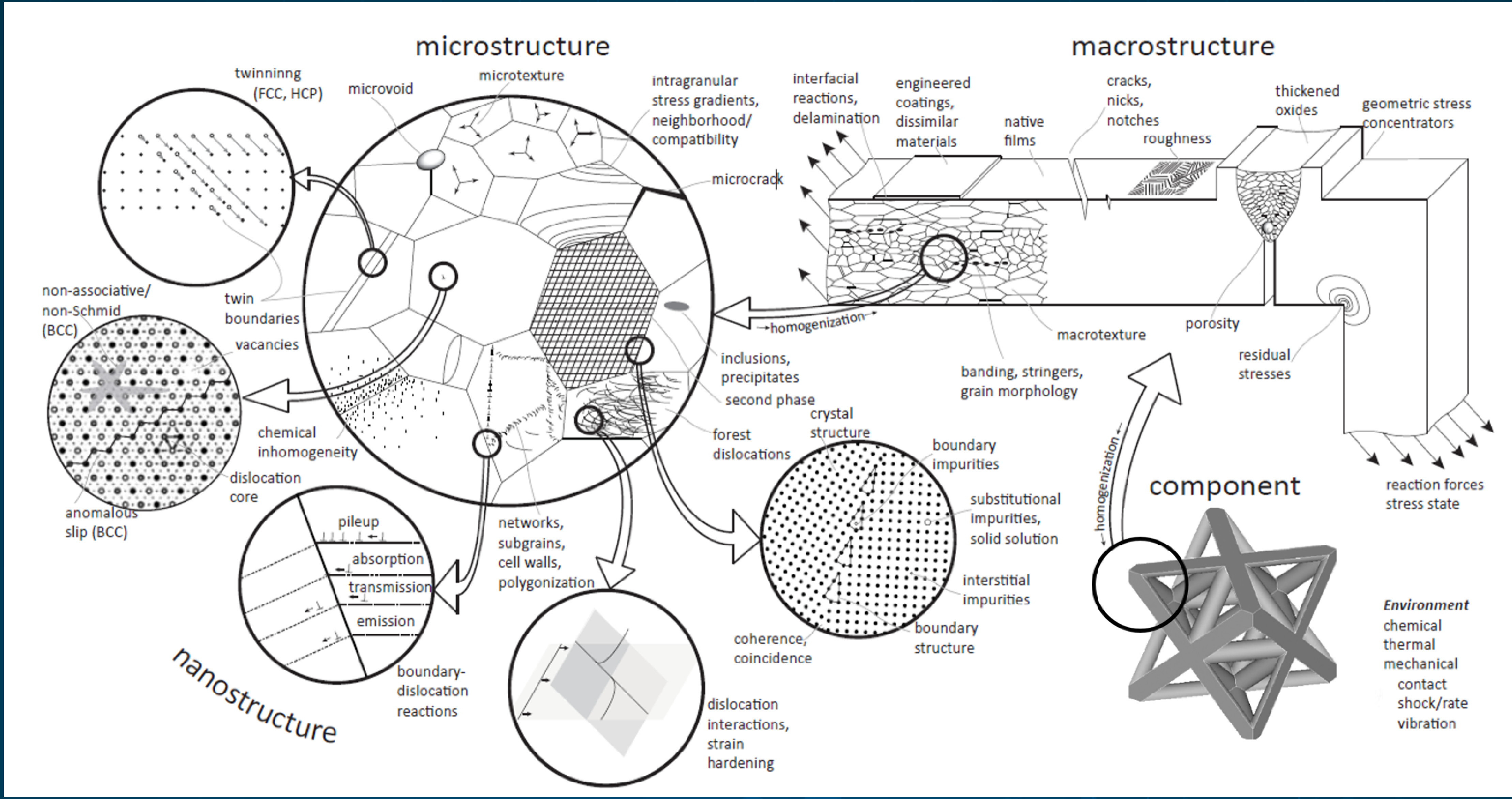
Explicit Direct Numerical Simulation





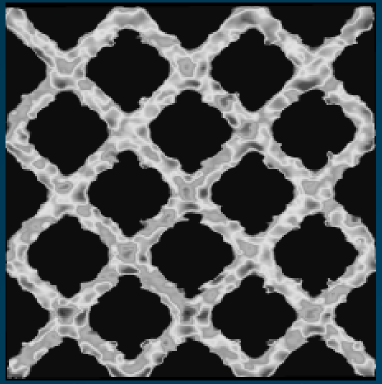
A.M. Roach et al, Additive Manufacturing, 2020

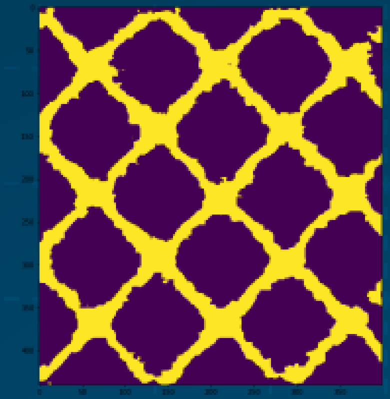
Pandora's Box… what do we need to capture explicitly?



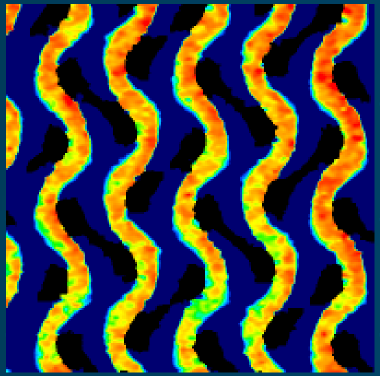
Method 1: requires laboratory measurements of structure

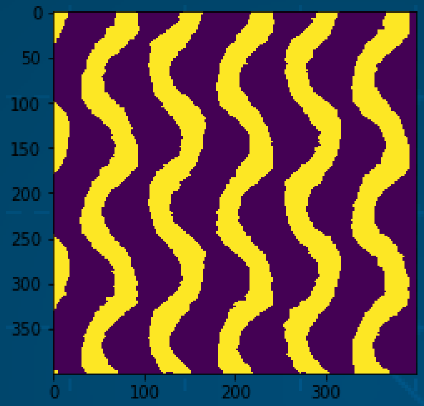
Expert guided assumption: surface roughness and strut/wall thickness are the primary factors influencing crush energy absorption.



