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Neural networks capture the deformation of lattice metamaterials

PRESENTED BY

Brad L. Boyce

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BRUKER

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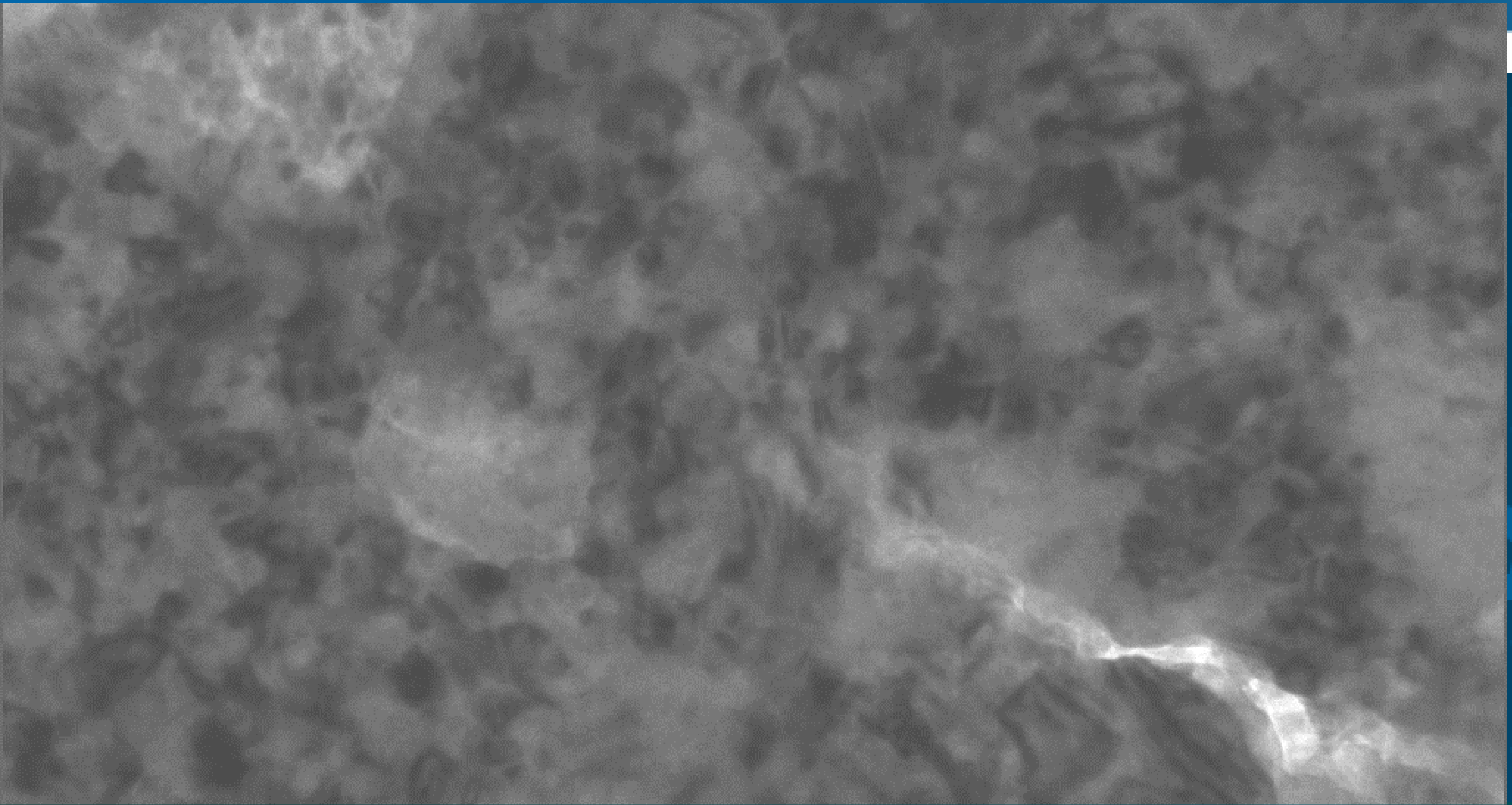
Nanomechanical Testing Conference

February 23–24, 2021 | 16:00 - 21:00 CET / 9:00AM – 2:00PM CST

VIRTUAL EVENT, ACTUAL SCIENCE



Nanocrystalline Cu
Cyclic fatigue loading at 300 Hz

Loading direction

100 nm

Lattices: tailorable properties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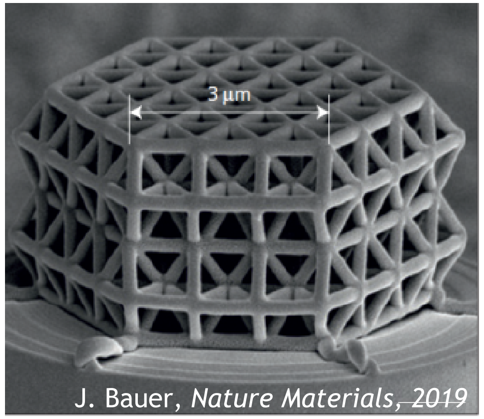
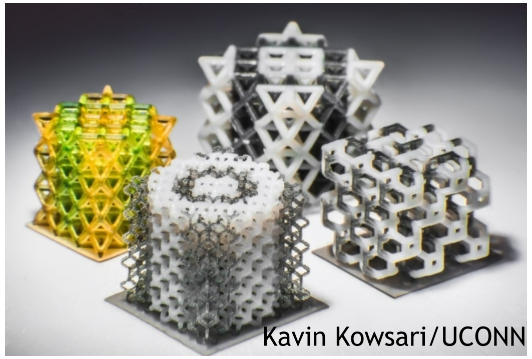
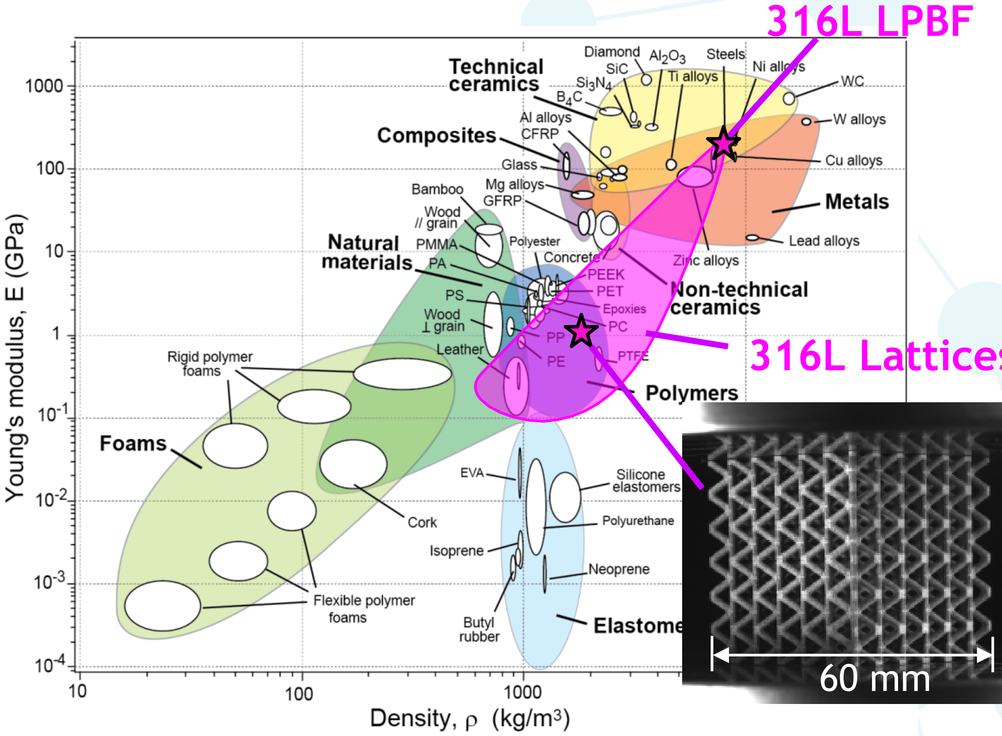
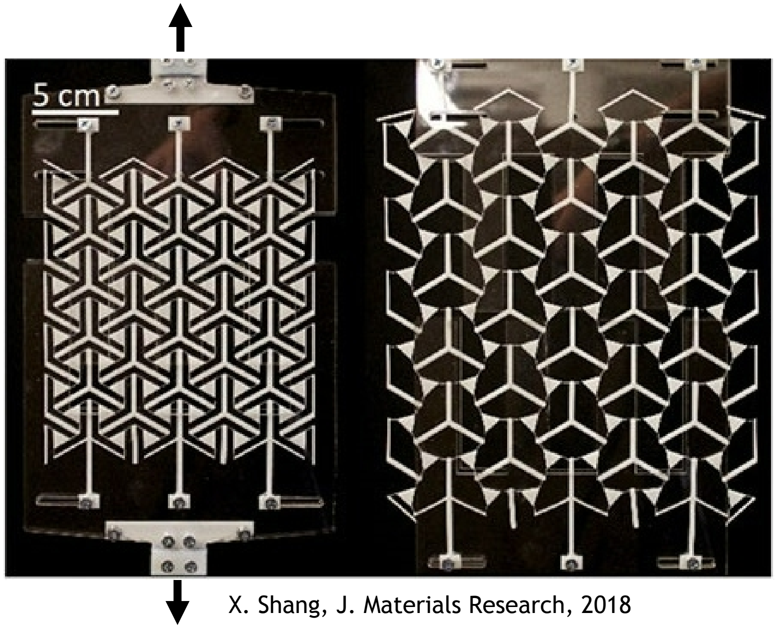


