



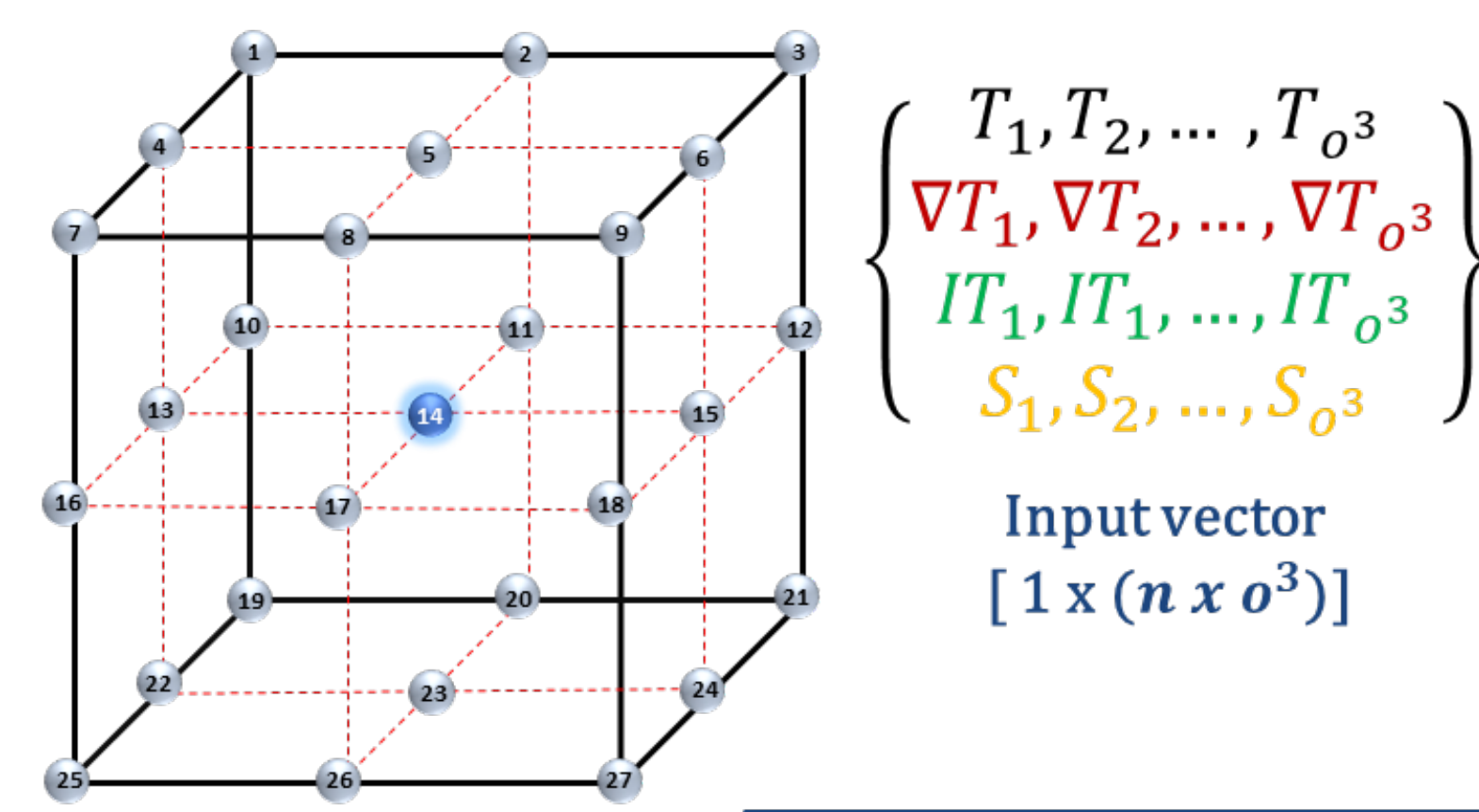
### Overview

**Objective:** Develop a deep learning scheme for detecting defects in the LPBF process.

**Target:** Prediction of defects using thermal signatures and spatter counts obtained through cost-effective equipment.

**Purpose:** Enable in-situ defect prediction during manufacturing and repair of defects via rescanning. Additionally, investigate defect formation mechanisms through feature importance analysis.