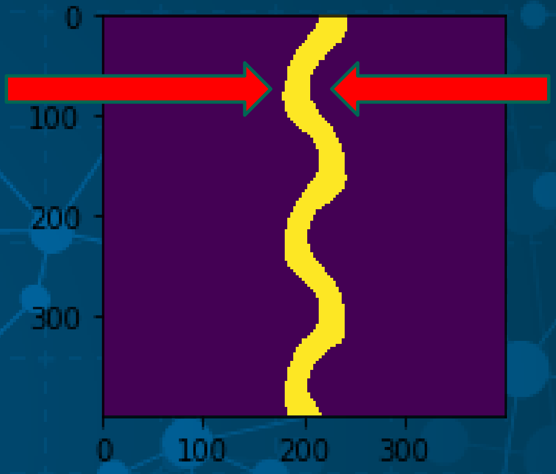


Extract strut width OR estimate with density and Surface Roughness



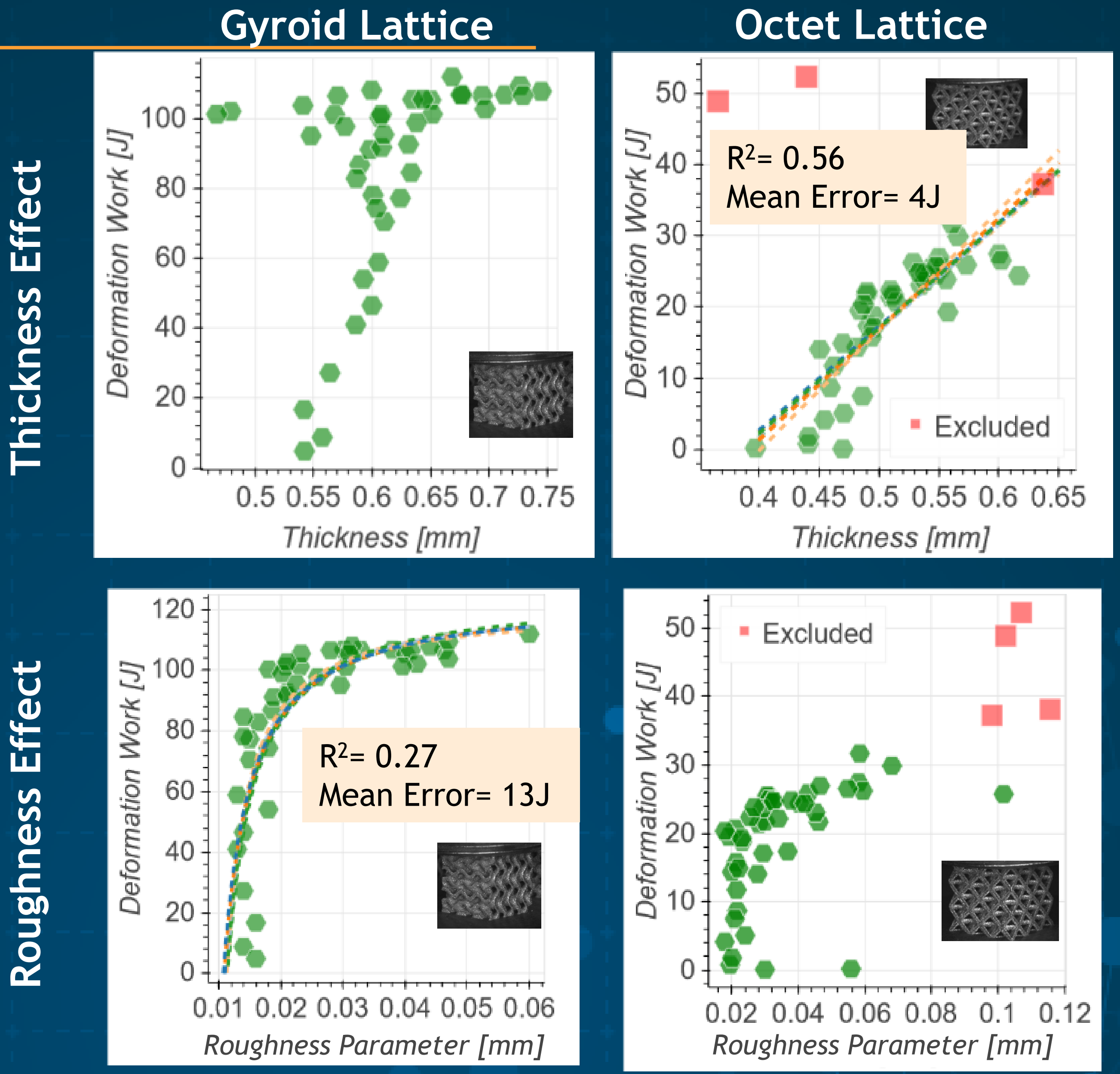


Measure Width

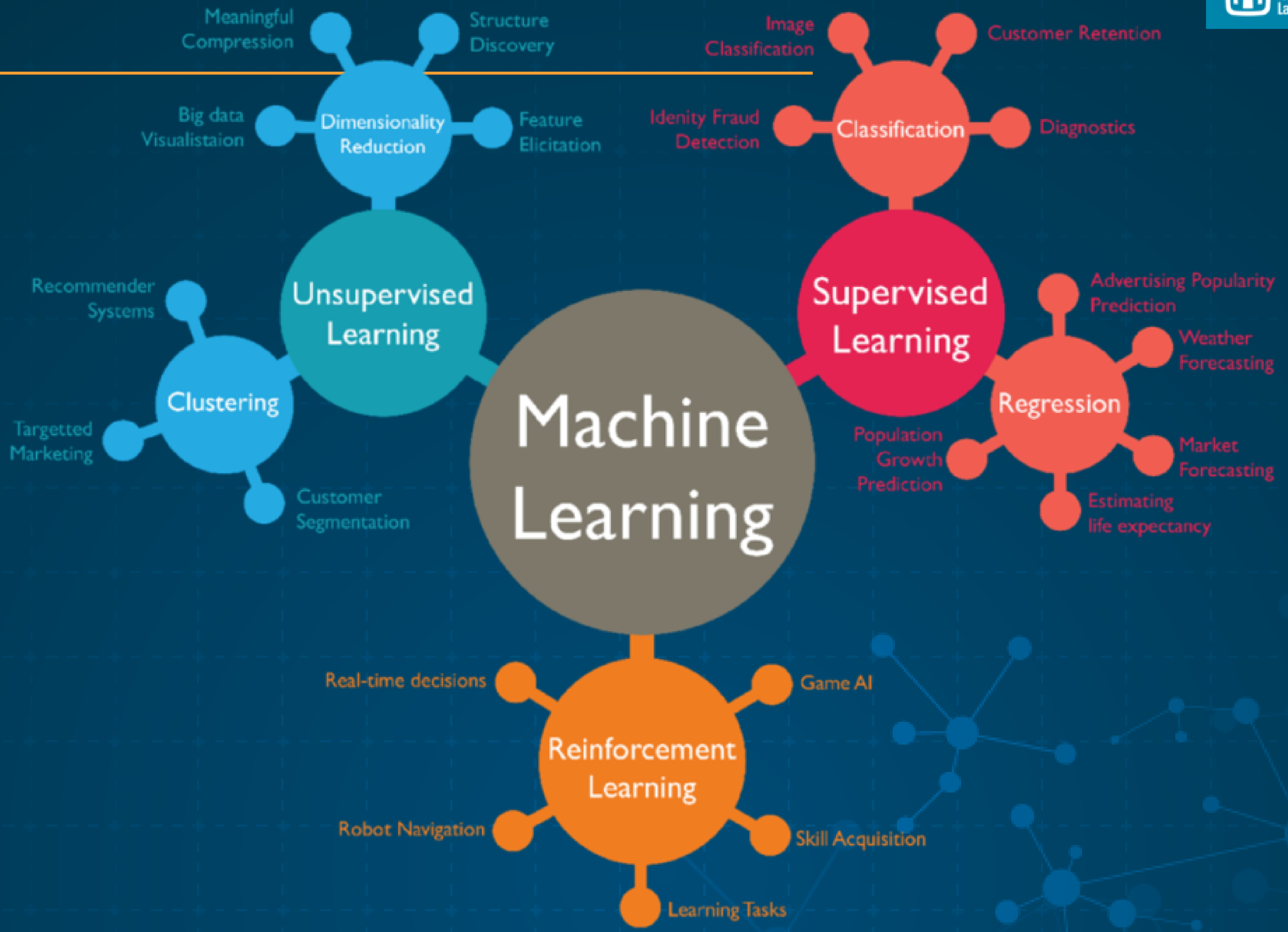


Correlate feature dimensions with properties

Neither surface roughness nor strut/wall thickness correlated very well with deformation response