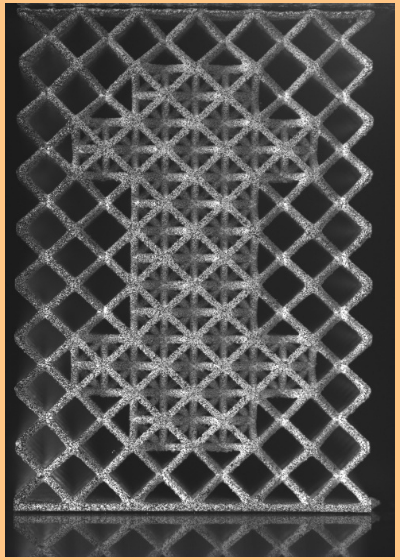
J. Bauer, *Nature Materials, 2019*


Kavin Kowsari/UCONN



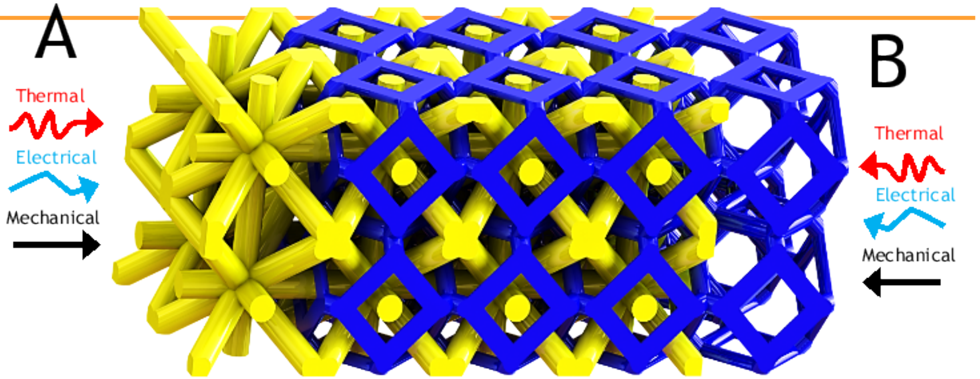


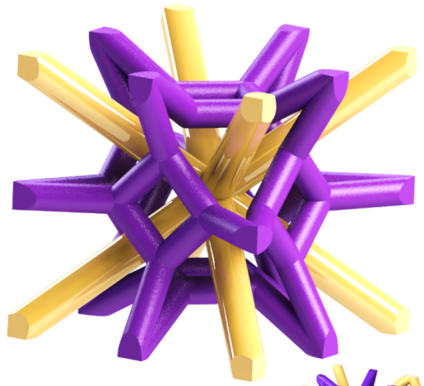
X. Shang, J. Materials Research, 2018

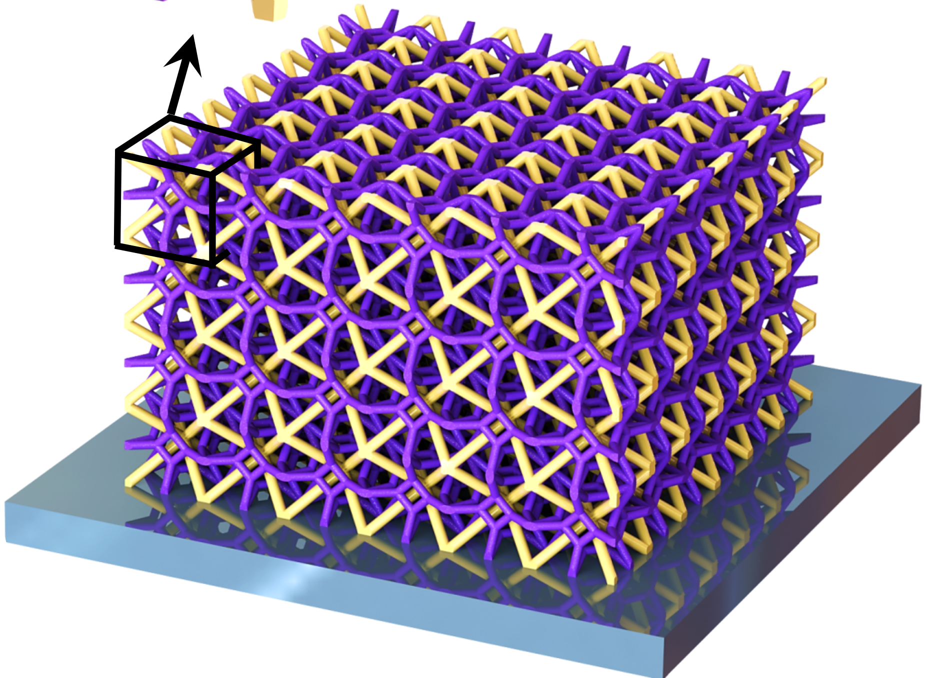

Our work: Alberdi, *Materials and Design*, 2020

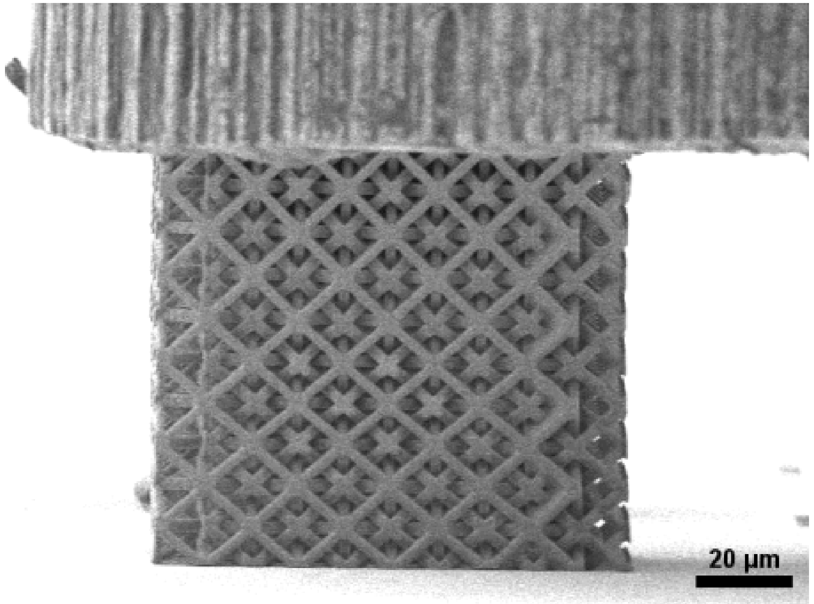
How do we design and manufacture lattices to be good plastic energy absorbers?