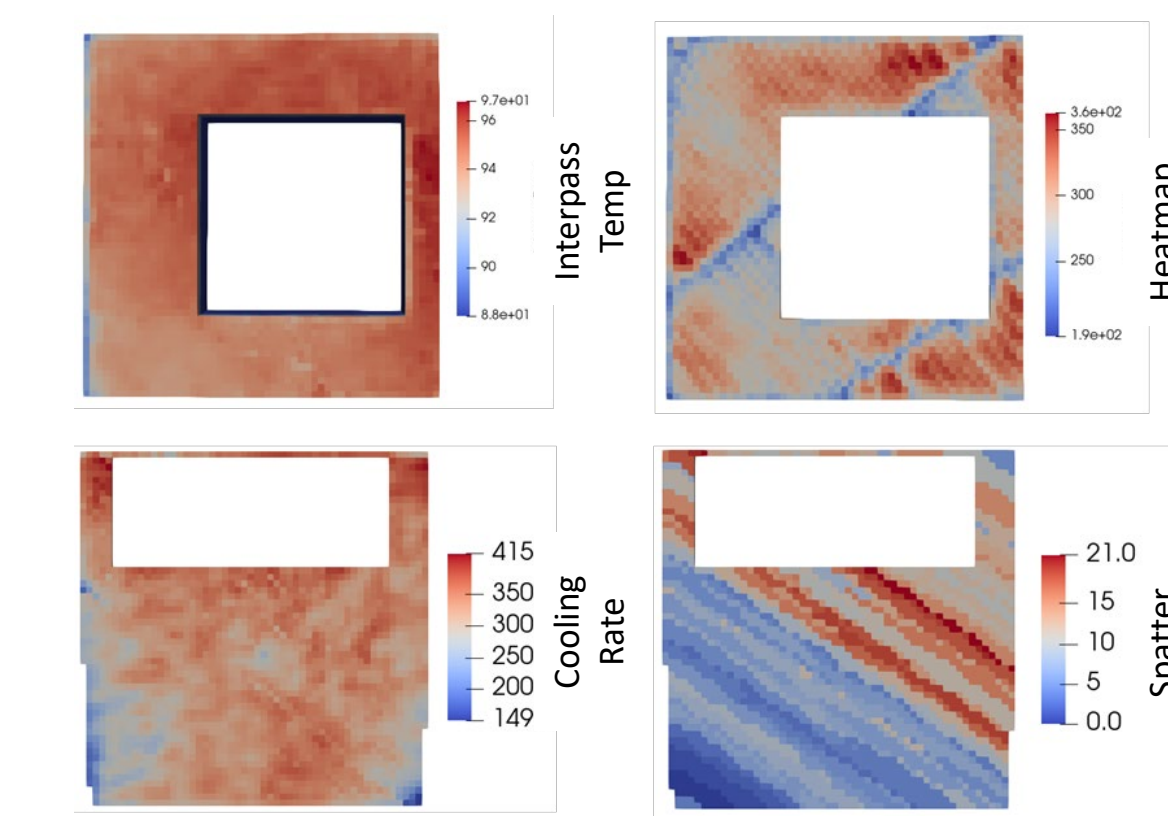
### In-Situ Defect Detection Using IR Imaging and Machine Learning



