Pixilation and uncertainty in Dynamic Image Analysis (DIA) of powders for Additive Manufacturing (AM)

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Goal – advance capability for powder size and shape characterization.

1) Effect of DIA pixel-scale resolution;
2) Apply to AM powder processes.

Approach – use Machine Leaning (ML) for low resolution perimeter measurement.

1) Experimental data for a variety of metal AM powders obtained using DIA.*
2) High resolution particle images are used as reference data.
3) Train models using coarsened images: A) Regression; B) ML image reconstruction.

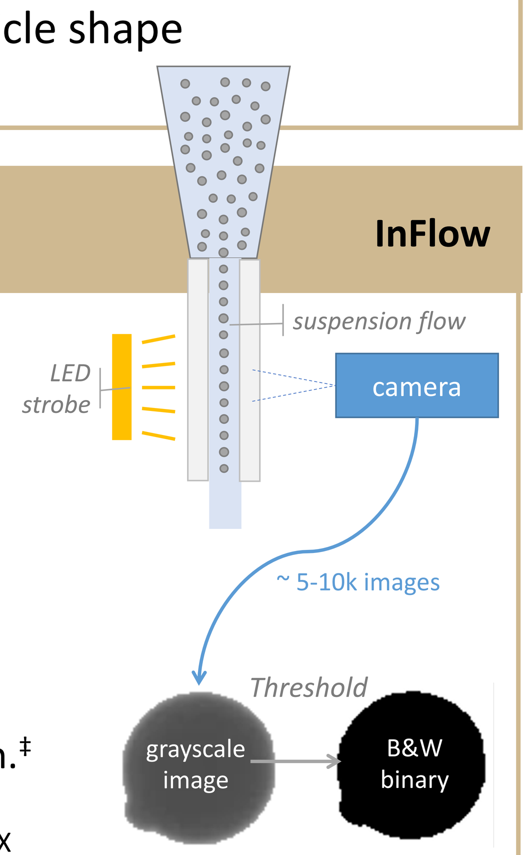
Background and Motivation

Purdue MSE has active research using multiple types of AM equipment, including powder-bed fusion (PBF) and directed energy deposition (DED) We are working on methods and standards to enable and improve characterization of AM powders, and link same to AM process and product quality optimization.

Purdue's Center for Particulate Processes (CP3) includes capability for both distributed (i.e., size, shape) and ensemble (i.e., flow) characteristics.

This poster focuses on particle shape characterization.

Experimental DIA



AM metal powder samples are pre-wet with isopropanol and suspended in aqueous HPC (~300 cP). The InFlow* has a dilution system to control flow through analysis cell.

Pixel resolution is 0.344 um.

