CITRINE INFORMATICS

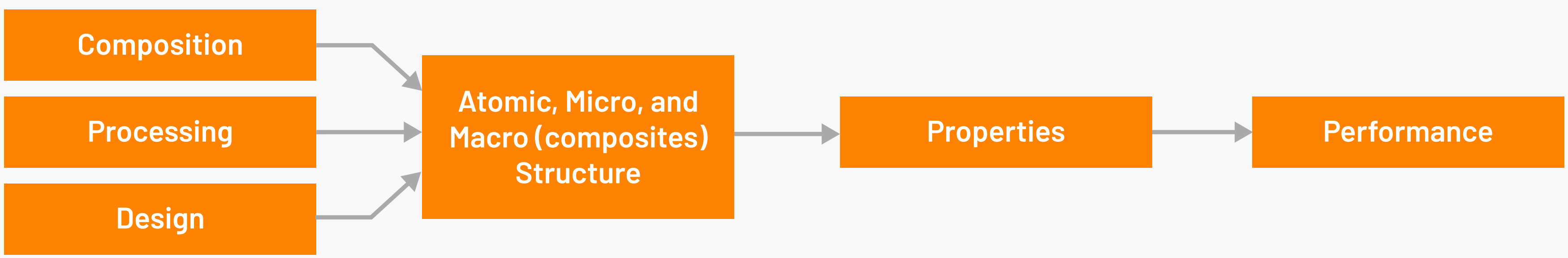
EBook

AI for AM

- Artificial Intelligence and the Future of Additive Manufacturing

AI for AM

Additive Manufacturing (AM), regardless of the material used, is inherently complex. The performance of the manufactured part depends on the properties of the material, the design of the part, the reliability of the processing equipment, the orientation of the print, and the process parameters used. The ability of processing equipment to reliably create consistent parts is improving but is not yet up to the same standards as older technologies. The thermal effects that occur when a part is built up layer by layer are also not sufficiently understood to reliably predict the final properties of a new component.



Additive Advantages and Difficulties

AM is able to produce unique, near-net-shape designs, without the need for bespoke tooling. It has been used in prototyping for decades.

Great strides have been made in the last decade, with new AM methods developed; AM equipment able to hit tighter process tolerances; better monitoring of processes and more data gathered; more design guidelines developed; and new AM-ready materials developed.

Fundamental challenges remain:

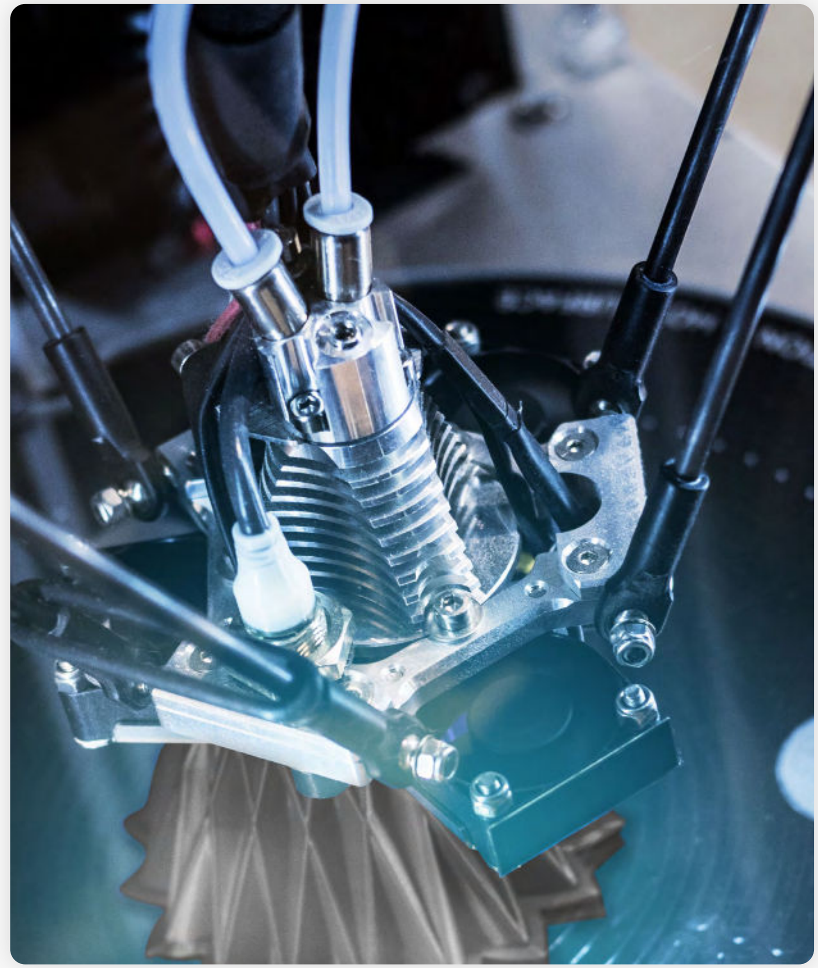
- Metal alloys that perform well in AM remain limited (some traditional aerospace alloys result in a flaky biscuit-like microstructure when used in powder form in AM).
- The mechanical properties of UV-curable thermoset polymer resins (used in DLP (Digital Light Processing) & SLA (Stereolithography)) tend to lag behind those of the thermoplastics used in FDM (Fused Deposition Modeling) and SLS (Selective Laser Sintering).
- Recyclability of materials in certain types of AM is limited without further research toward discovery/optimization of brand-new chemistries (e.g., photopolymers in DLP & SLA, also polymer-matrix composites).
- Part variability is still too high, both in terms of dimensional tolerance and material properties.
- A better understanding of the connections between composition, processing, geometry, and structure is needed.
- More reliable processing is still needed.
- Getting accurate property measurements of final parts (standardized tests are usually performed on samples of a standard shape and size, but measurements can have a large degree of variability from run to run).
- Formulating/synthesizing a new experimental recipe, followed by printing the part and measuring it, is a slow process, so iterative experimentation is slow.
- AM is being explored in aerospace and medical device applications but qualifying new materials in highly regulated industries is expensive.
- Lots of data can be generated from metrology of the build process, but using it to improve part performance (i.e., in situ build corrections) remains a challenge.