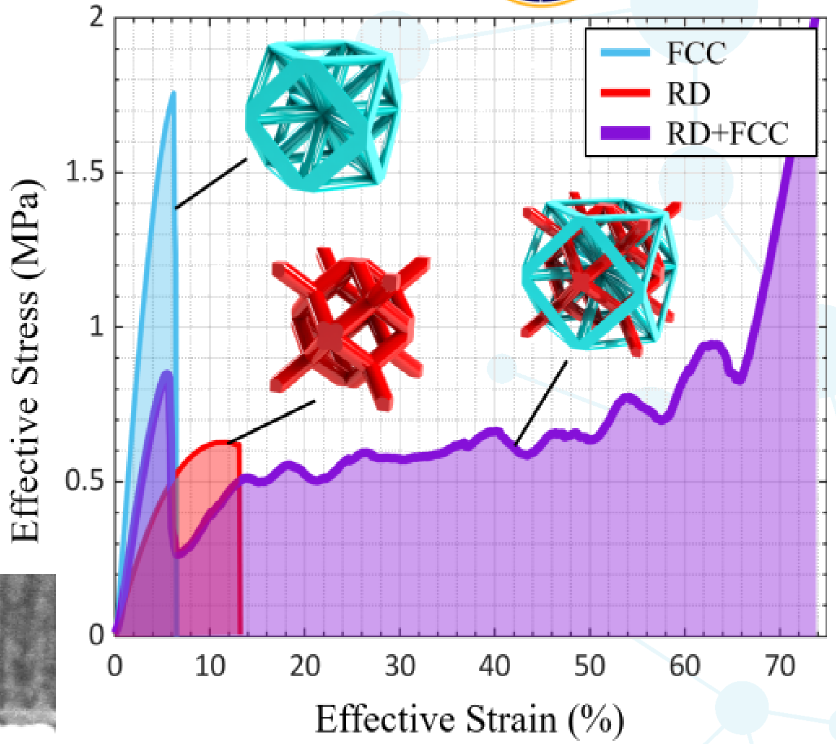
Interpenetrating Lattices…







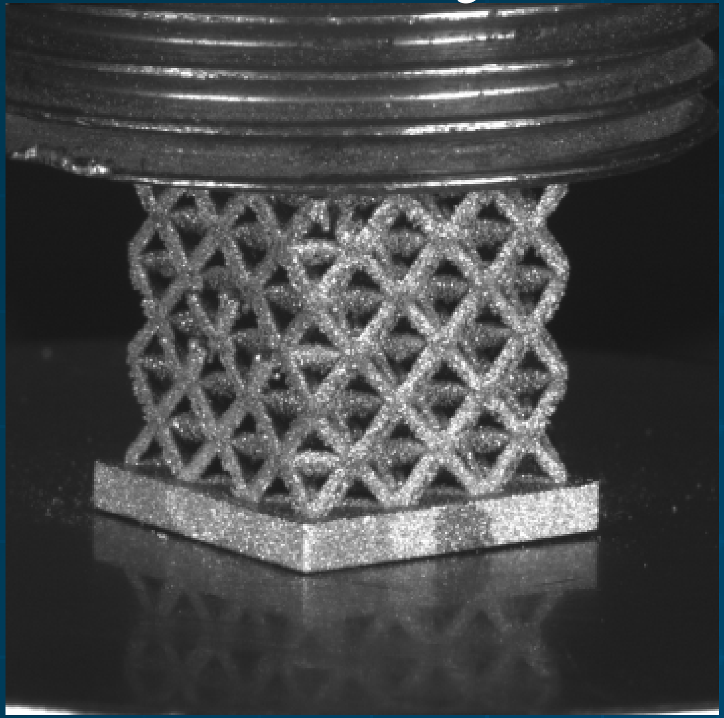




White…Boyce, *Additive Manufacturing*, 2021

The ridiculous proposition

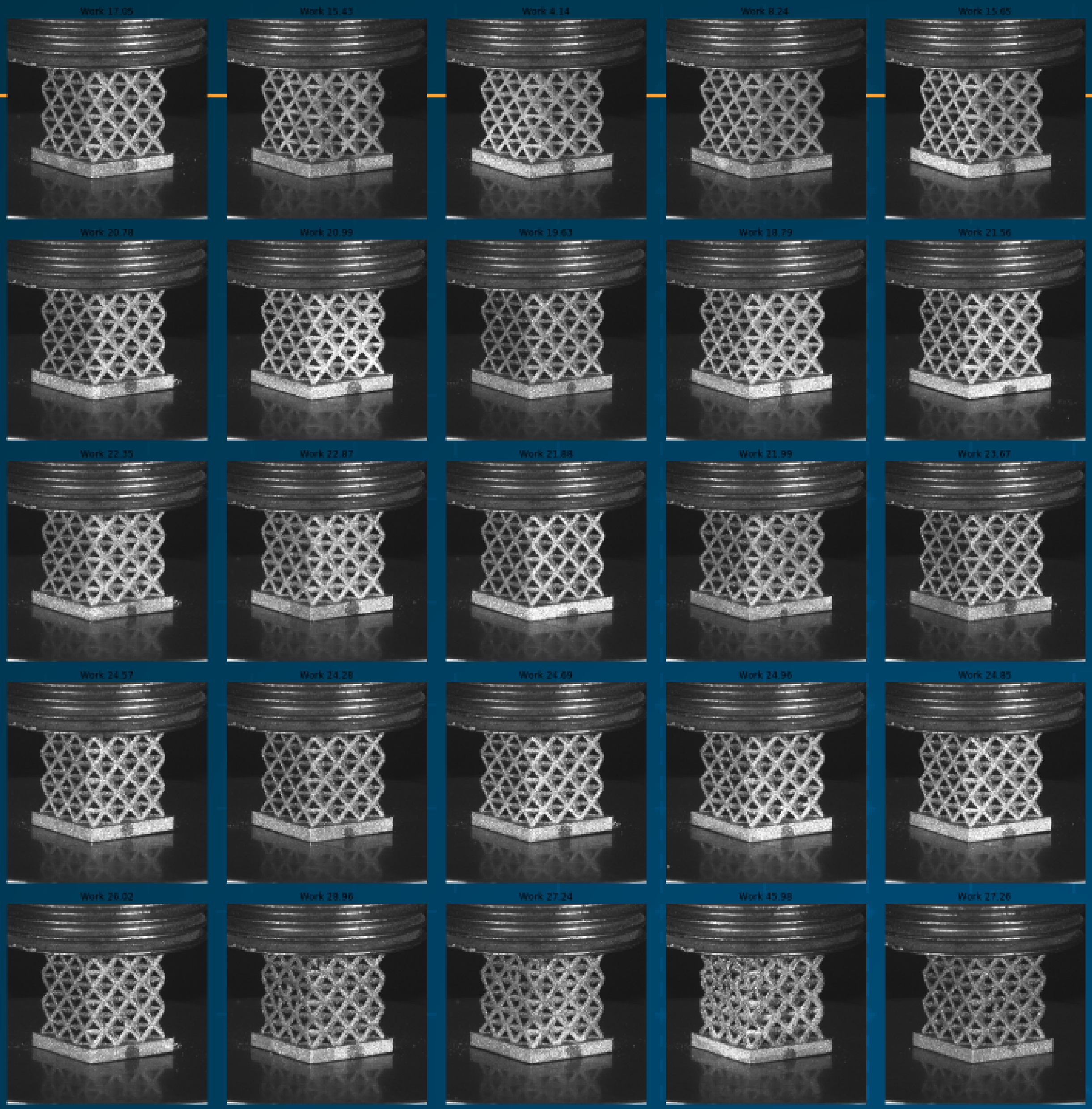
Initial image

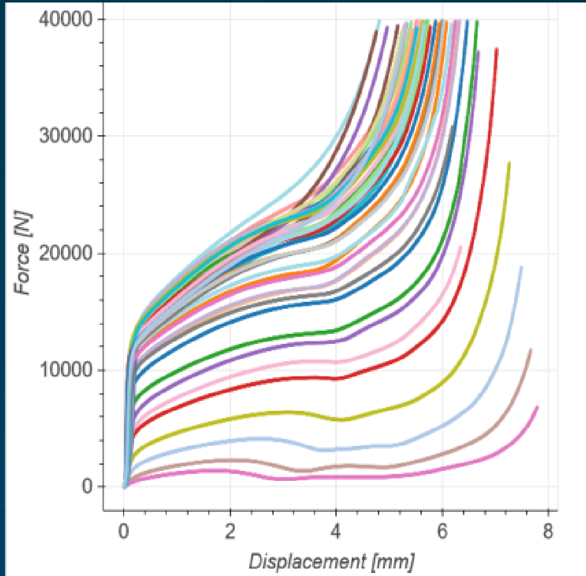


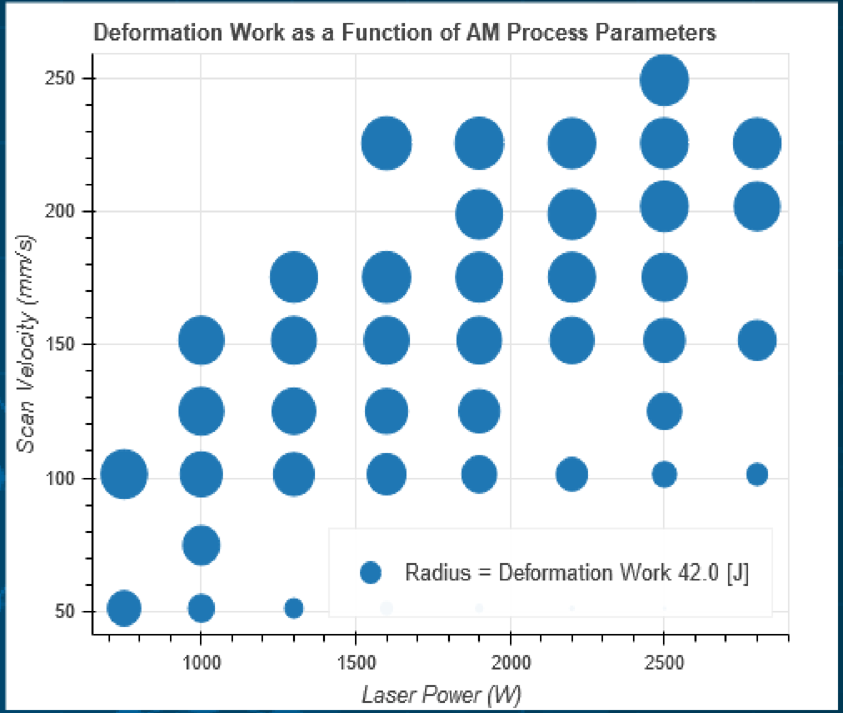
prediction

How much energy will it absorb when crushed?