Raw data are accessible for detailed analysis using NI Vision.‡

*InFlow, JM Canty, Buffalo, NY
‡ LabView NI Vision, National Inst., Austin, TX

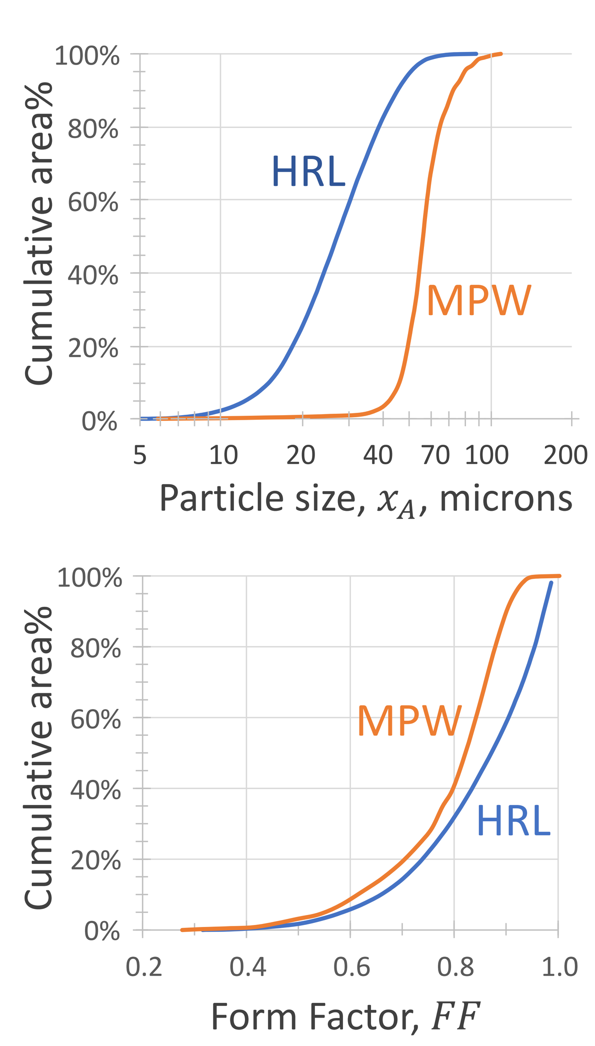
AM powder samples

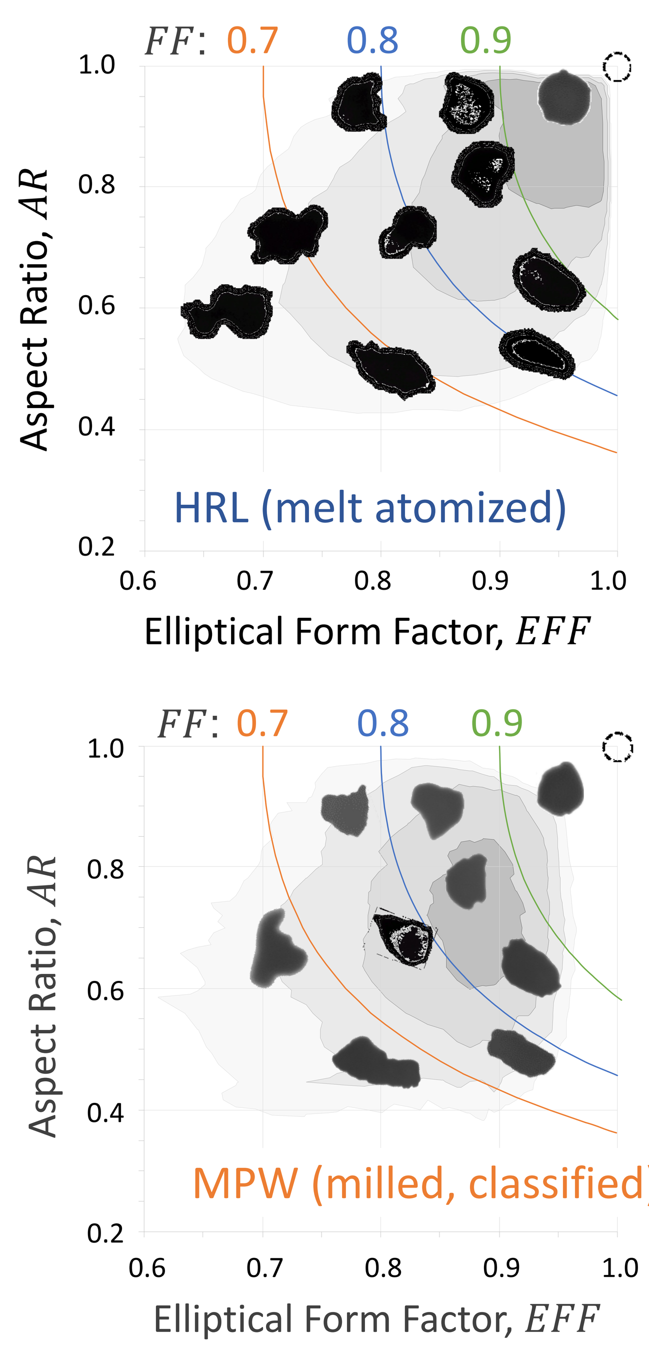
Comparison of two powdered aluminum samples:*

HRL) Melt-atomized
MPW) Milled and classified

Size and shape distributions obtained using the InFlow :

