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UNSUPERVISED PROMPTABLE DEFECT SEGMENTATION IN LASER ADDITIVE MANUFACTURING

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INTRODUCTION

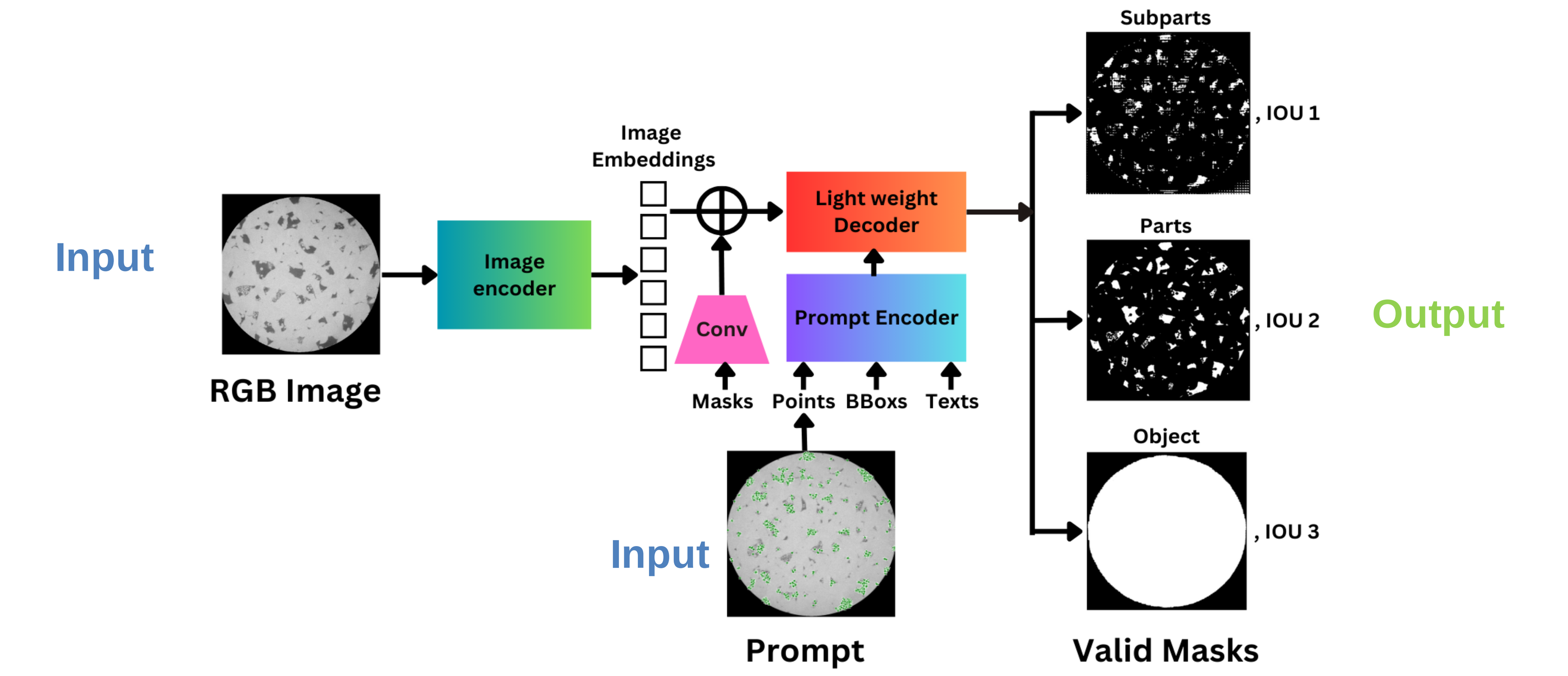
- **Porosity,** a common defect in Laser Additive Manufacturing (LAM), affects the mechanical properties like tensile strength, stiffness, and hardness compromising the final print quality.
- It is tenuous to identify and measure inter-layer porosity from **X-ray Computed Tomography (XCT) data [1]** manually.
- **Image-based Defect Segmentation** is crucial to detect pores in LAM printed parts.

MOTIVATION

- To deal with the lack of labels of LAM data in real-life scenarios.
- To reduce the overhead of supervised model fine-tuning.