Artificial Intelligence Cuts Through Complexity

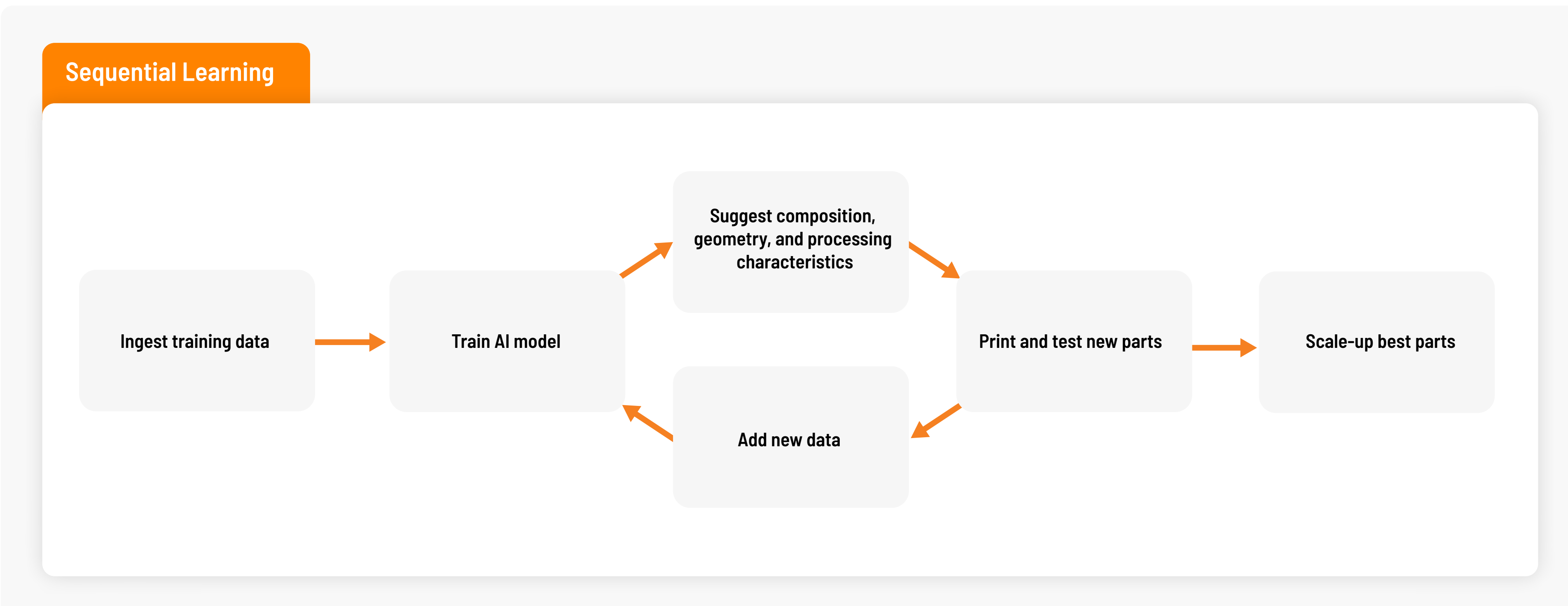
Artificial Intelligence (AI) is particularly useful on 1) challenges that are high-dimensional and produce lots of data, 2) areas where cause and effect are unknown and need to be worked out, and 3) projects with tight time and resource constraints.

1. **High dimensionality and large data sets**
   AI excels at evaluating high-dimensional problems, which leads to faster results with fewer experiments than traditional trial-and-error or Design of Experiment (DOE) approaches. This is especially important in AM, where composition, processing parameters, and part geometry all need to be optimized at the same time. AI can also rapidly evaluate time-series data from sensors. AM metrology produces more data than typical manufacturing methods, requiring AI to process it efficiently.

2. **Cause and effect not always known**
   There are still a lot of unknowns in AM. Each new material presents its own intricacies. AI takes an agnostic approach on which inputs affect the outcome. While a researcher using traditional methods would have to make a judgment call about which inputs are the most important to vary and experiment around, AI can systematically create models using all combinations of inputs and then use the model that has the lowest calculated uncertainty to predict the final properties.