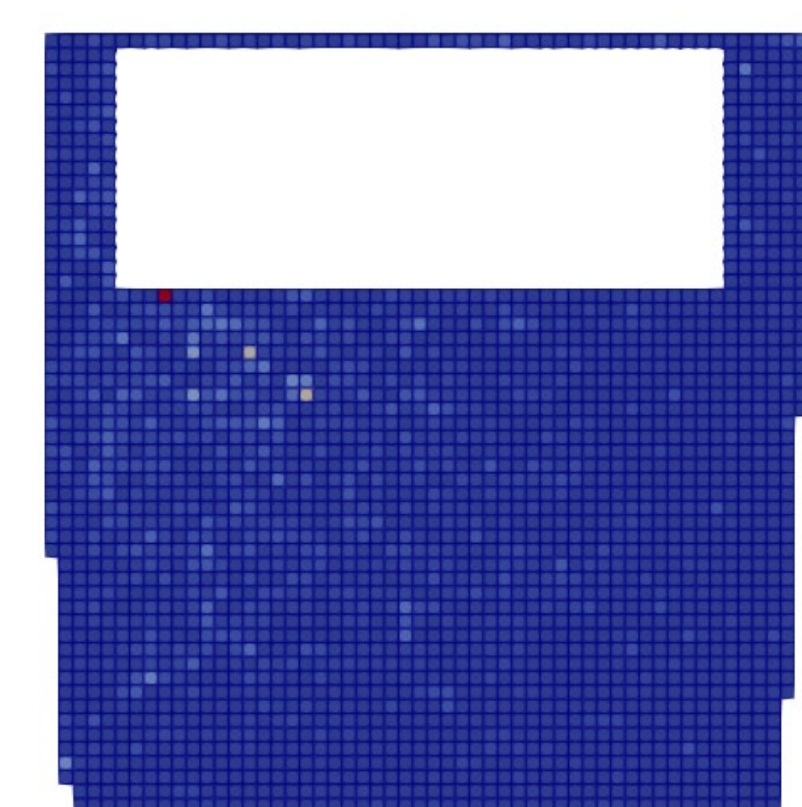
- $T$  : Heatmap value
- $\nabla T$  : Cooling rate
- $IT$  : Interpass temperature
- $S$  : Spatter count
- $o$  : Neighbor order
- $n$  : Number of main features

{Porosity %}  
[1 x 1]

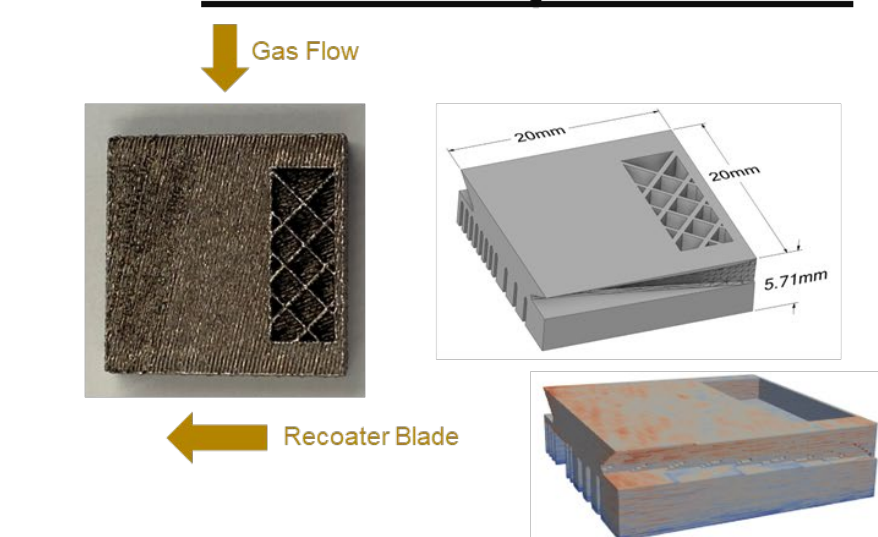
#### Inputs (12 Images in Total)