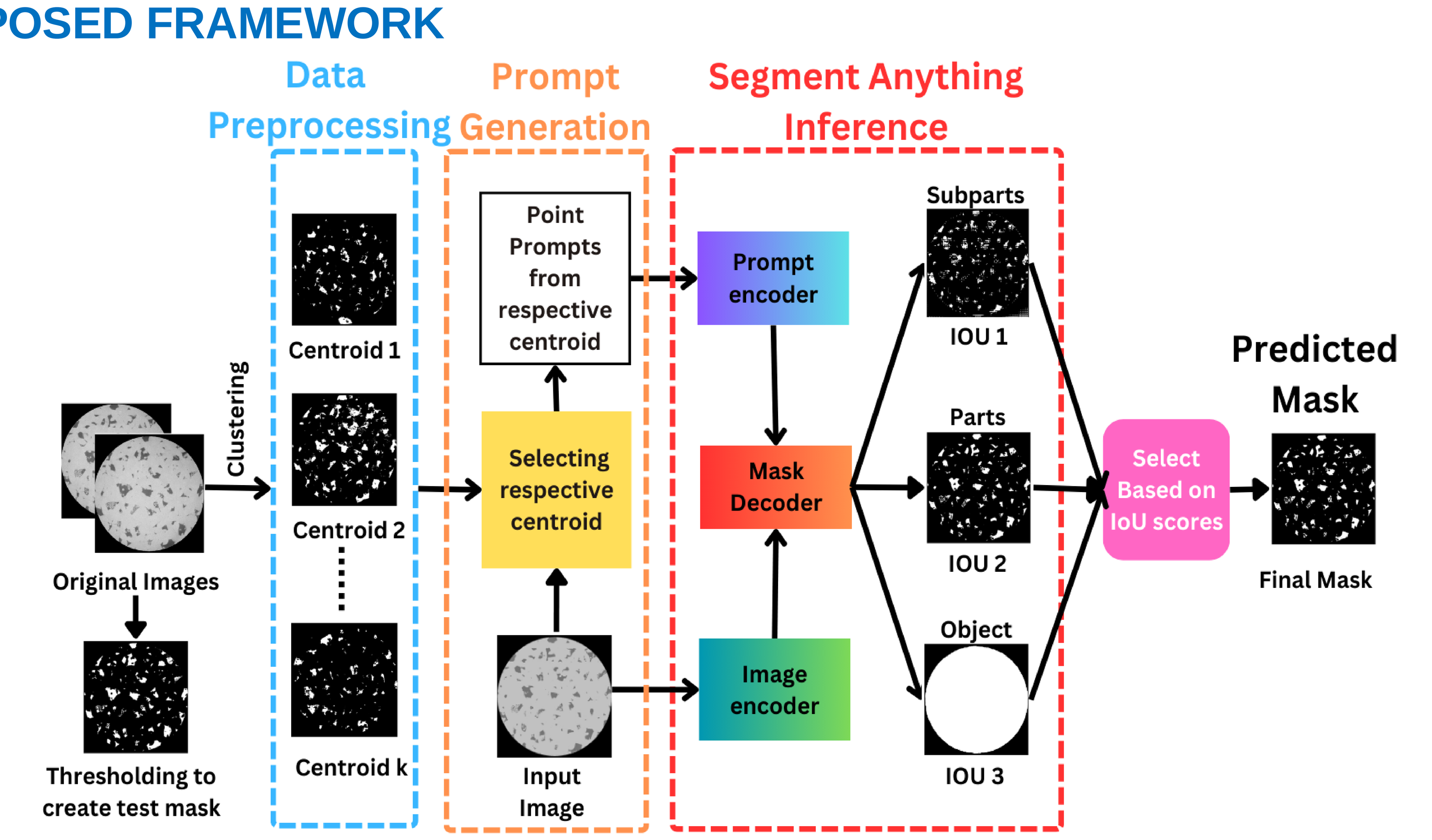
To address these challenges, we propose a novel framework with Vision Transformer-based Foundation models like Segment Anything Model (SAM) [2].

SEGMENT ANYTHING MODEL (SAM) ARCHITECTURE



SAM's architecture consists of-
- **An Image Encoder**: Takes RGB images as input.
- **A Prompt Encoder:** Takes both Sparse and Dense Prompts as input.
- **A Mask Decoder:** Returns single or multi-masks output and a predicted IoU score.