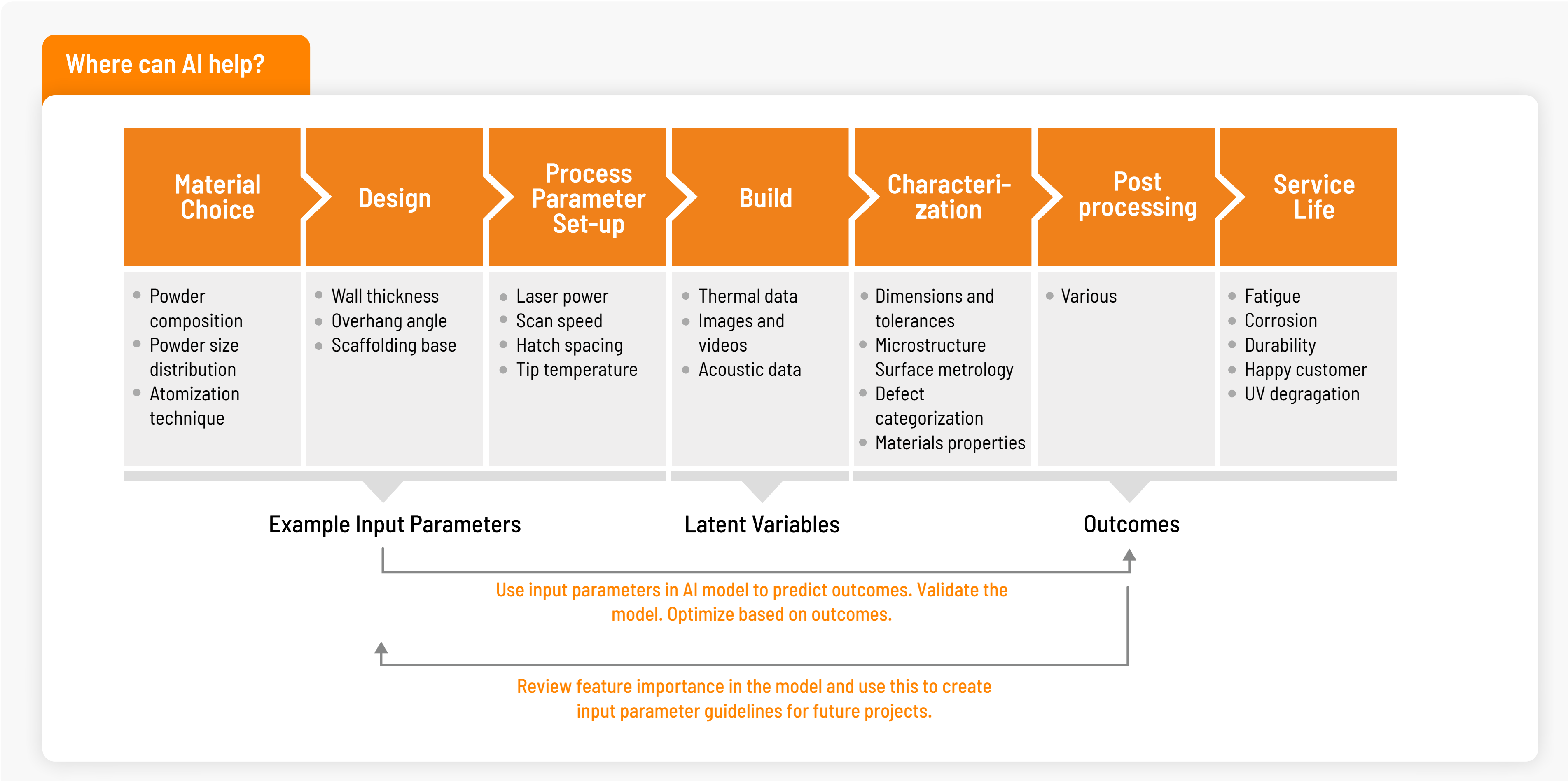


3. **Reduced time and resources**
   Using artificial intelligence as a co-pilot for AM allows product developers to both predict the properties of a final part and evaluate the uncertainty in each prediction. This means that resource-intensive physical testing can be concentrated on areas of promise OR areas of highest uncertainty. In contrast, traditional Design of Experiment methods treat all experiments in the matrix as equally valuable. Sequential Learning (SL) is an iterative process that exploits this extra information to efficiently explore a search space. The SL process consists of ingesting data, training an AI model, predicting properties, printing and testing a small group of high-potential candidates, feeding the data from the tests back into the platform, retraining and improving the AI model, and testing again until the required results are produced or no more improvement is seen. This process has been shown to reduce the number of experiments needed by 50–70% - a dramatic improvement in situations where customers have limited time or resources, or time-to-market is key to economic success. For polymer AM, specialty chemical companies may be asked to develop formulations that can hit customer target properties in very short timescales, making an AI workflow essential for agility. Often target properties (e.g., tensile strength and elongation at break) conflict with each other, making it hard for formulators to find formulations that satisfy multiple targets at once.



Where can AI help?

AM is a multi-step process, and AI can be helpful in fine-tuning many of these steps.



The three following case studies illustrate the use of AI and materials informatics in various stages. In the first, Citrine's customer designed novel materials specifically to take advantage of the AM process. In the second, Citrine worked with a team to optimize build parameters for a specific part geometry. In the third, Citrine was able to characterize the input to metal AM, metal powders.