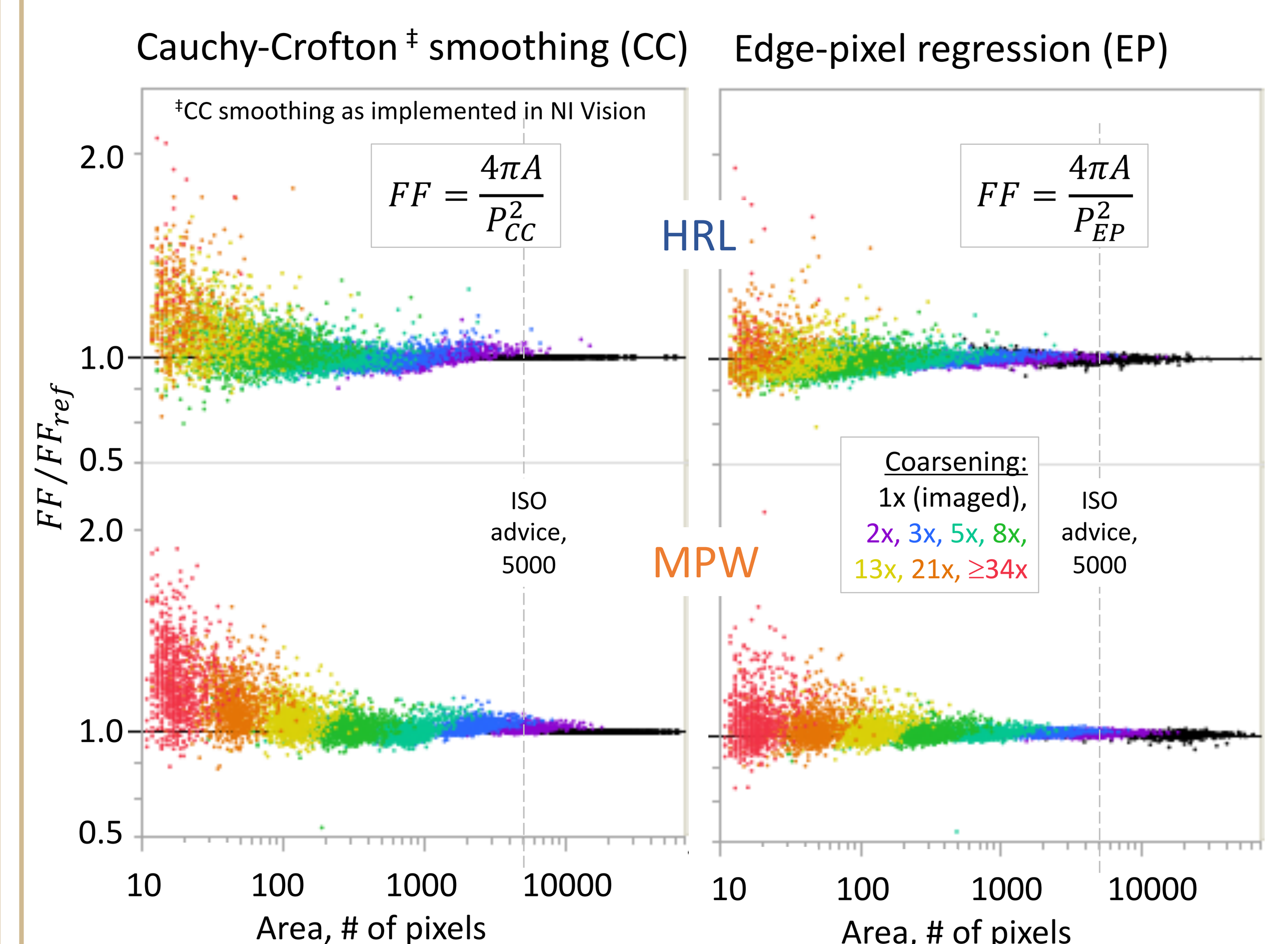
*Barnes Group, Inc., Bristol, CT.





A) Regression model:

Perimeter and Form Factor

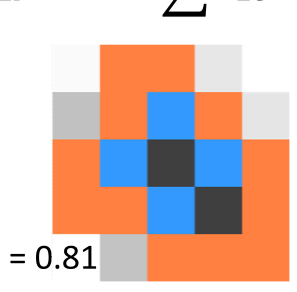


Results, combined data:

Coarsening	$<A>$ pixels	FF/FF_{ref} CC	FF/FF_{ref} EP	RSD CC	RSD EP
1	12611	1.00	1.00	0.00%	0.93%
2	3153	1.00	1.00	2.00%	1.03%
3	1399	1.01	1.01	2.58%	1.27%
5	504	1.00	1.00	3.87%	2.49%
8	199	1.02	1.00	5.64%	3.58%
13	83	1.07	1.01	8.07%	4.90%
21	41	1.13	1.04	10.1%	6.55%
>=34	19	1.21	1.06	13.3%	12.5%

EP perimeter

$$P_{EP} = 5.9 + \sum N_{EC} \cdot \alpha$$



FF = 0.81

EC	α	N
E0C1	1.258	4
E1C0	-0.83	0
E1C1	0.62	2
E1C2	0.98	2
E2C1	0.16	1
E2C2	0.31	4
E2C3	0.38	3
E3C2	-0.64	0
E3C3	-0.39	0
E3C4	-0.22	0

Particle Shape, Standard Features

ISO-9276-6 describes several shape factors derived from 2D image analysis of particle projections; these can be grouped as: 1) length dependent, e.g., Aspect Ratio, AR; and 2) area/perimeter dependent, e.g., Form Factor, FF.