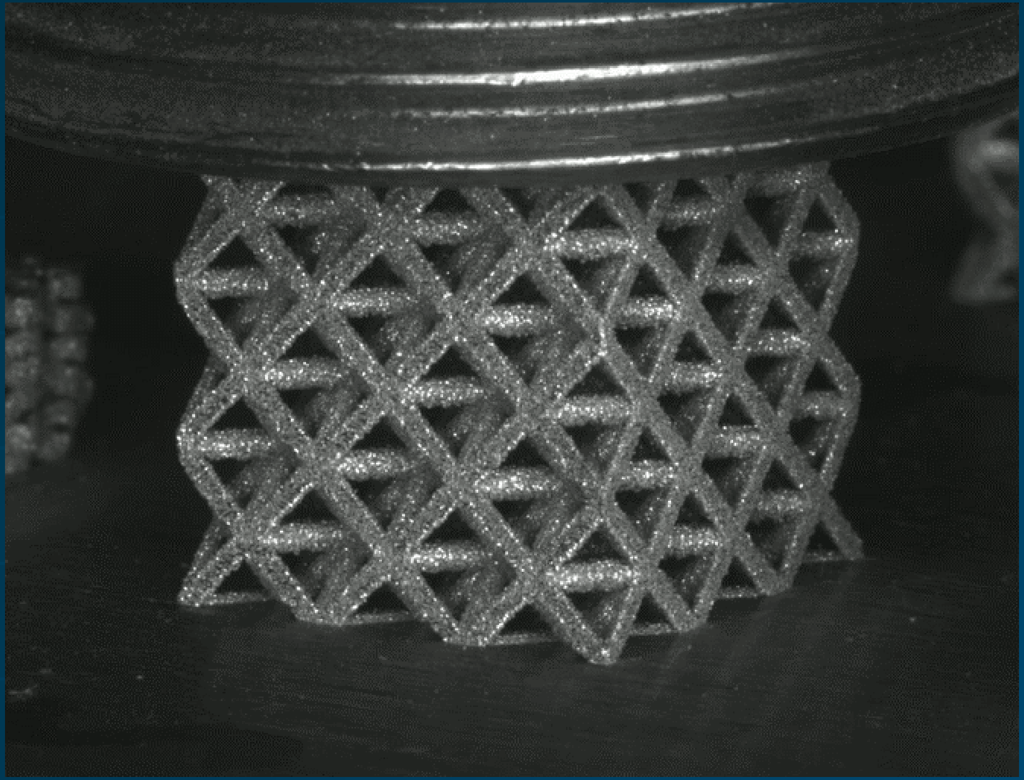
A convenient dataset…



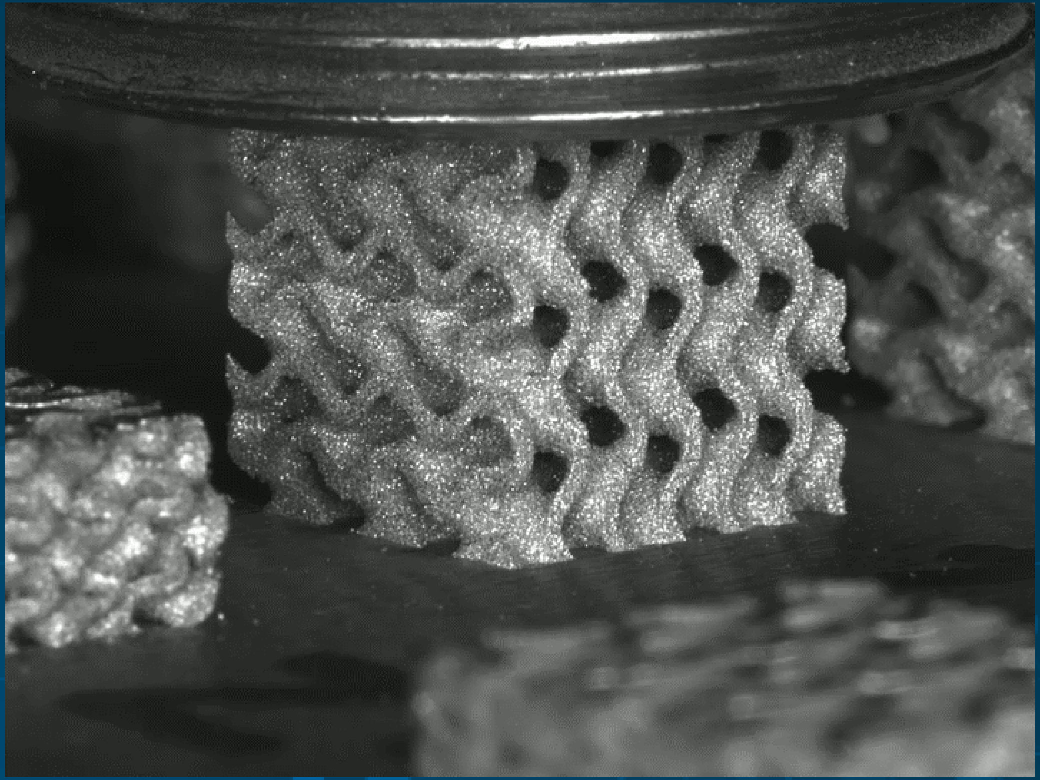




Example images for both octet and gyroid structures



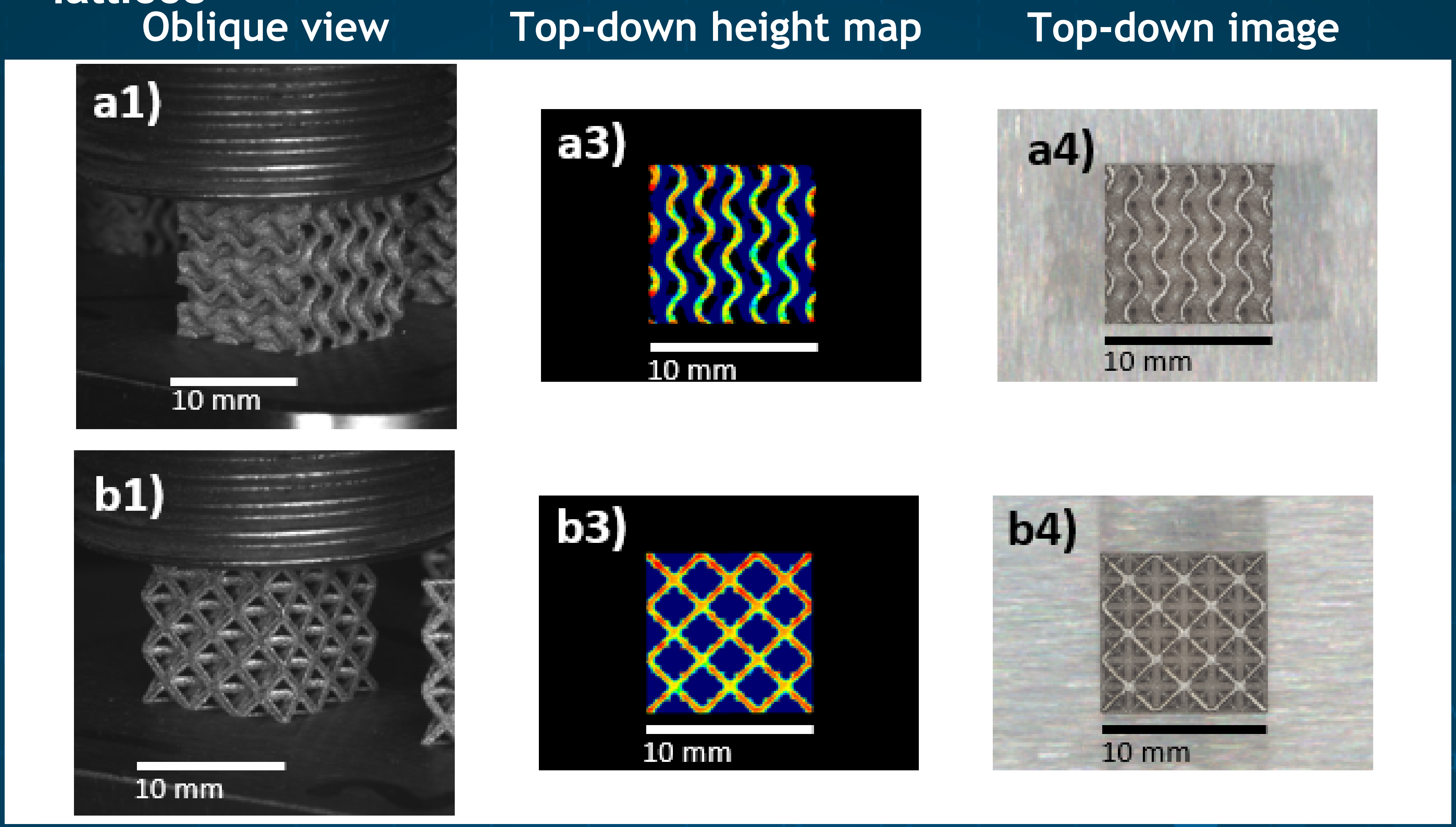
48 octet lattices



43 gyroid metamaterials

Source data: initial images before deformation

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



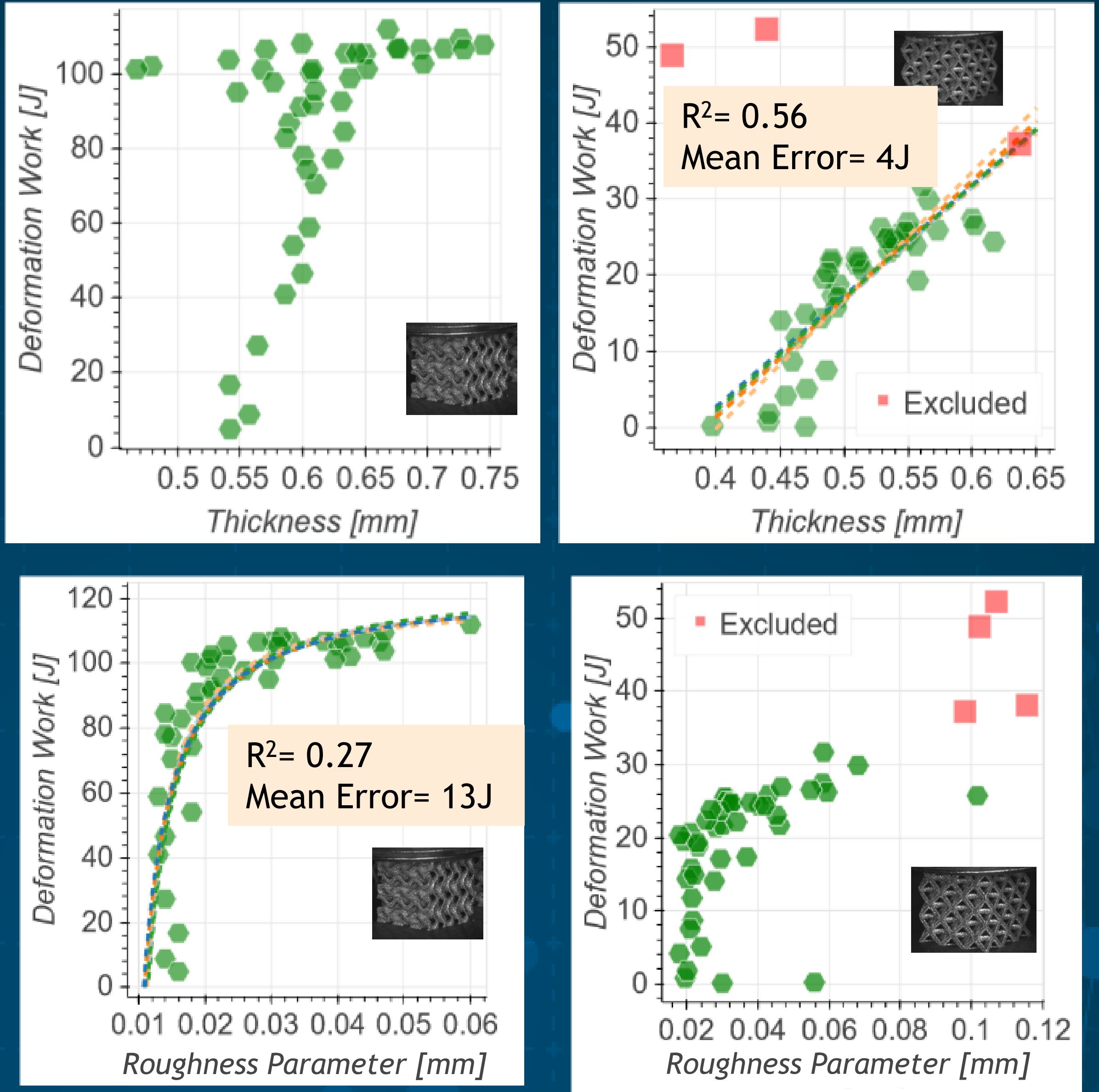
Correlations with feature dimensions was not strong