3D PRINTABLE AEROSPACE-GRADE ALLOY DEVELOPMENT REDUCED FROM YEARS TO DAYS

The Challenge

HRL Laboratories, which carries out research for Boeing and GM, wanted to develop an aerospace-grade aluminum powder that would make strong parts when 3D printed. (Traditional aluminum alloys when turned into powder and 3D printed are brittle, as the microstructure produced is similar to a flaky biscuit.)

The Methodology

HRL wanted to find nanoparticles that would nucleate a microstructure less prone to hot cracking, a phenomenon where cracks form during the solidification of 3D-printed metal. Citrine combined classical nucleation theory, rules on lattice spacing, thermodynamic stability, density, and materials informatics, to rapidly search through 11.5 million combinations of powders and nanoparticles.

The Impact

Citrine identified 100 candidate combinations of powder and nanoparticles that optimized the desired properties for the HRL team to test. The resulting material AL 7A77 is the first high-strength Aluminum Alloy powder feedstock for off-the-shelf AM machines that is registered with the Aluminum Association. The first commercial customer for this new product is NASA Marshall Space Flight Center.

Aluminum 7A77.60L powder from HRL. Copyright 2021 HRL Laboratories, LLC.

More details on this project can be found in this research paper in Nature.

DATA-DRIVEN OPTIMIZATION OF DESIGN IN ADDITIVE MANUFACTURING

The Challenge

The Alliance for the Development of Additive Processing Technologies (ADAPT) and its partners used Citrine's technology to create a new, additively manufactured door hinge for MRAP light tactical vehicles. The hinges of the heavy, armored doors were failing in service, endangering the vehicles crew and causing vehicles to be out of service for up to 2 years. The project was to design a hinge that could be 3D printed and therefore available in much shorter lead times.

The Methodology

Using Citrine technology and pre-existing data from other ADAPT projects, the team predicted the fatigue performance of an AM manufactured direct replacement. The model achieved an 84% prediction accuracy of build parameters on the first print, produced using a completely new materials/printer combination. This first build allowed the team to move their focus on to how to create a lighter, stronger hinge. The AI model predicting build parameters was used in an iterative Sequential Learning loop, as described above.

The Impact

The data-driven, ML-guided methodology that the ADAPT researchers applied to the redesign of the MRAP hinge reduced development time and resources normally consumed during the standard trial-and-error process parameter tuning approach. Key design and performance improvements from the original OEM hinge include:

- Single-piece design vs. six pieces for the OEM part
- Significant increase in strength to avoid the breakage the OEM hinges were suffering
- Part design that can be printed on demand, requiring no inventory
- Faster part fabrication and delivery – the redesigned hinge can be printed in 24 hours and finished and delivered in days – not weeks, months, or years

A set of MRAP hinges built using ADAPT's Optimize for AdditiveSM strategy were ready for ground vehicle testing by the Army in mid-2019.

POWDER SIZE DISTRIBUTION

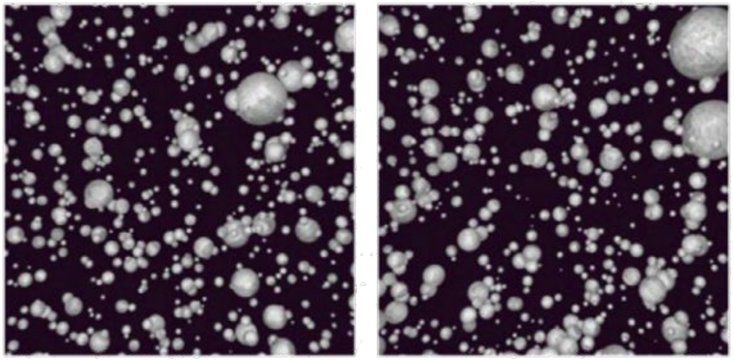
The Challenge

Metal powder particle size and size distribution has a significant effect on the final properties of AM parts. It is therefore important to be able to quickly measure this, so that it can be a known input to the process. Citrine's researchers partnered with Brian DeCost and Elizabeth Holm at Carnegie Mellon University to use SEM image data to predict powder particle size and distribution.