#### Output



#### The Complex Part

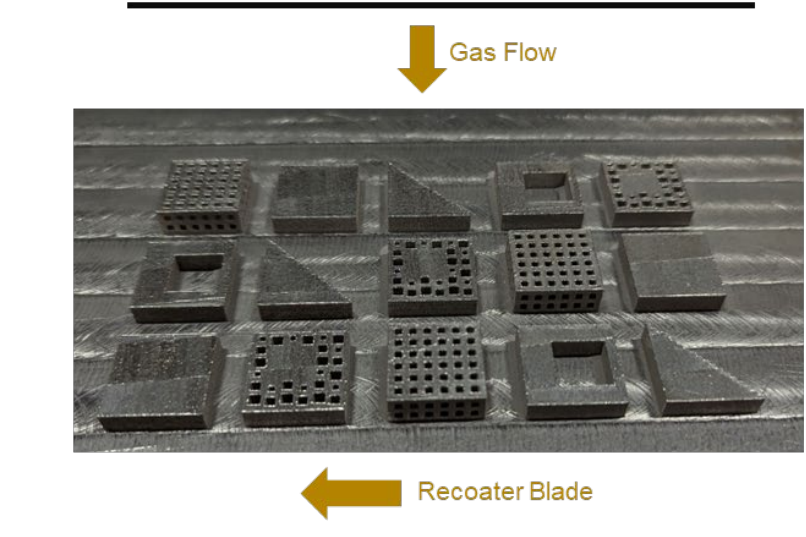


**Parameters**

- $P = 350$  W
- $V = 1000$  mm/s
- Hatch distance = 0.168 mm
- Layer thickness = 0.08 mm
- Rotation = 67°
- No stripes

**LOF REGIME**

#### The Other Blocks



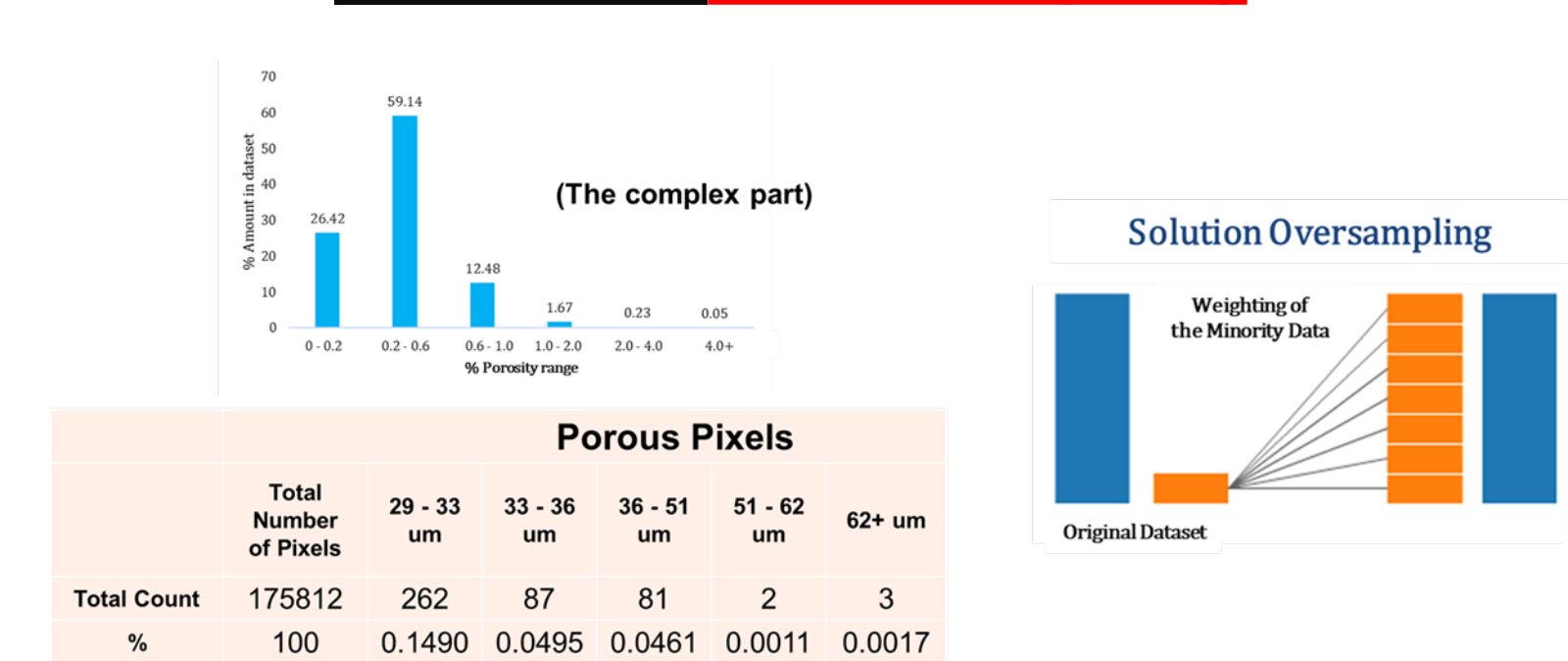
**Standard EOS Parameters**

- $P = 285$  W
- $V = 960$  mm/s
- Hatch distance = 0.11 mm
- Layer thickness = 0.04 mm
- Rotation = 67°
- 5 mm stripes