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

Gyroid Lattice | Octet Lattice

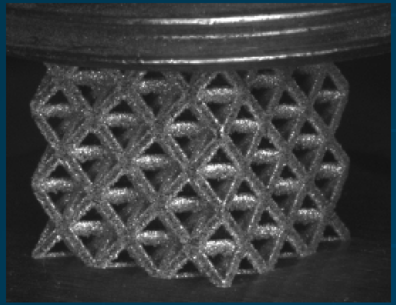
Thickness Effect

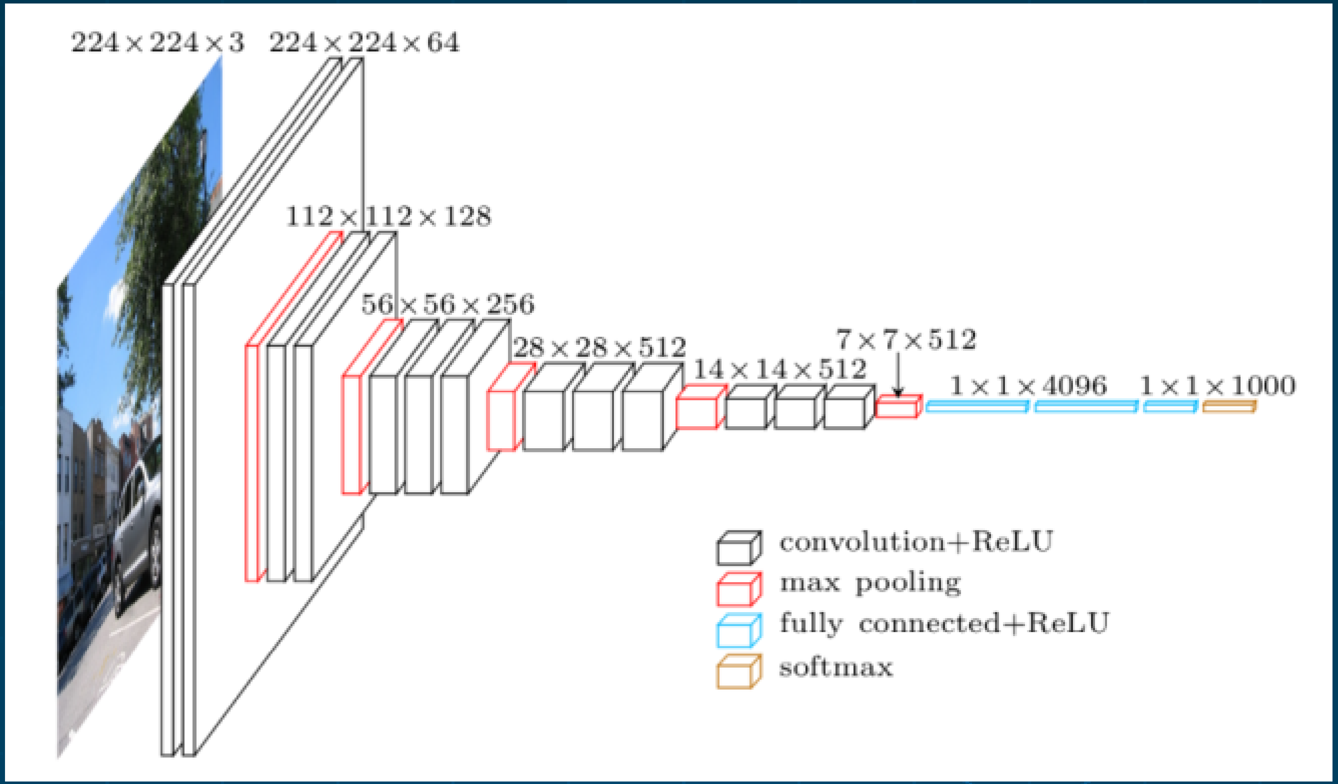
Roughness Effect



Deep convolutional neural network

Input Image





Predicted Deformation Energy

fast.ai

Residual Network Model: ResNet 16

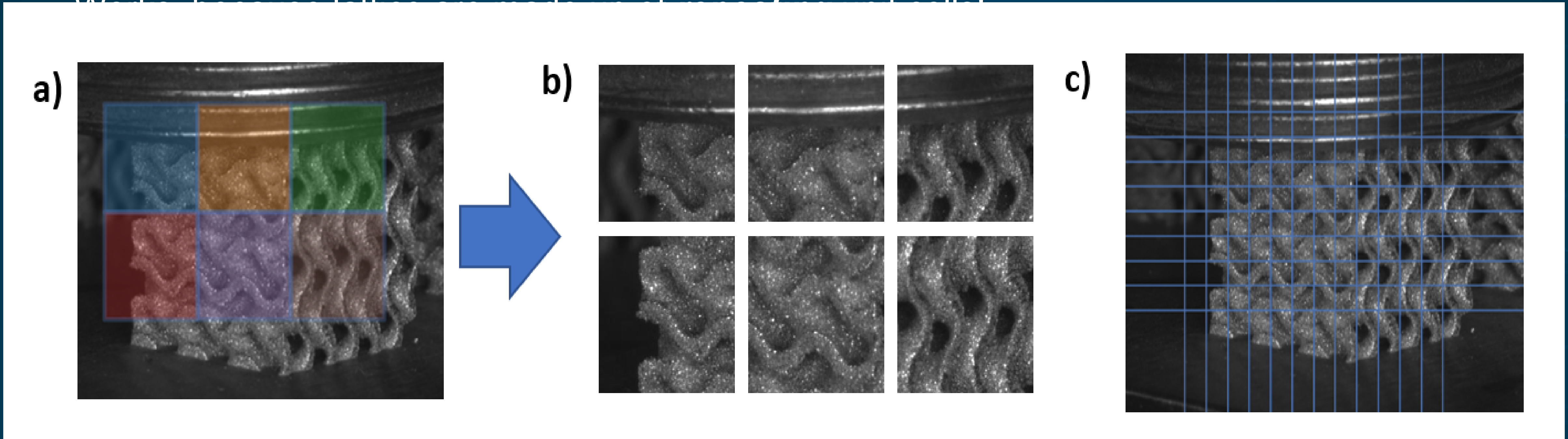
fast.ai library (wrapper around pytorch)

Challenge with an ML approach

Very little data!

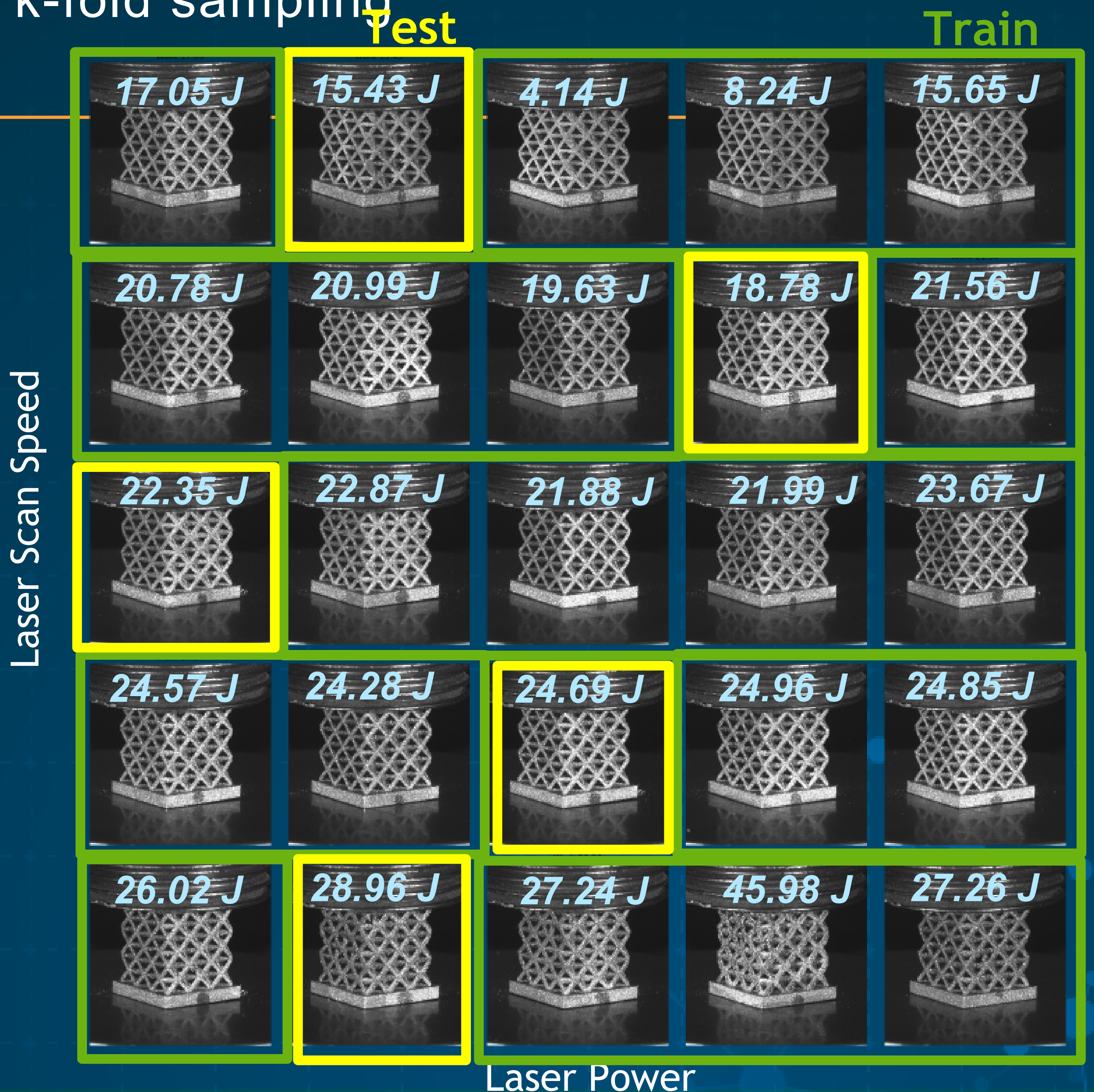
1. 48 octet data points
2. 43 gyroid data points

Solution: Subdivide images into representative subimages



Avoid biased training!