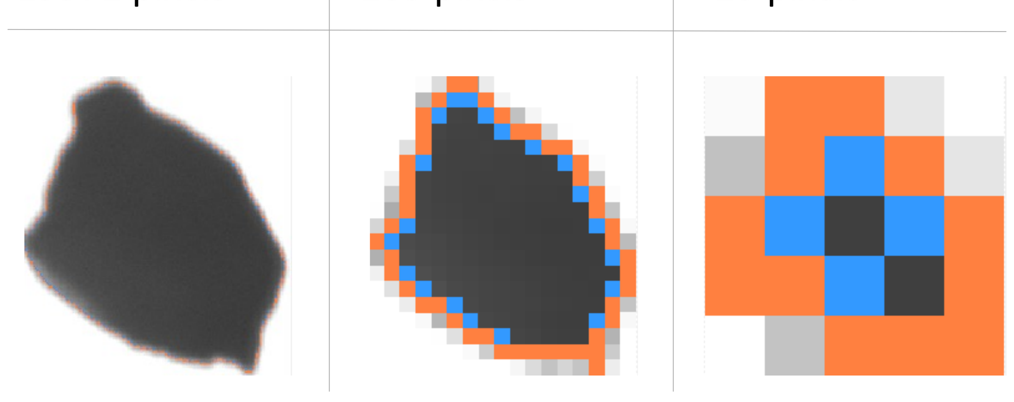
The Form Factor includes combined effects of elongation and perimeter irregularity. Elliptical Form Factor, EFF, is sensitive to perimeter features and is orthogonal to the aspect ratio.

- $AR = x_{Fmin}/x_{Fmax}$;
- $FF = 4\pi A/P^2$;
- $EFF = \beta\pi A/P^2, \beta = \left(1.5 \cdot (1 + AR)/\sqrt{AR} - 1\right)^2$;

where x_F is Feret length, A is area, and P is perimeter.

For perimeter-based shape factors, ISO recommends using a Cauchy-Crofton method of pixel smoothing with at least 5000 pixels/particle. We focus on achieving useful shape distribution analyses at lower pixel resolution.

As imaged: 19972 pixels	10x coarsening: 205 pixels	34x coarsening: 23 pixels



A = 2363 (0.11%), μm²	A = 2428 (1.31%), μm²	A = 3174 (7.3%), μm²
P = 189 (0.21%), μm	P = 196 (2.23%), μm	P = 211 (6.3%), μm
FF = 0.83 (0.37%)	FF = 0.79 (4.08%)	FF = 0.90 (11.3%)

Measurement uncertainty (RSD%) evaluated using image rotation

Perimeter pixel codes:
- Inside corner pixel: E0C1
- Edge pixels: E1C0, E1C1, E1C2, E2C1, E2C2, E2C3, E3C2, E3C3, E3C4