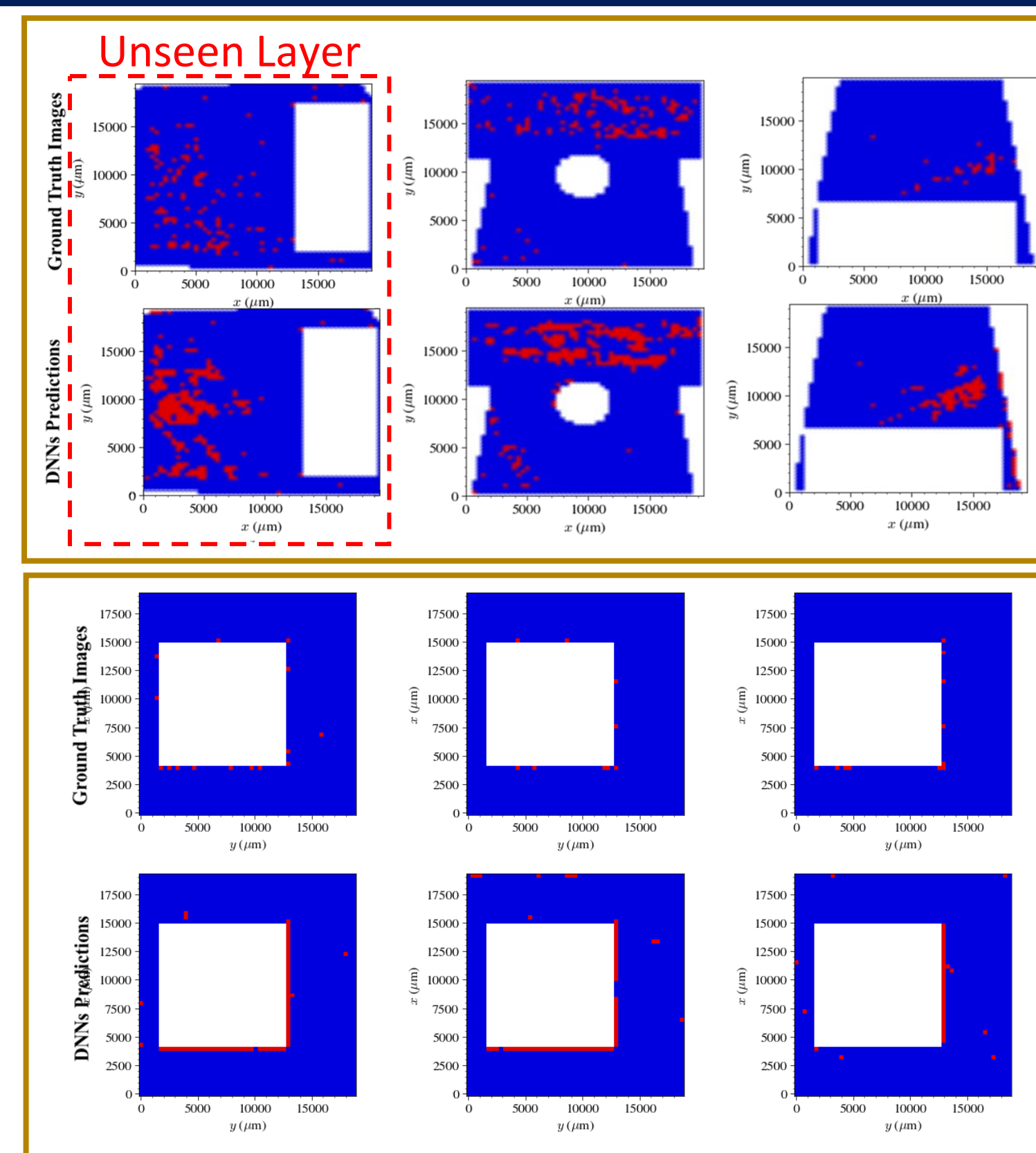
**STANDARD REGIME**

#### Highly Unbalanced Dataset Problem

**Solution: Oversampling**

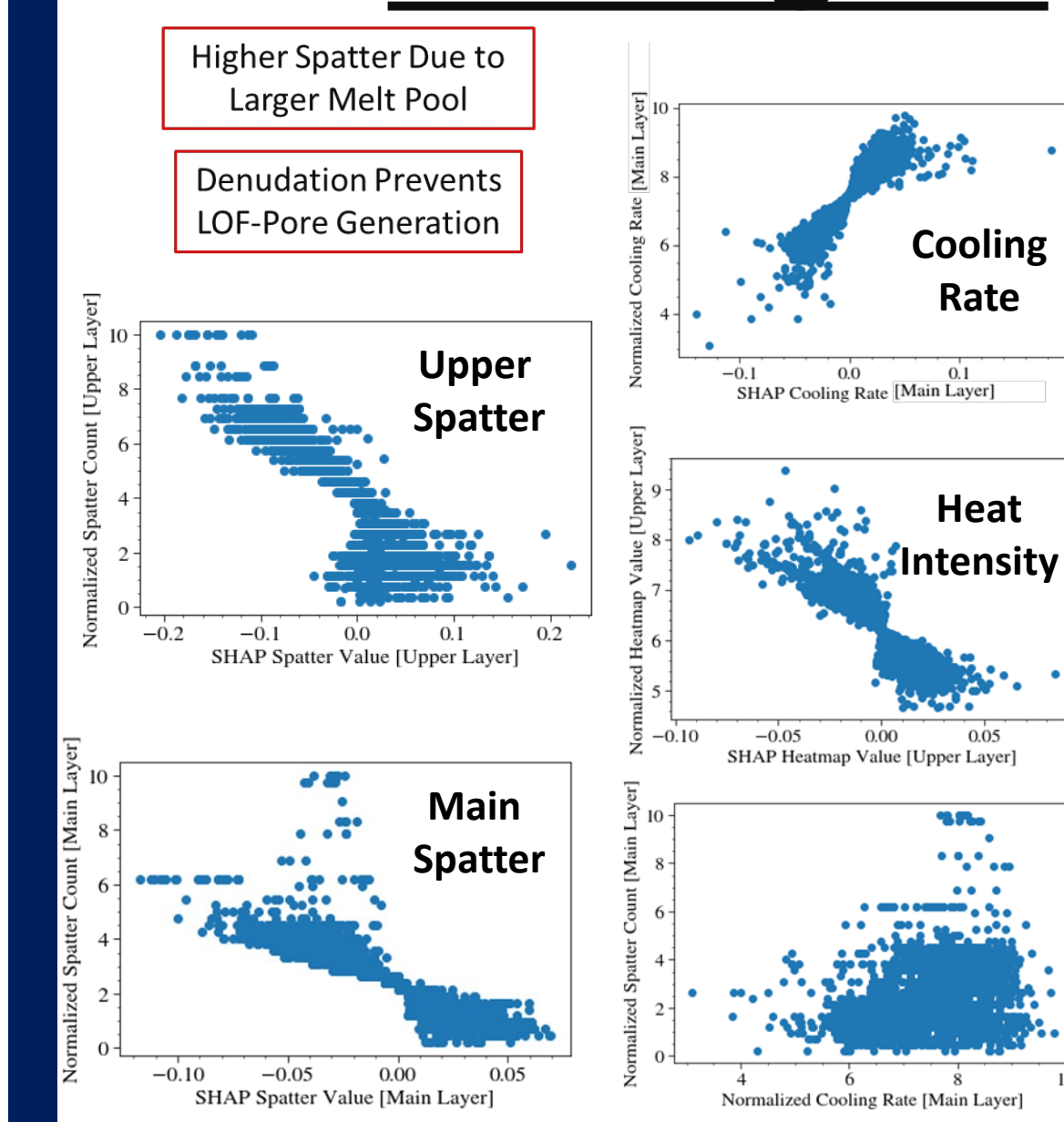


### +95% True Positive Ratio on Test Set

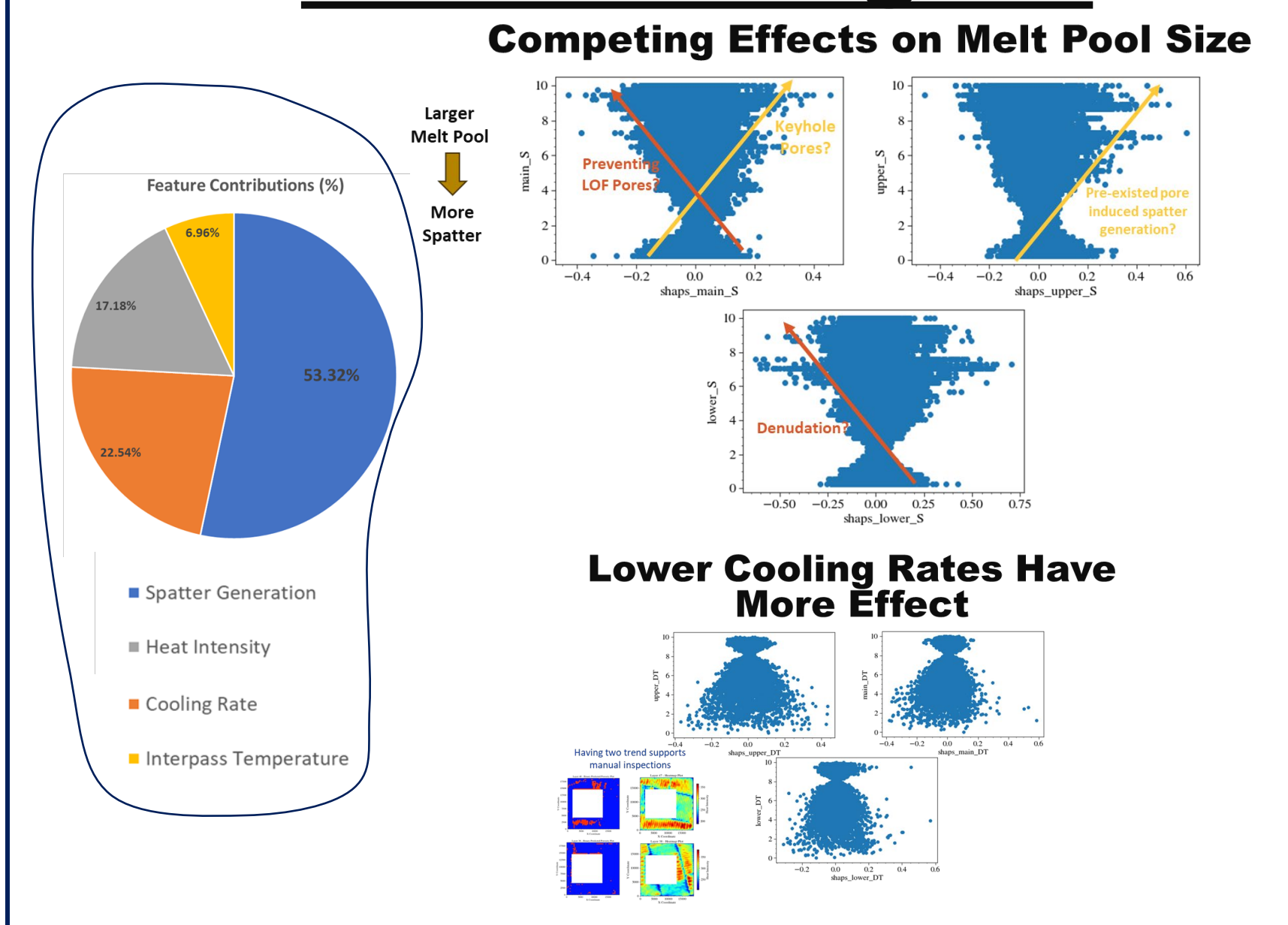


### Feature Importance Analysis

#### LOF Regime



#### Standard Regime



### Conclusions

- 95% of total pores could be predicted both in LOF and standard regime in the test set.
- The most crucial feature for porosity prediction is the spatter generation in both standard and LOF regimes.
  - Competing effects in standard regime
  - Denudation and larger melt pool prevents pore generation in LOF regime
- The cooling rate is the second most dominant feature.
  - While lower cooling rates fix the LOF pores, sometimes they may cause keyhole pore generation.