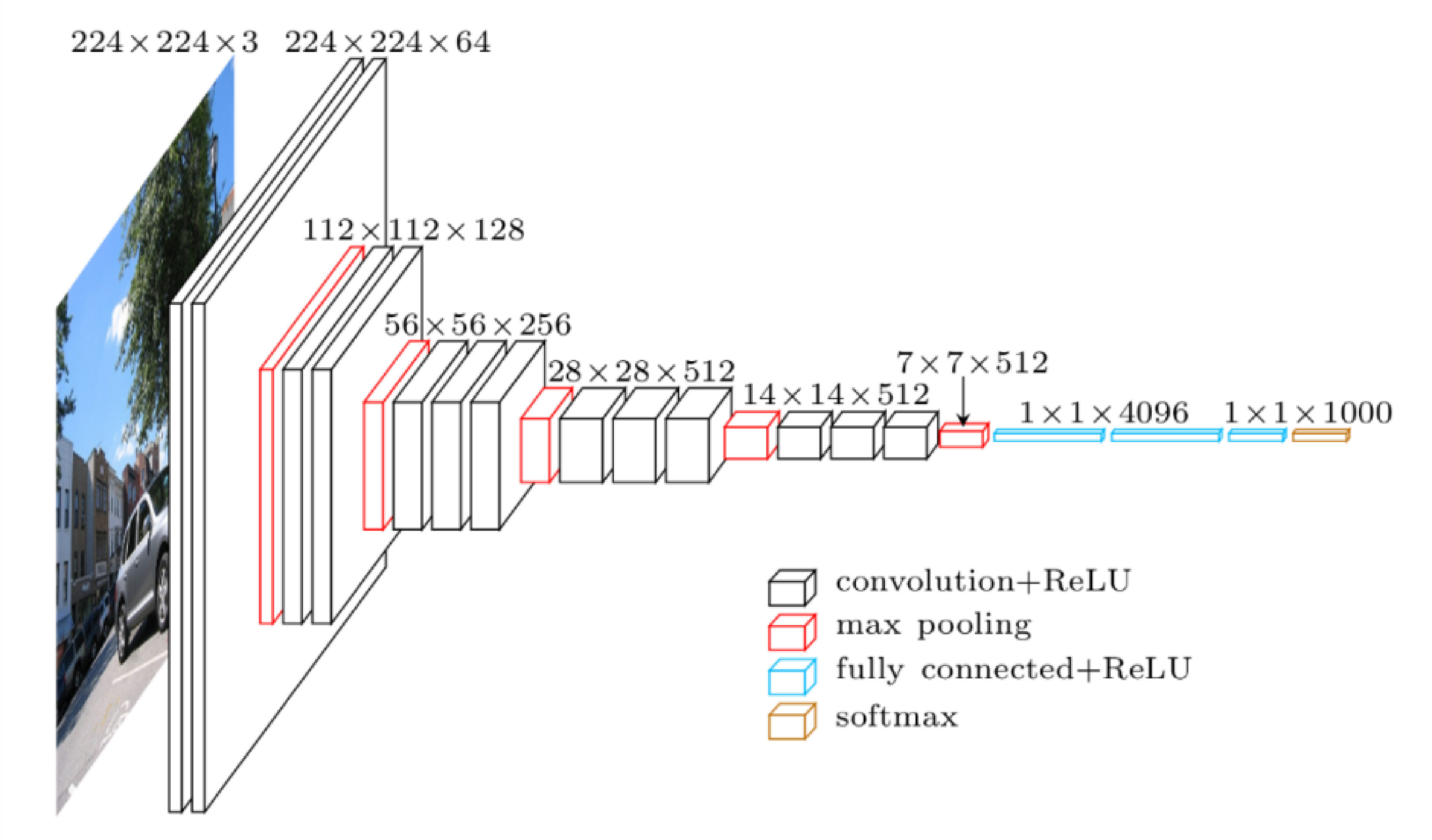


Method 2: Property correlations revealed by machine learning



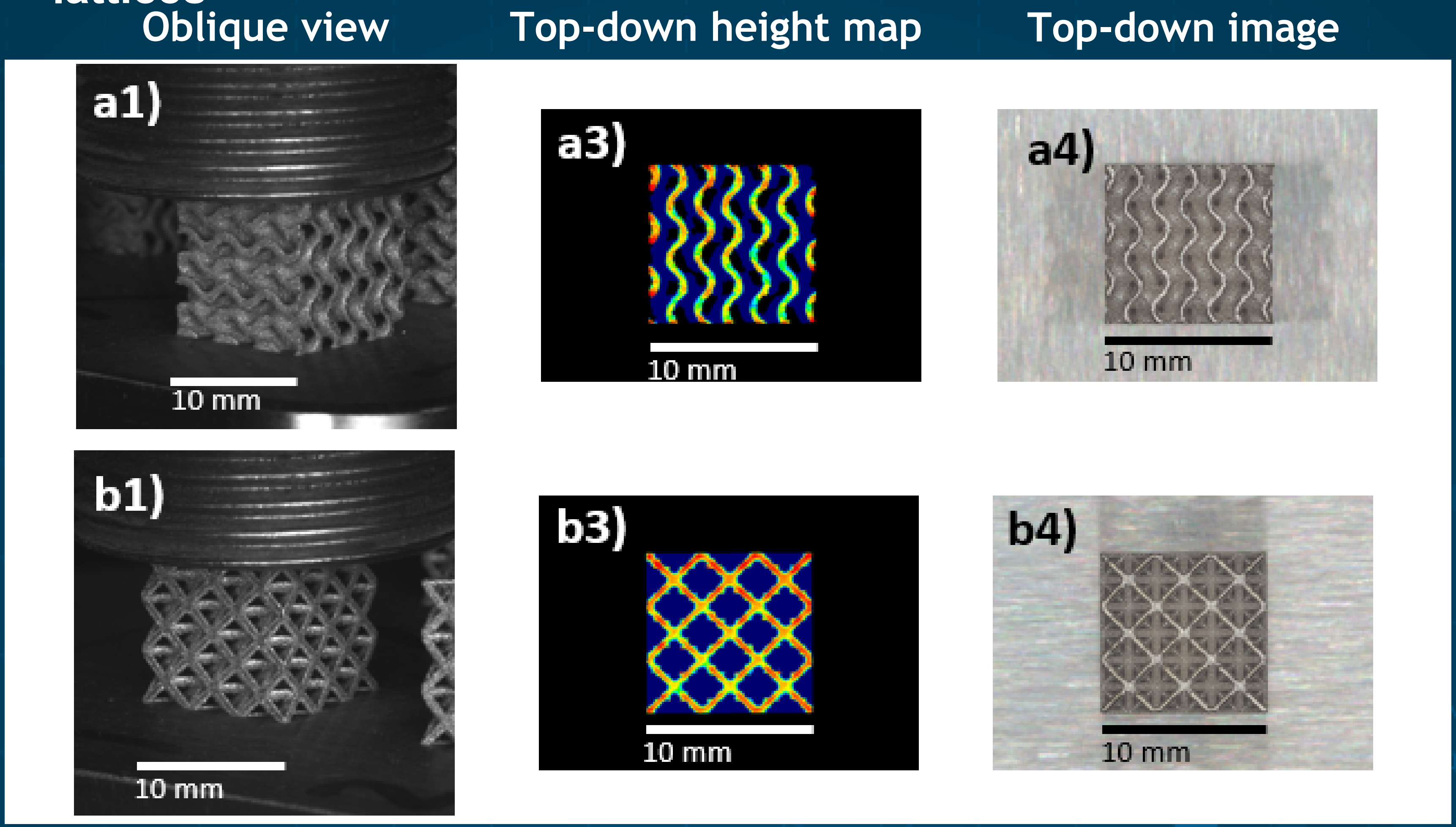
Machine Learning
Unsupervised Learning
Dimensionality Reduction
Meaningful Compression
Structure Discovery
Big data Visualistaion
Feature Elicitation
Clustering
Recommender Systems
Targetted Marketing
Customer Segmentation
Supervised Learning
Classification
Image Classification
Customer Retention
Idenity Fraud Detection
Diagnostics
Regression
Advertising Popularity Prediction
Weather Forecasting
Population Growth Prediction
Market Forecasting