PROPOSED FRAMEWORK



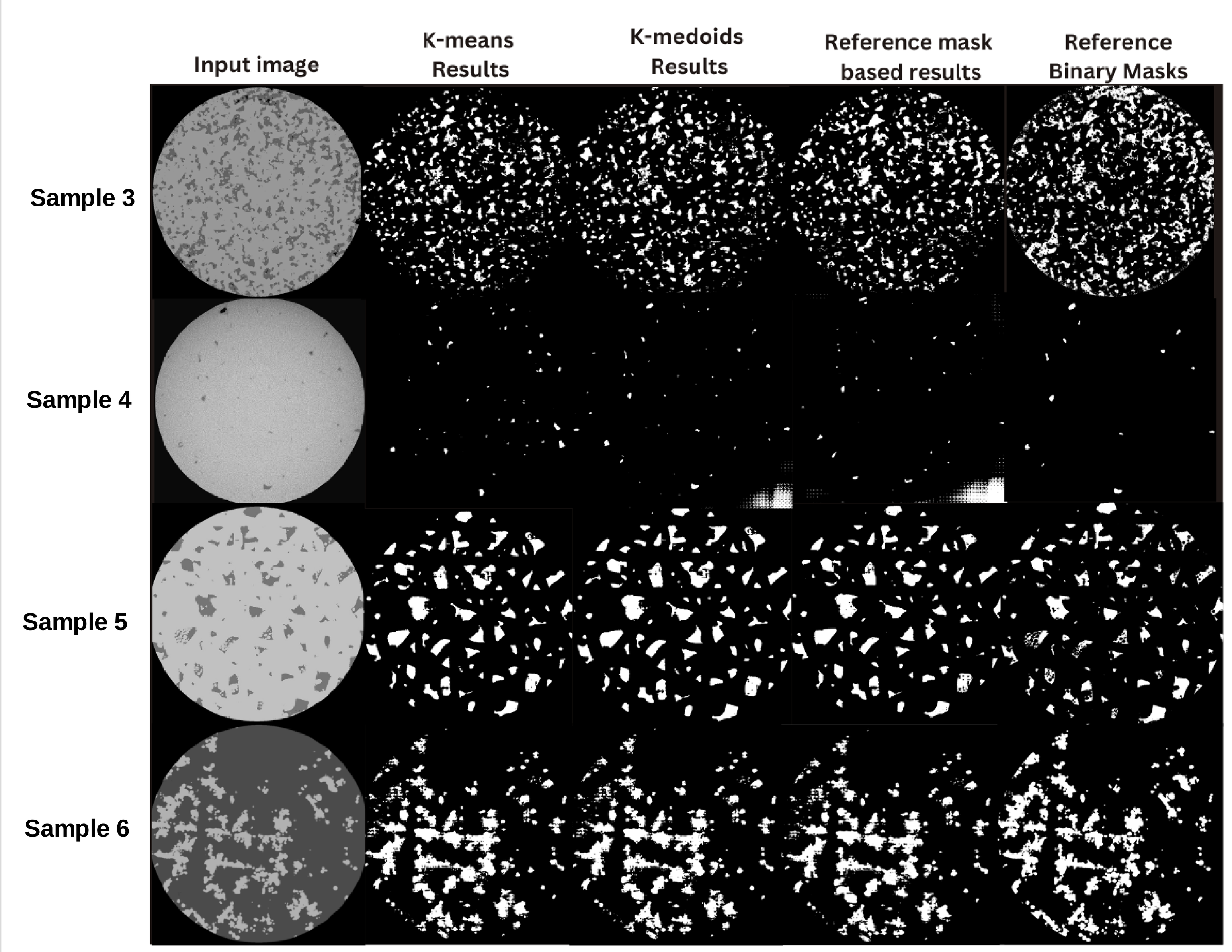
- **Data preprocessing:** Run the unsupervised clustering on XCT images to collect the centroids.
- **Prompt Generation:** Take 2D location coordinates from the foreground pixels of these stored centroid images and use them as point prompts during inference.
- **SAM inference:** Input the XCT images and the point prompts to the SAM inference model. Collect the accurate mask from the multi-mask output of SAM based on the IoU scores predicted by it.

**We generated Reference Binary Masks using K-means clustering and Binary thresholding to evaluate the performance of the framework.

ABSTRACT:

In the domain of Laser Additive Manufacturing (LAM), precise image-based defect segmentation is crucial for ensuring product quality and enabling real-time process control. However, this task presents several challenges, including the absence of labels and the overhead of supervised fine-tuning of models. To address these challenges, we've devised a novel framework for image segmentation employing a state-of-the-art Vision Transformer (ViT)-based Foundation model, known as the Segment Anything Model. Foundation models are currently driving a paradigm shift in computer vision tasks for various fields including biology, astronomy, and robotics among others, leveraging user-generated prompts to enhance their performance. Our approach incorporates a novel multi-point prompt generation scheme through unsupervised clustering eliminating the need for data labels or supervised model fine-tuning. We apply this framework to porosity segmentation in a case study of laser-based powder bed fusion (PBF) and achieve high Dice Similarity Coefficients (DSC) without the requirement for supervised fine-tuning in the model.