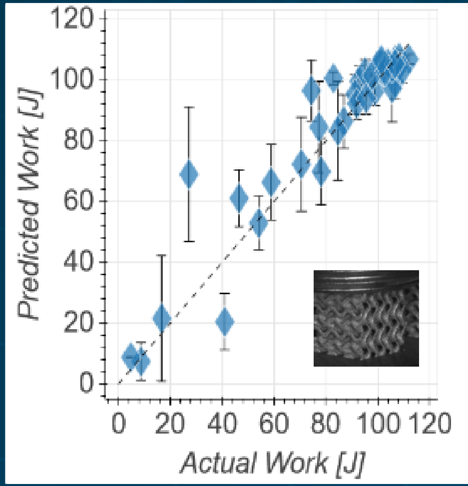
Stratified k-fold sampling

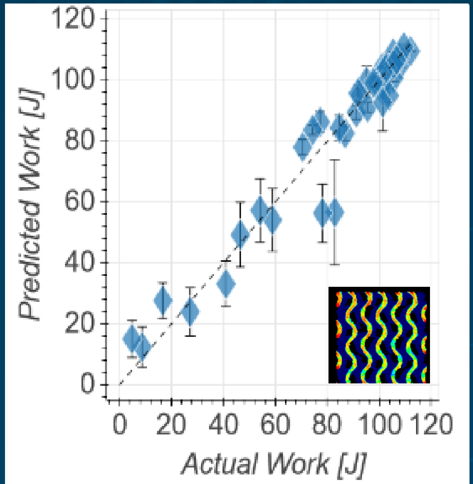


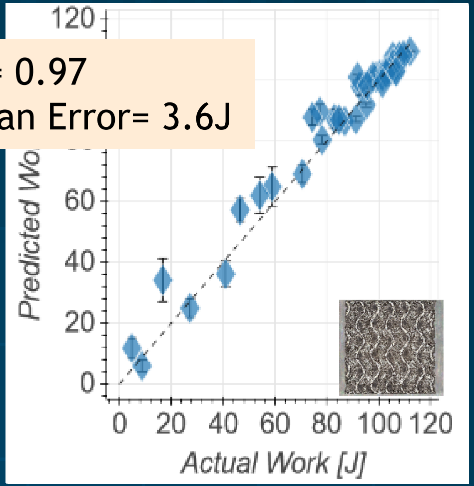
Results

Oblique view | Top-down height map | Top-down image

gyroid

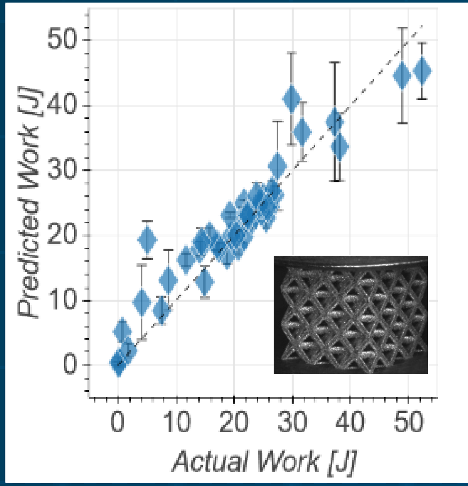


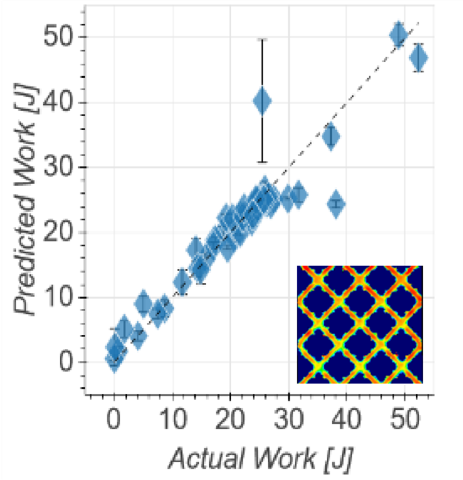




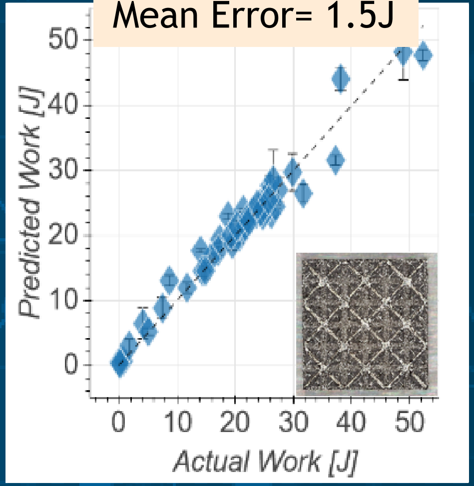
R^2= 0.97
Mean Error= 3.6J

octet





R^2= 0.96
Mean Error= 1.5J

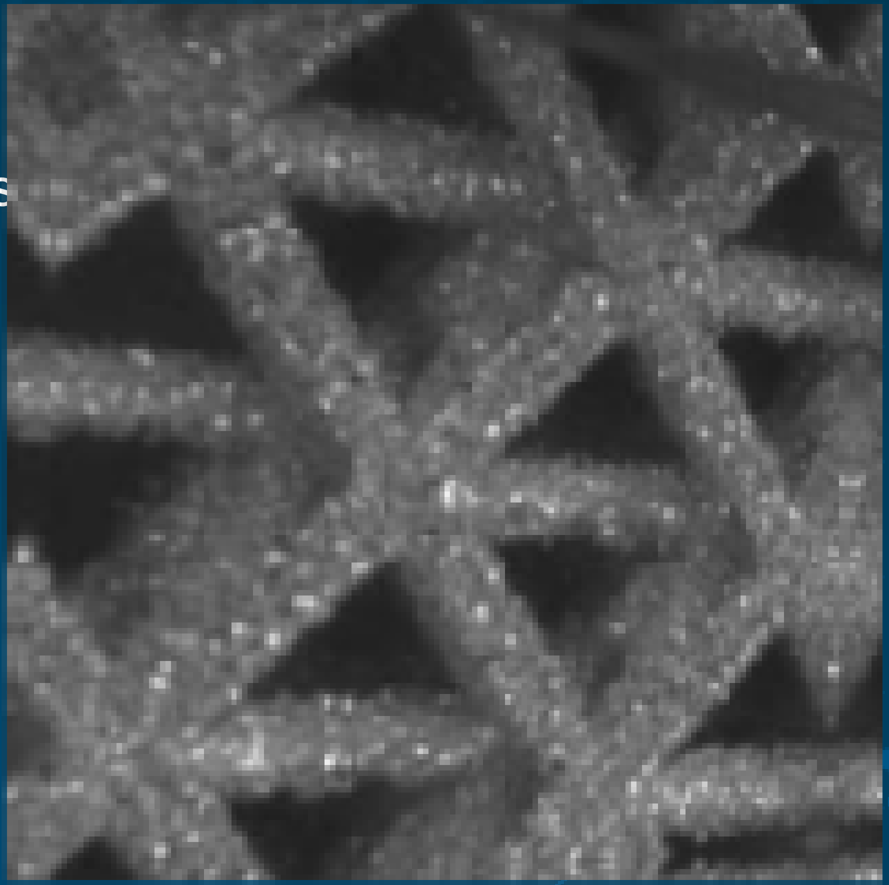


Why did this work?