Estimating life expectancy
Reinforcement Learning
Real-time decisions
Game AI
Robot Navigation
Skill Acquisition
Learning Tasks

Deep convolutional neural network: image-based classification or regression



Method 2: Machine learning source data

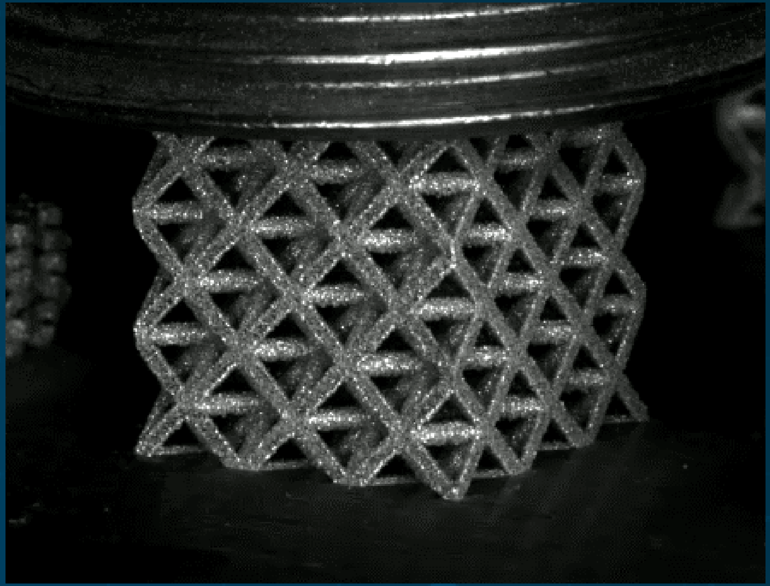
Non-traditional source data: camera images of the as-printed lattices



Challenge with an ML approach

Very little data!

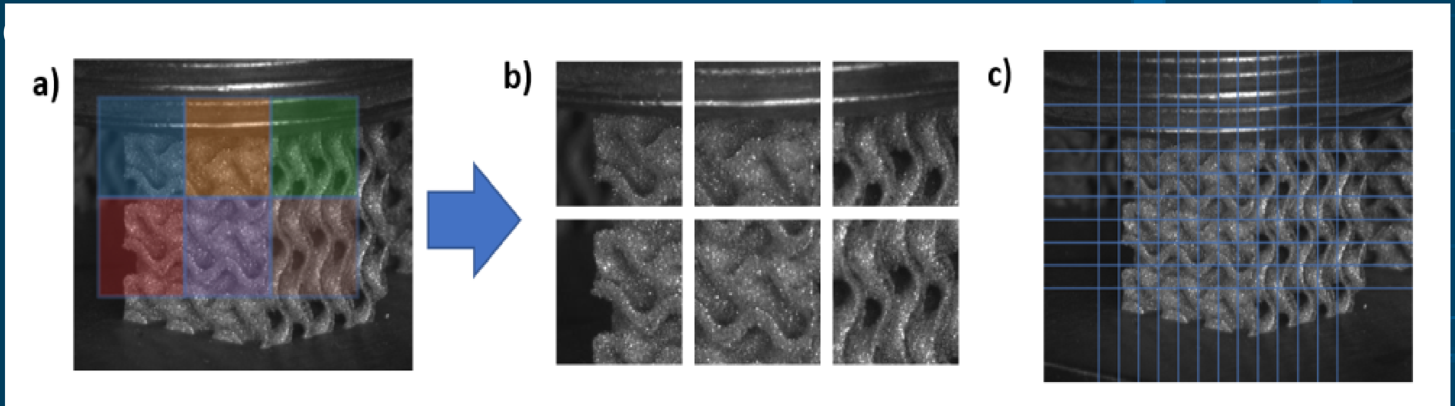
1. 48 octet data points
2. 43 gyroid data points (5 gyroids didn't survive the printing process and can't be tested)



Every octet lattice image available.