The Methodology

The team used a data set of 2,048 images of synthetic SEMs of powder materials relevant to additive manufacturing applications. There were 8 different particle size distributions, with 256 images representing each distribution. On simple visual inspection it was very difficult to discern or quantify differences. A random forest classifier was trained to classify the 8 different distributions based on the SEM images.

A 3-step process was used to classify the powder images into 8 different size and size distribution classes; (a) the images were processed using a convolutional neural network (CNN)[1] , the network was used to convert the raw pixel data into a tensor format that contained information about what patterns were present in the image, (b) texture featurization methods were used to identify distinguishing features, classify and count them, and (c) lastly, a random forest classifier used the featurization data to classify the images into different sets depending on particle distribution and size.

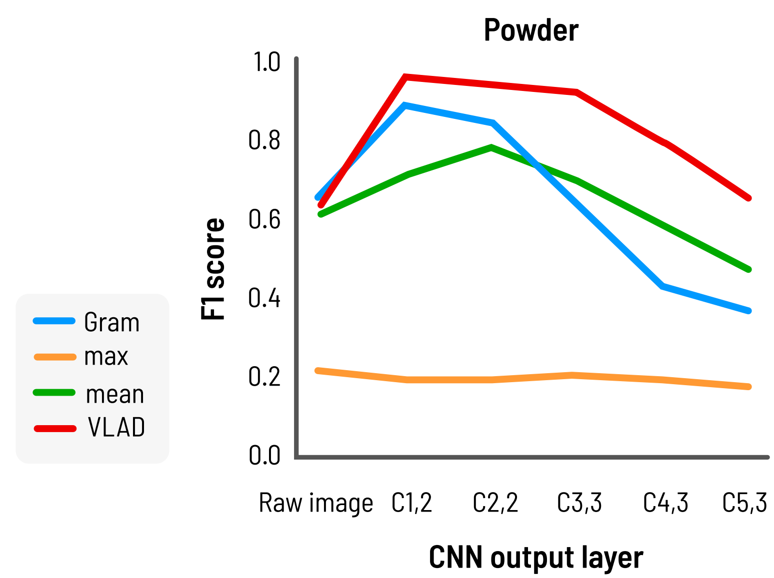


a. Distribution 1 b. Distribution 2

[1]Technology not currently native on the Citrine Platform.

POWDER SIZE DISTRIBUTION (cont.)

The CNN consist of stacks of layers that apply 2D convolutional filters to the image to detect the presence or absence of various patterns. Different layers are better at spotting different patterns than others. In this case, 5 different layers were compared. Four different texture featurization methods were also compared (represented by different colors in the plot here). The F1 score is a measure of the accuracy of the model. It has a value of 1.0 for a perfect classifier and 0.0 for a classifier that is always wrong.



The Impact

The high F1 value for the VLAD featurization method using the middle layers of the CNN shows that the model could be used to determine powder particle distribution size from SEM images. As this information is an important input to additive manufacturing projects and significant variation is seen in powder supplies, having a quick and accurate method to determine this is very useful.

SUMMARY

Additive Manufacturing (AM) has a large number of dimensions that need to be optimized simultaneously. Although large data sets are now being collected, the correlation between part design, process parameters, composition, post-processing, and the resulting part properties are not yet well enough understood. AI can cut through that complexity and help researchers to optimize particular parts and develop design guidelines for the future. Citrine Informatics has significant experience on projects involving the design of additive manufacturing materials, additive manufacturing design optimization, and the characterization of AM metal powders. Contact us to discuss how the Citrine Platform can be used to support your AM projects.

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Citrine Informatics Inc.
2629 Broadway St
Redwood City, CA 94063

citrine.io
info@citrine.io