1) sufficient training data

2) careful sampling

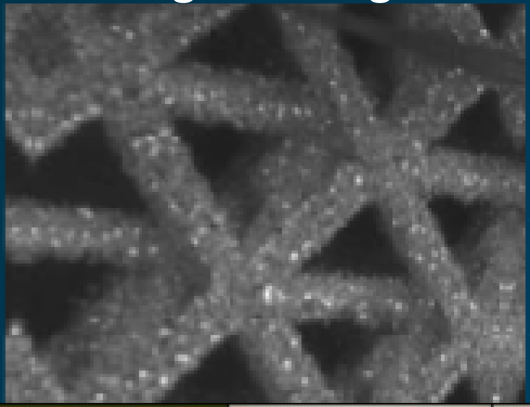
3) source data has representative features



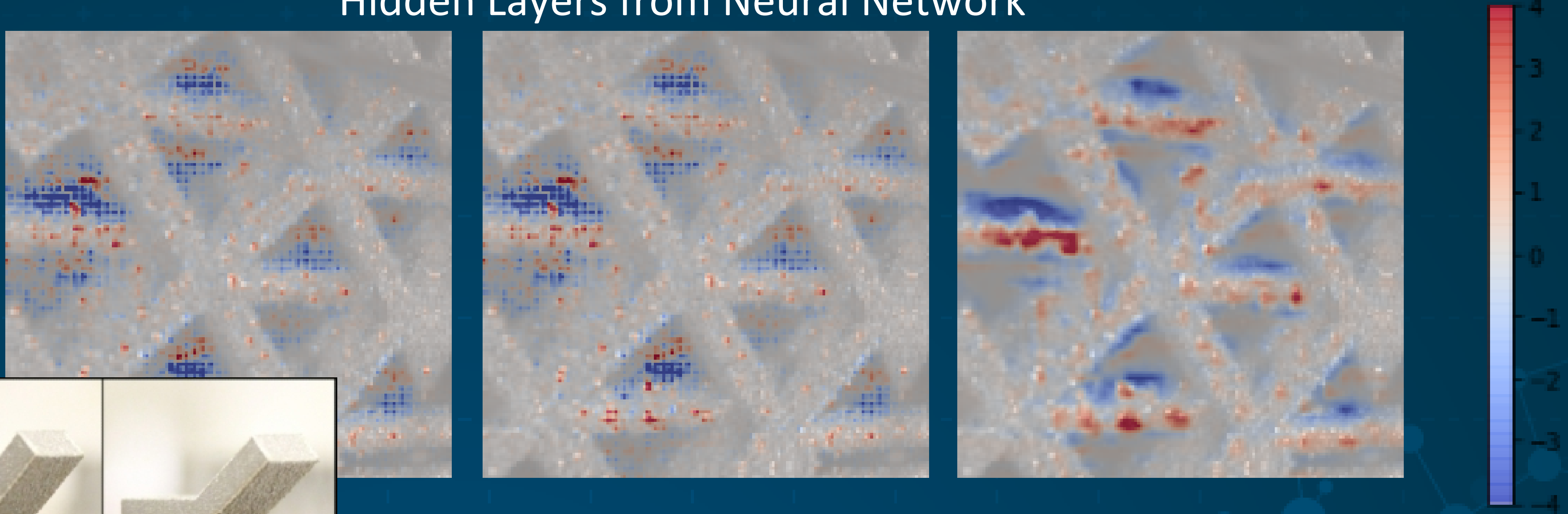
Surface roughness
Strut diameter
Broken struts
What else???

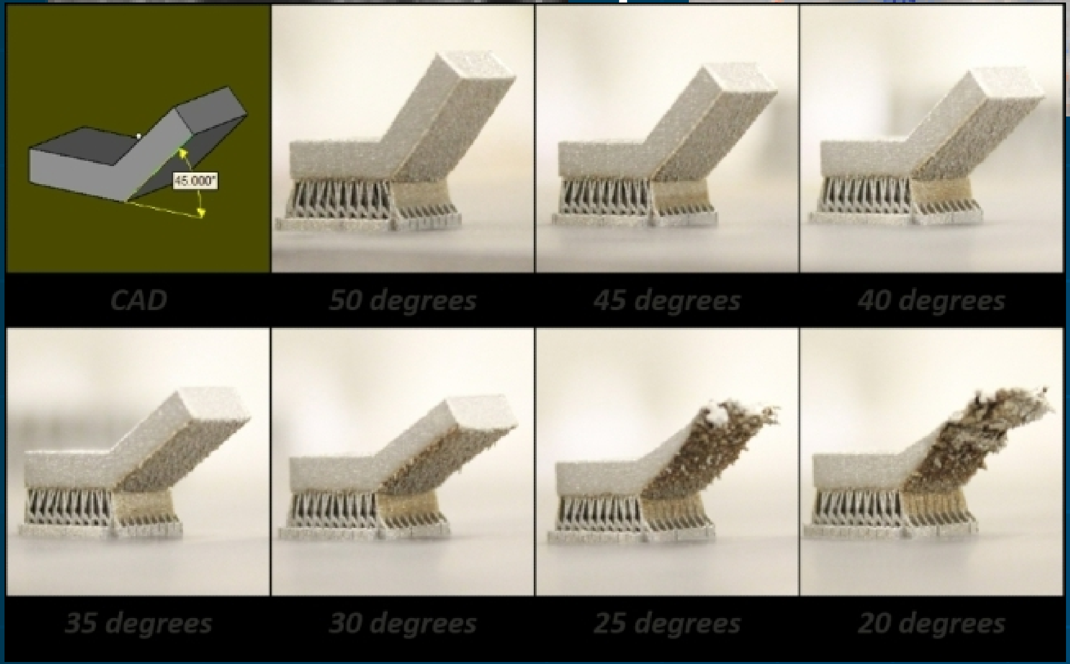
Interpretability

Original Image



Hidden Layers from Neural Network

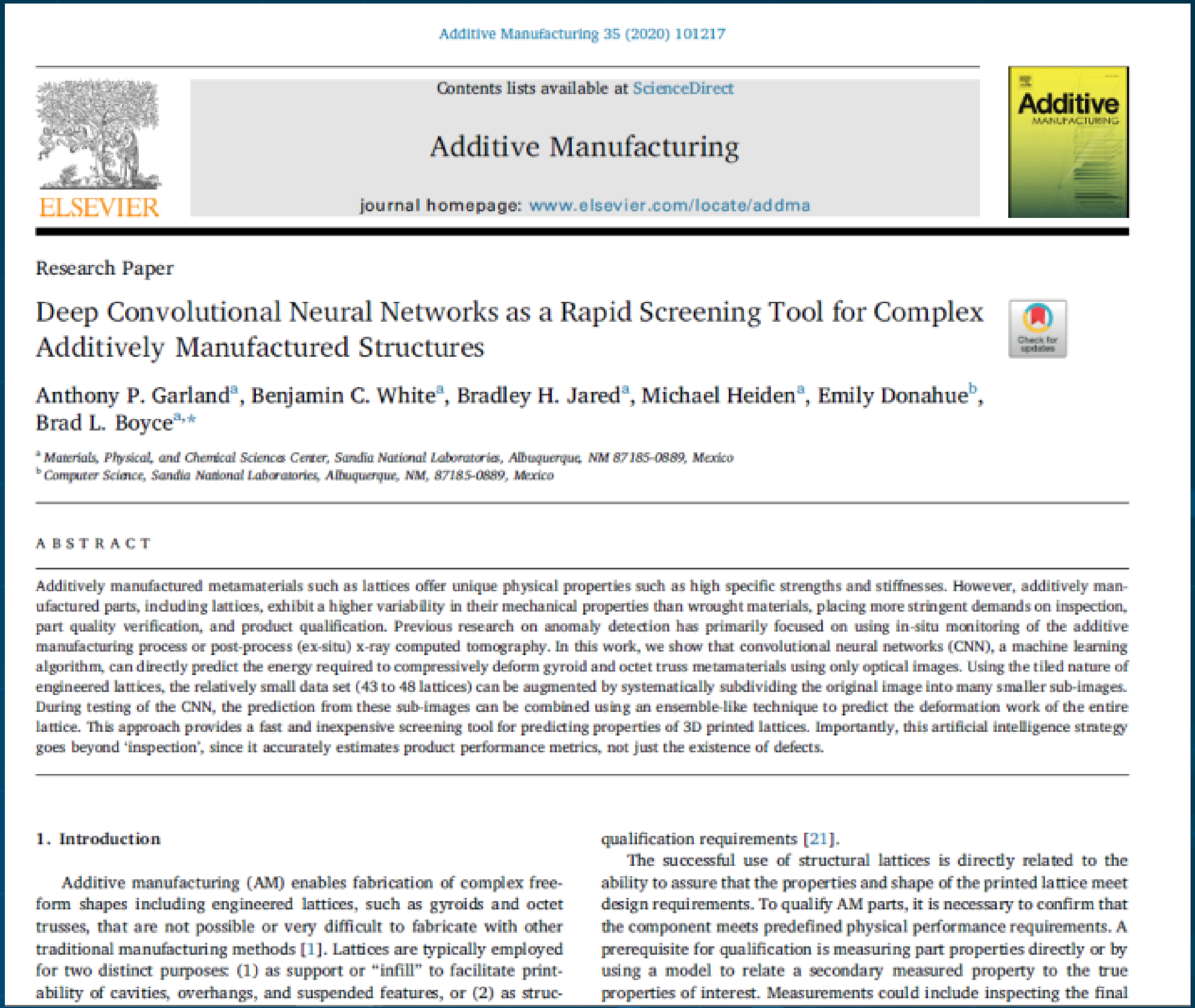




Downward-facing unsupported overhangs (courtesy: Protolabs)

More information

Email: blboyce@sandia.gov



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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

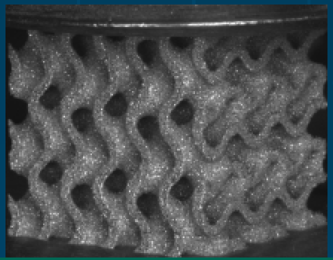
Additive manufacturing (AM) enables fabrication of complex free-form shapes including engineered lattices, such as gyroids and octet trusses, that are not possible or very difficult to fabricate with other traditional manufacturing methods [1]. Lattices are typically employed for two distinct purposes: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

Can such a tool inform topological design?