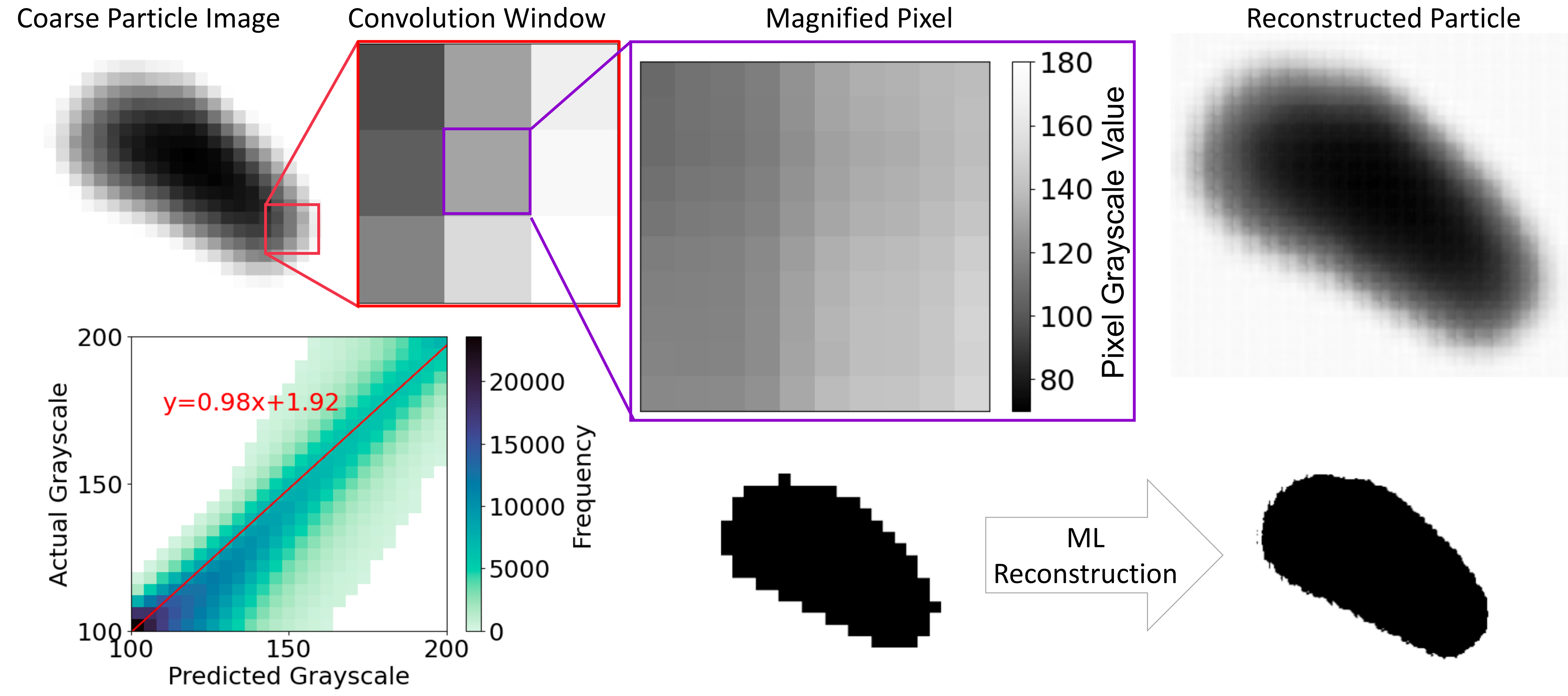
Form Factor has a logical range, $FF \in (0,1]$, and is sensitive to the effects of pixilation on perimeter measurement. Illogical values, $FF > 1$, can occur with standard methods of perimeter smoothing, especially at low pixel resolution.

ISO-9276-6, Representation of results of particle size analysis - part 6: Descriptive and quantitative representation of particle shape and morphology, in: Technical Committee ISO/TC 24, International Org for Standardization, 2008.

B) Machine Learning – discrete particle image reconstruction

High-resolution In-Flow images were used as training data for a **deconvolutional neural network**, used to enhance coarser images from a lower resolution imaging system, e.g., JM Canty SolidSizer. Enhanced images meet ISO guidance for perimeter measurements.

1. Obtain high resolution images.
2. Pad images and coarse-grain to target [low] resolution.
3. Extract 3 x 3 patches from coarse images (**Convolution Window/Training Input**)
4. Extract 100 x 100 patches corresponding to the center pixel of each Convolution Window from high-res images (**Magnified Pixel/Training Target**)
5. Reconstruct coarsened images; validate size and shape characteristics.



Conclusion

ISO guidance for high resolution (>5000 pixels) provides for robust perimeter measures using Cauchy-Crofton (CC) smoothing. At lower resolution, CC smoothing underestimates perimeter, resulting in an upward skew in the Form Factor.

- For shape-factor distributions, resolution can be relaxed significantly (i.e., >100 pixels) using Edge-Pixel Regression for perimeter calculation.
- Alternatively, low-resolution images can by enhanced using a Deconvolutional Neural Net to increase their pixel count for smoothing.

✓ Improves shape assessment over broader size distributions (i.e., range in resolution).

✓ Enable process monitoring and control applications requiring accurate shape distributions.