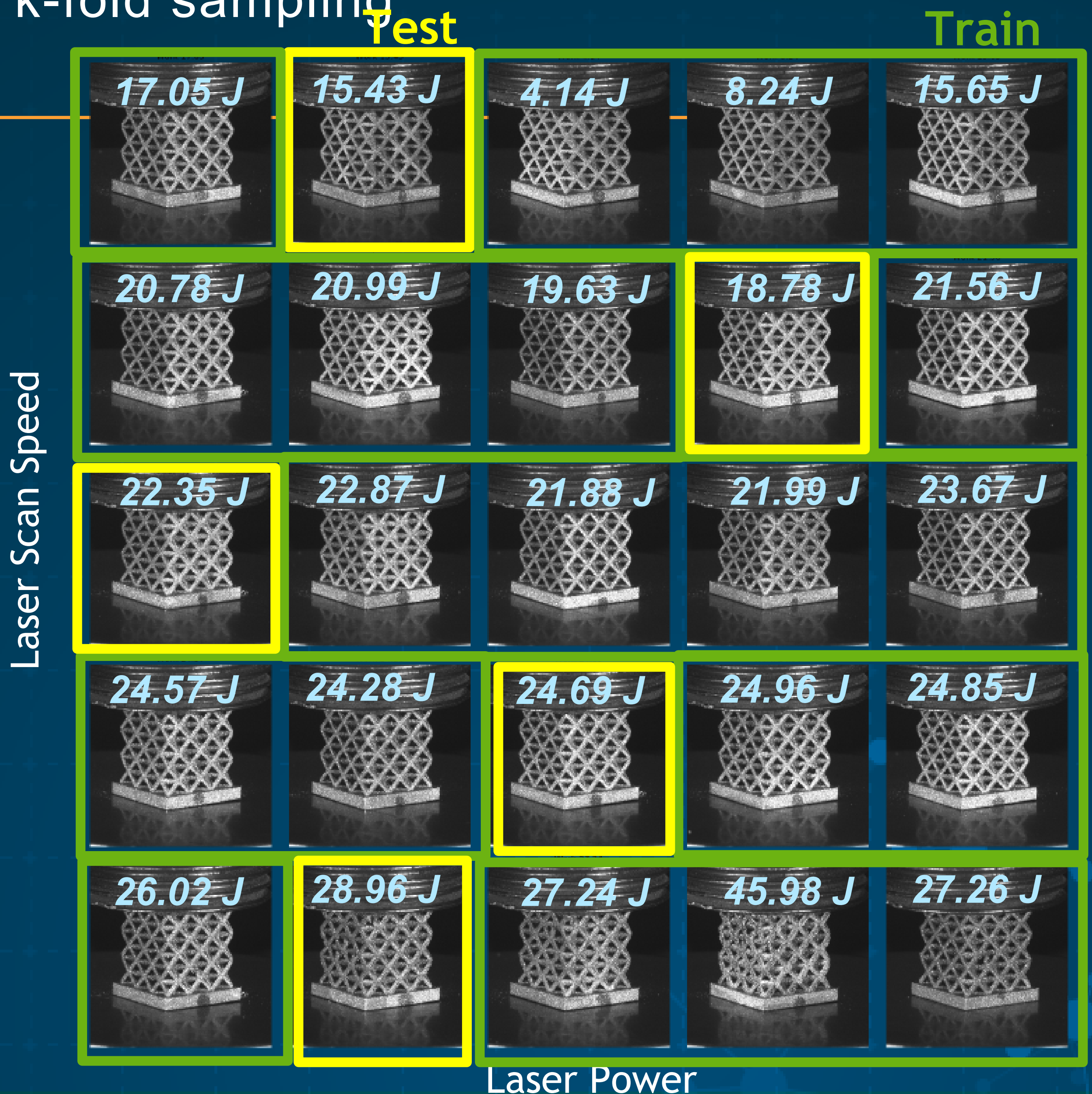
Solution: Subdivide images into representative subimages

Works, be



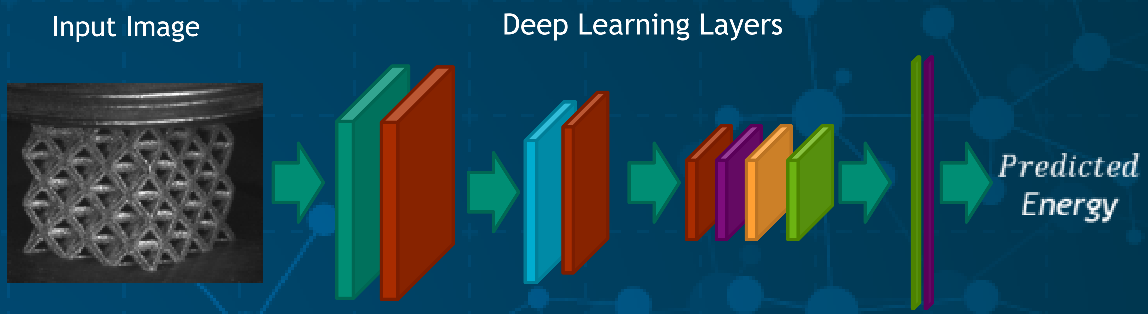
Biased sampling!

Stratified k-fold sampling



ML Model and Setup

1. Use Stratified K-fold testing.
    - Subdivide the data into classes or quantiles.
    - Perform normal k-fold testing, but the test data must equally sample all classes.
2. Data Augmentation
    - Cut each image into 48 subimages
    - Do the normal data augmentation tricks (flipping LR [not up-down], warping, zooming, cropping, skewing, lighting changes)
3. Model: ResNet 16



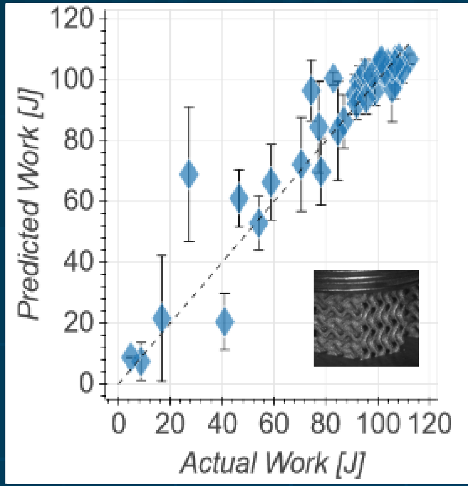
Technology

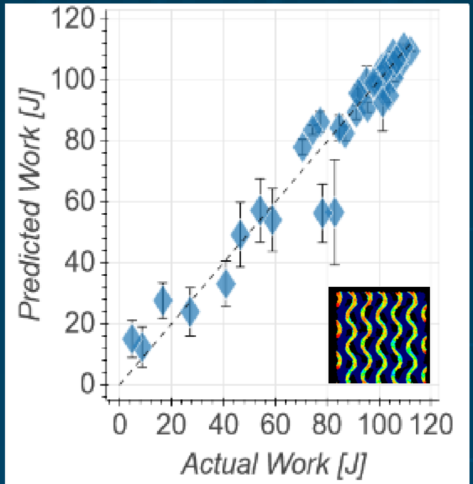
fast.ai library (wrapper around pytorch)

Scikit-learn for stratified k-fold.