Qualification



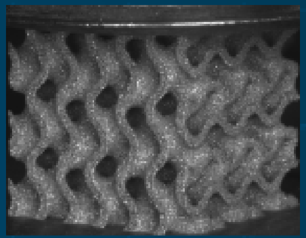
ML

Property

Design

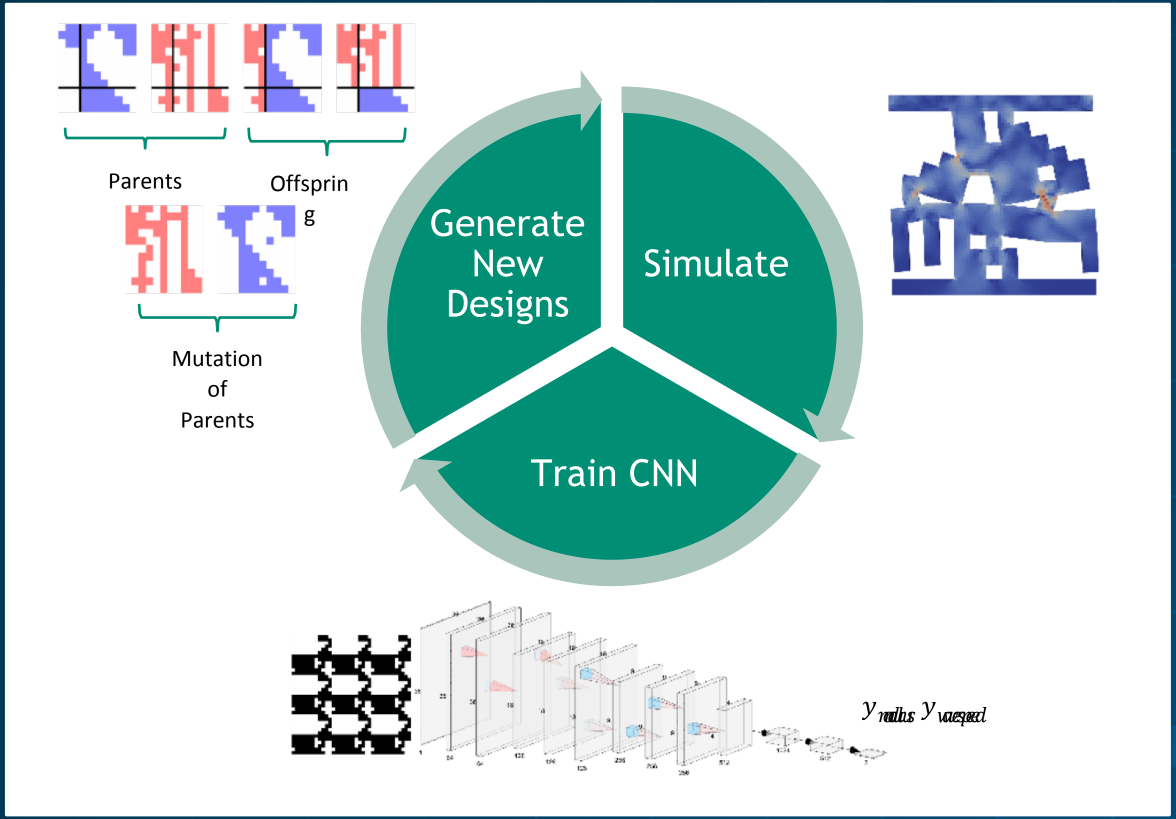
Target Property

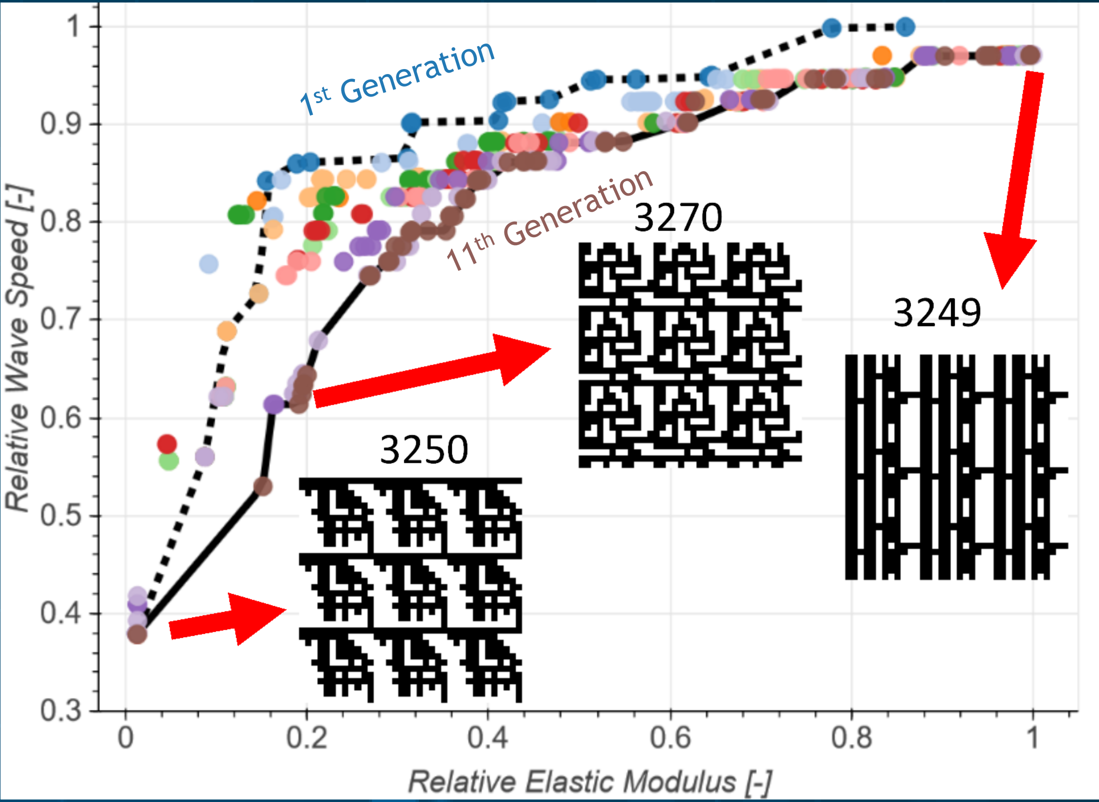
ML



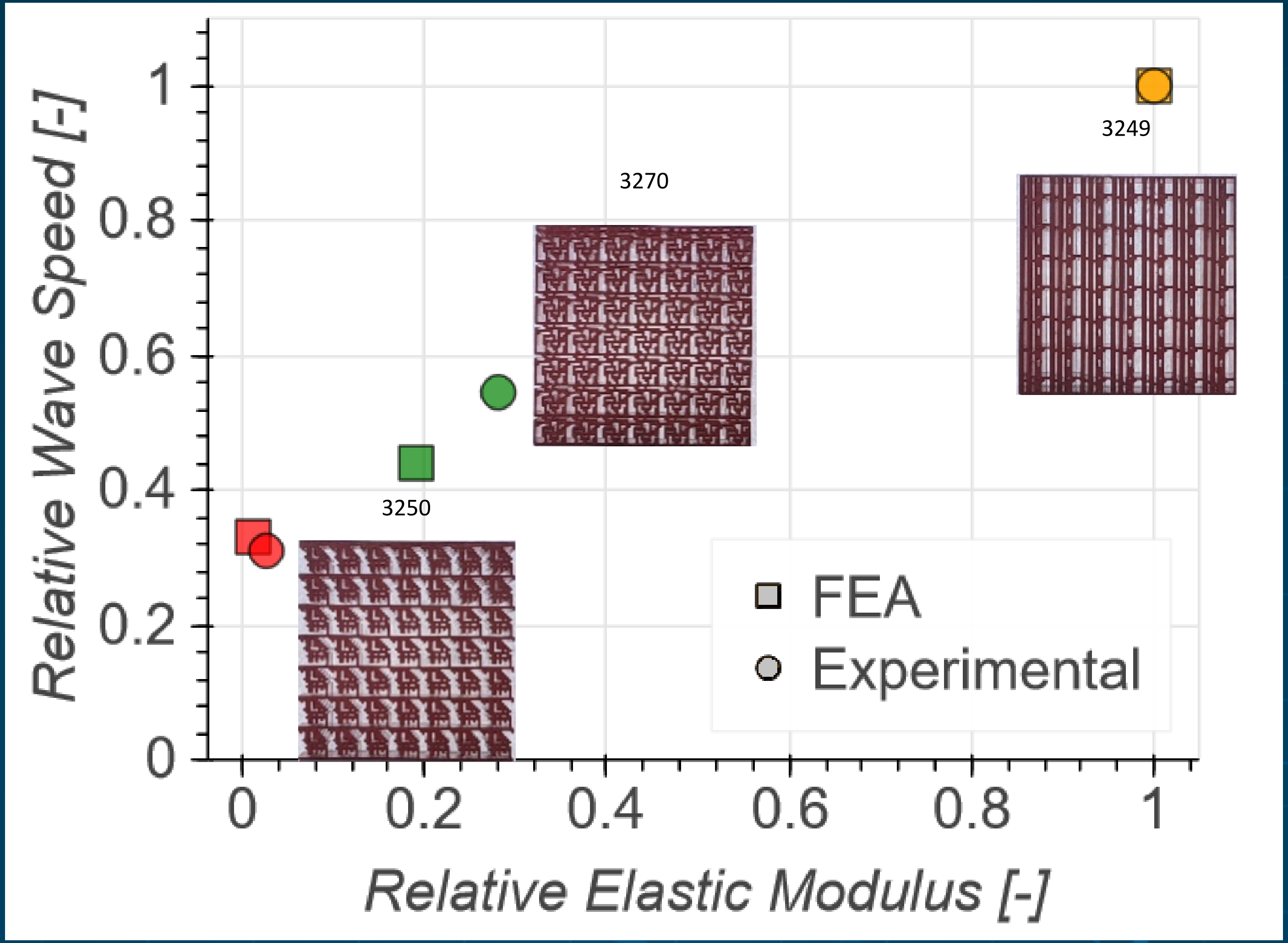
Active-learning based lattice design:
two objectives: stiffness and elastic wave delay

- Initial seed designs are randomly generated
- The initial designs are predicted by FEA (stiffness and effective wavespeed)
- The FEA results train a CNN, which is 6 orders faster than FEA
- The best solutions are hybridized by splicing two parents into offspring
- Offspring are screened based on the CNN





Experimental validation



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. While ML is accused of being a "black box", the ***causation*** may be partly explainable by analyzing the intermediate transfer functions (hidden layers).

4. Such approaches may serve as ***fast screening tool***, useful not only for product acceptance, but also for design.