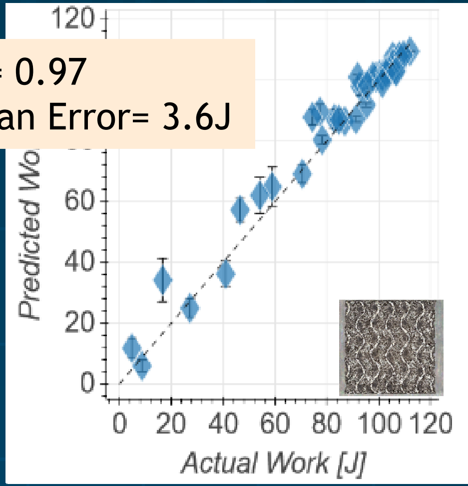
Results

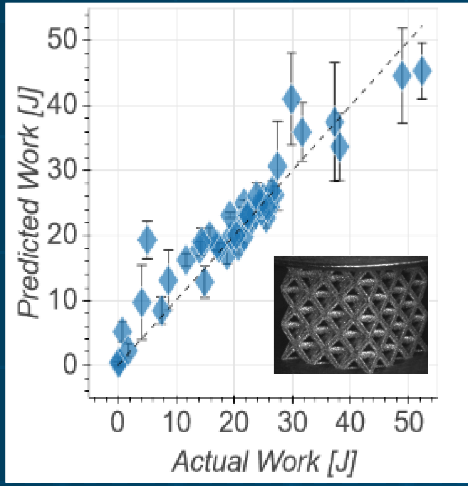
Oblique view	Top-down height map	Top-down image

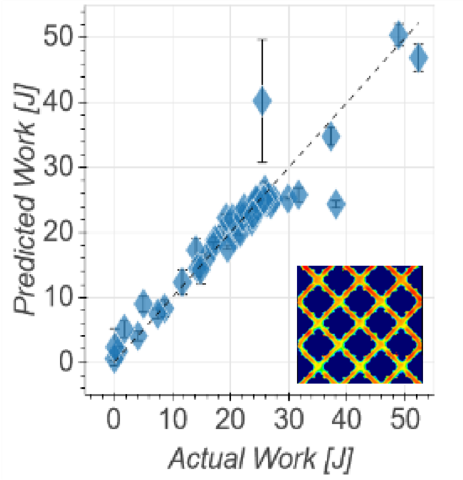




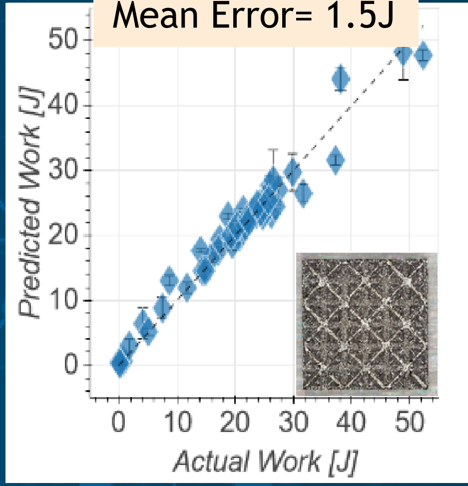
R^2= 0.97
Mean Error= 3.6J







R^2= 0.96
Mean Error= 1.5J

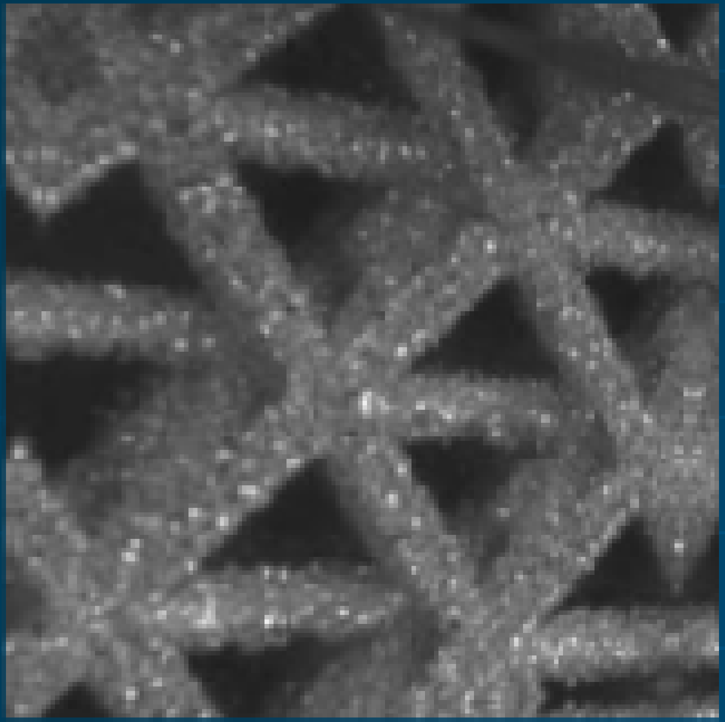


Why did this work?

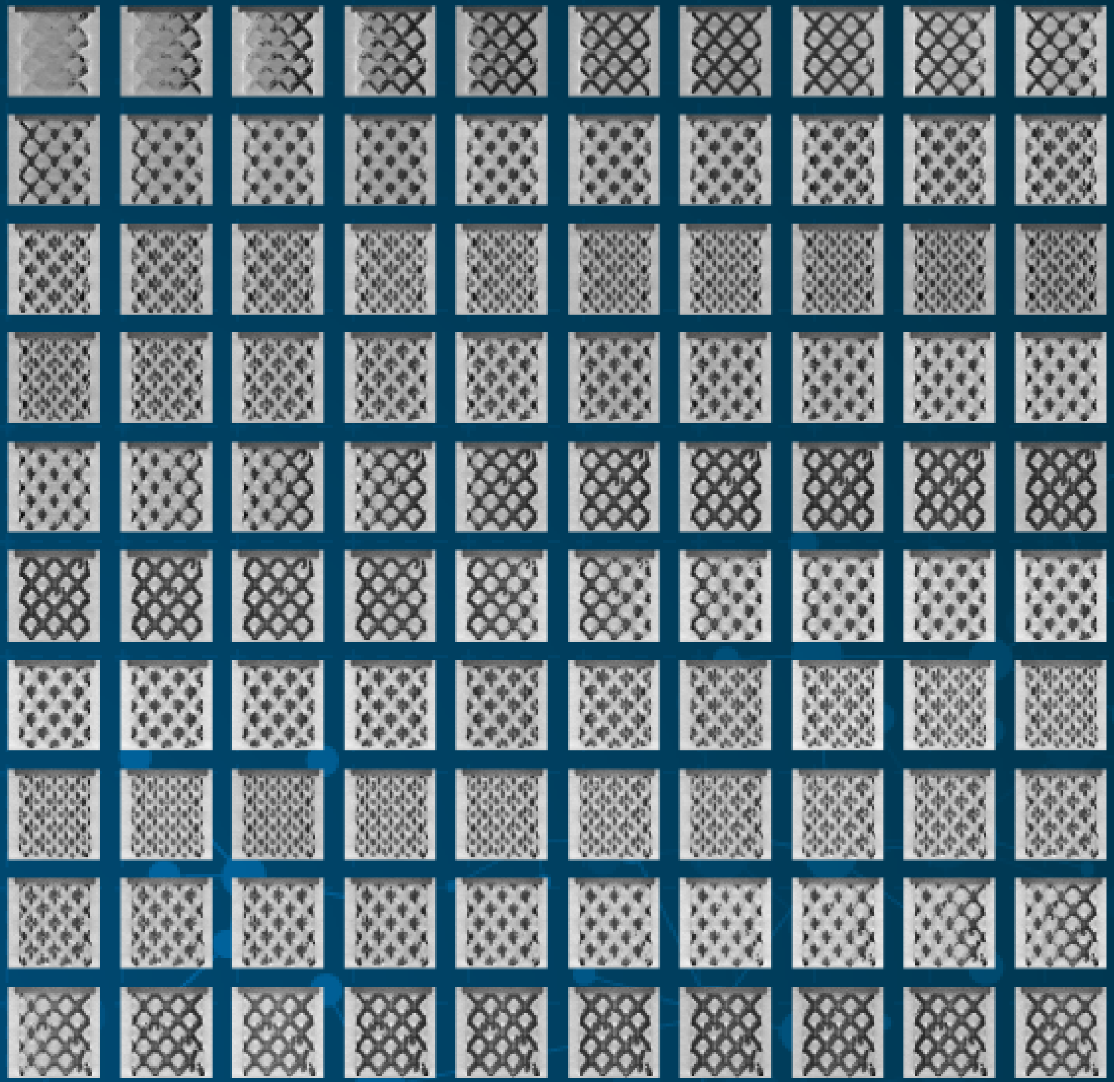
1) sufficient training data

2) careful sampling

3) source data has representative features

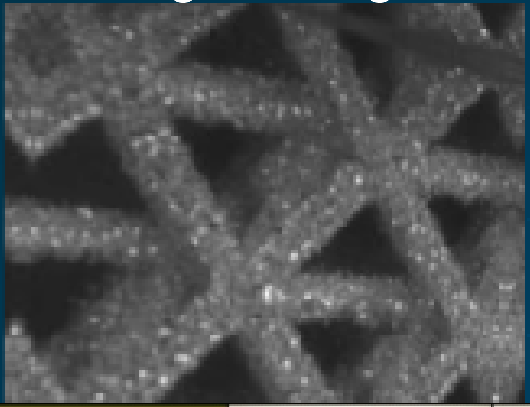


Surface roughness
Strut diameter
Broken struts
What else???

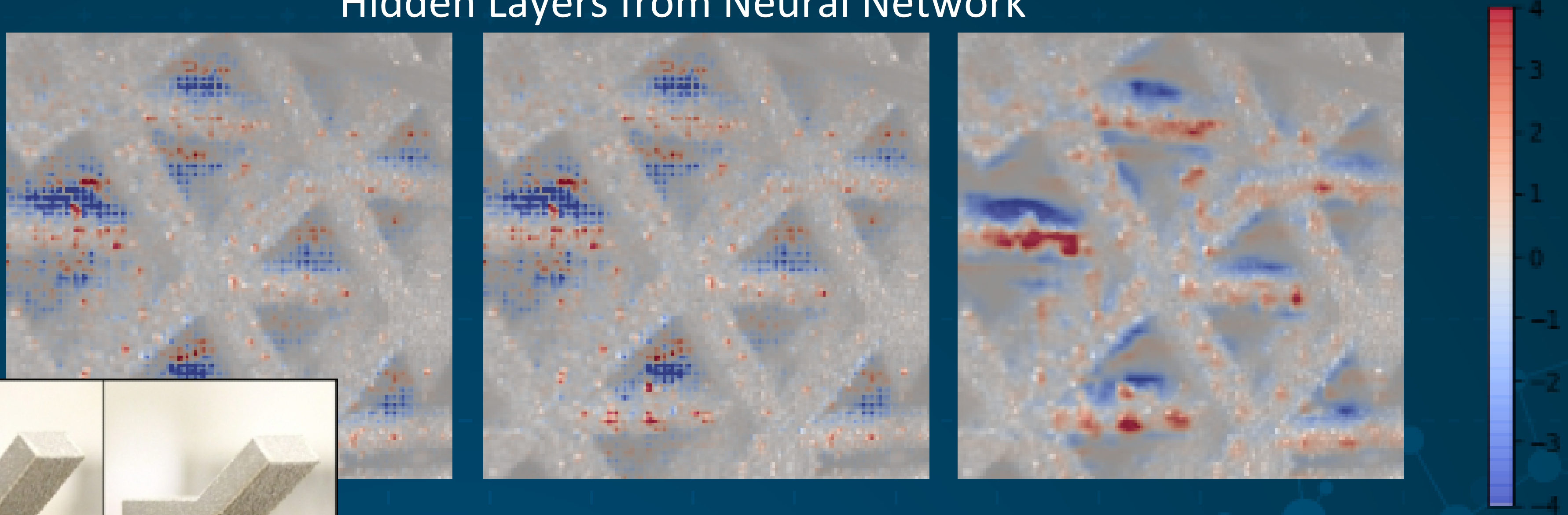


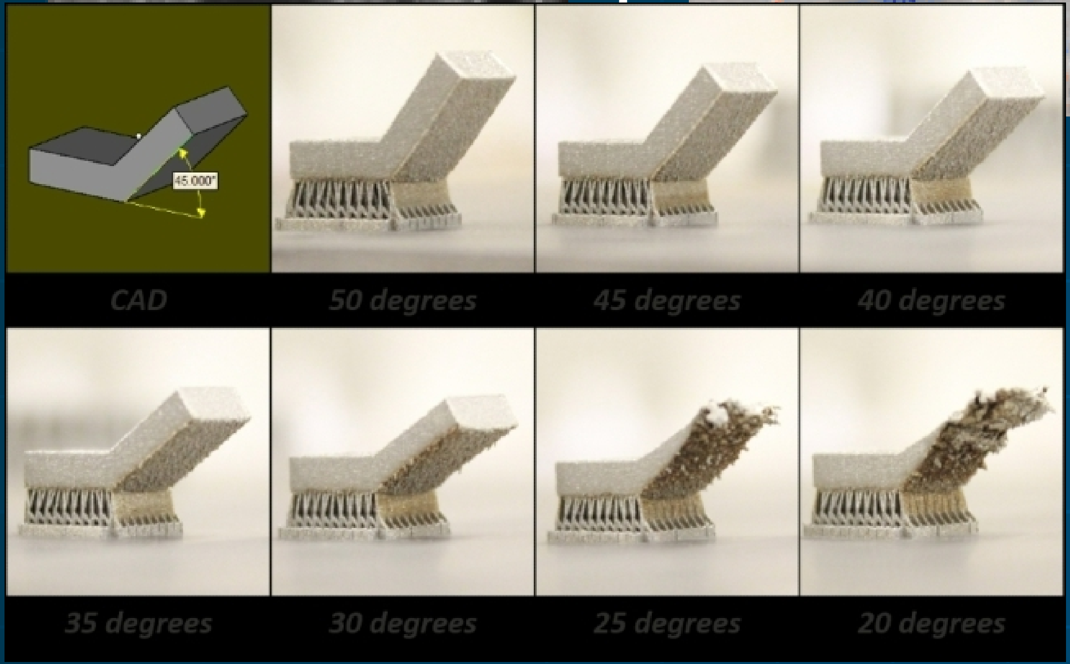
Interpretability

Original Image



Hidden Layers from Neural Network





Downward-facing unsupported overhangs (courtesy: Protolabs)

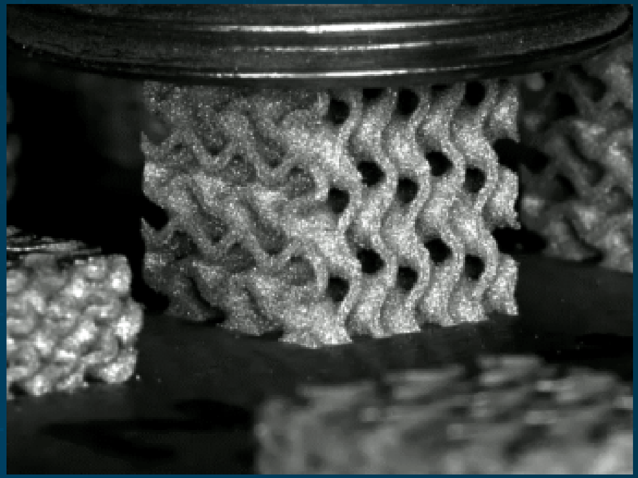
Take-home messages

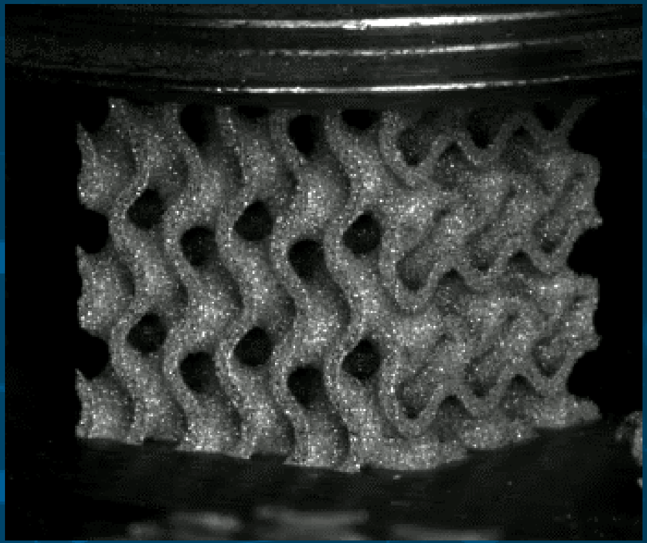
1. ***Complex structure-property relationships*** can be developed by a trained machine learning algorithm instead of by expert-guided modeling.

2. ***Non-traditional source datasets*** may have sufficiently encoded features that correlate to the underlying structural parameters governing behavior.

3. After a ML correlation has been developed, the ***causation*** may be explainable by analyzing the intermediate transfer functions (hidden layers).

4. Such approaches may serve as ***fast, efficient product screening tools.***





More information

Email: blboyce@sandia.gov

Read the paper:

Additive Manufacturing 35 (2020) 101217

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Research Paper

Deep Convolutional Neural Networks as a Rapid Screening Tool for Complex Additively Manufactured Structures

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A B S T R A C T

Additively manufactured metamaterials such as lattices offer unique physical properties such as high specific strengths and stiffnesses. However, additively manufactured parts, including lattices, exhibit a higher variability in their mechanical properties than wrought materials, placing more stringent demands on inspection, part quality verification, and product qualification. Previous research on anomaly detection has primarily focused on using in-situ monitoring of the additive manufacturing process or post-process (ex-situ) x-ray computed tomography. In this work, we show that convolutional neural networks (CNN), a machine learning algorithm, can directly predict the energy required to compressively deform gyroid and octet truss metamaterials using only optical images. Using the tiled nature of engineered lattices, the relatively small data set (43 to 48 lattices) can be augmented by systematically subdividing the original image into many smaller sub-images. During testing of the CNN, the prediction from these sub-images can be combined using an ensemble-like technique to predict the deformation work of the entire lattice. This approach provides a fast and inexpensive screening tool for predicting properties of 3D printed lattices. Importantly, this artificial intelligence strategy goes beyond 'inspection', since it accurately estimates product performance metrics, not just the existence of defects.

1. Introduction

Additive manufacturing (AM) enables fabrication of complex free-form shapes including engineered lattices, such as gyroids and octet trusses, that are not possible or very difficult to fabricate with other traditional manufacturing methods [1]. Lattices are typically employed for two distinct purposes: (1) as support or "infill" to facilitate printability of cavities, overhangs, and suspended features, or (2) as struc-

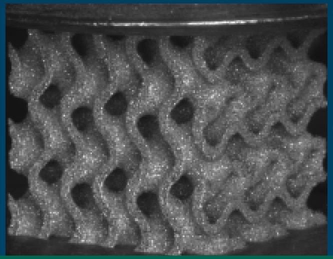
qualification requirements [21].

The successful use of structural lattices is directly related to the ability to assure that the properties and shape of the printed lattice meet design requirements. To qualify AM parts, it is necessary to confirm that the component meets predefined physical performance requirements. A prerequisite for qualification is measuring part properties directly or by using a model to relate a secondary measured property to the true properties of interest. Measurements could include inspecting the final

Future Works

1. We redid the entire experiment by printing 48 more octet lattices and we were able to replicate the results.
2. ML for lattice design (inverse problem)

Current Talk



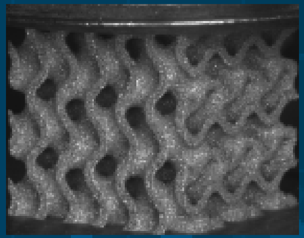
ML

Property

Future Work

Target Property

ML



3. Combining physics with ML to predict lattice properties with CT

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