RESULTS



PERFORMANCE EVALUATION

Dice Score Coefficient (DSC) = $\frac{2\times(X\cap Y)}{|X|+|Y|}$

X = Predicted pixels' labels, Y = Ground truth labels**

Sample #	Dice Score Coefficient values			
	K-means	K-medoids	Reference	No prompts
Sample 3	0.62 ± 0.034	0.62 ± 0.036	0.64 ± 0.029	0.0019 ± 0.0006
Sample 4	0.436 ± 0.12	0.35 ± 0.13	0.492 ± 0.11	0.0299 ± 0.0081
Sample 5	0.88 ± 0.019	0.88 ± 0.015	0.88 ± 0.016	0.0022 ± 0.0021
Sample 6	0.70 ± 0.09	0.75 ± 0.04	0.79 ± 0.098	0.0002 ± 0.0002

ALGORITHMS

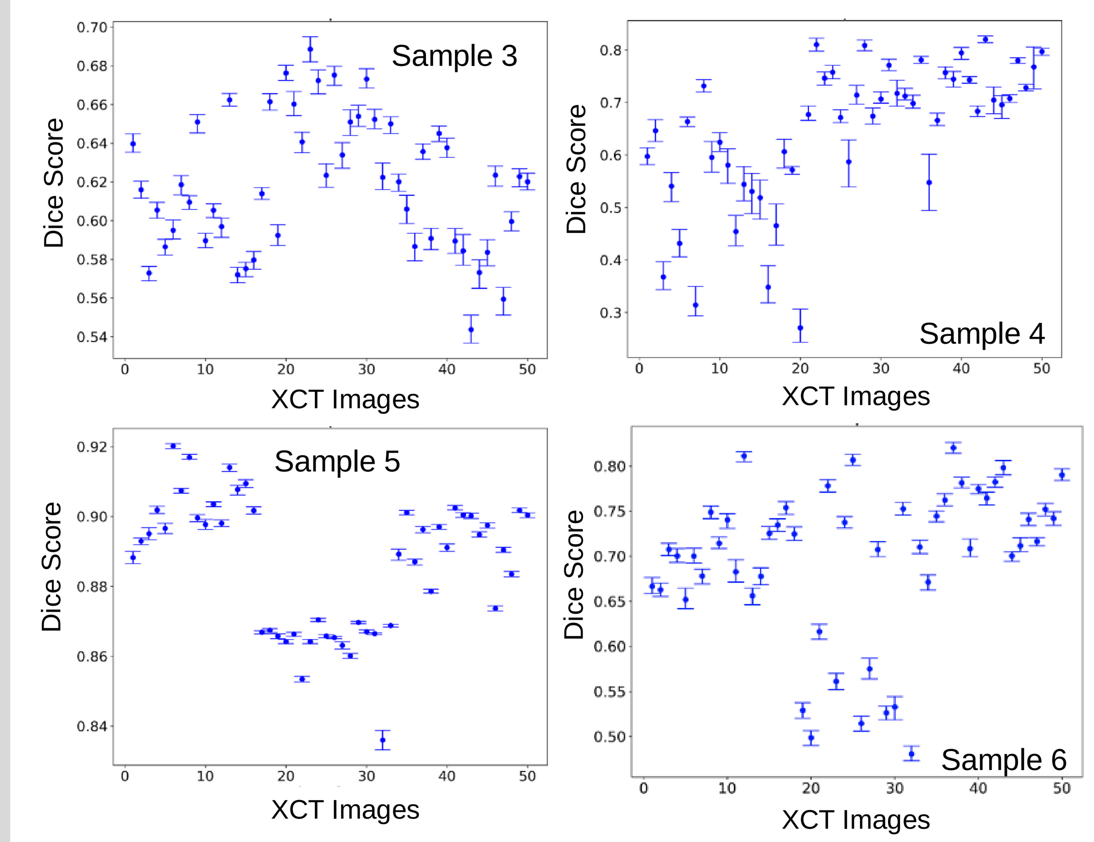
Algorithm: Prompt Generation

Input: Centroid Image C_k;
Output: 2D point coordinates p, Labels l;
Steps:
Select the respective centroid images C_k from cluster k;
Apply the Binary Thresholding
Collect $p = (x, y)$;
where, $(x, y) =$
$$\begin{Bmatrix}(x \subset (X,Y) \mid X \in \text{X axis coordinates of foreground in } C_k) \\ (y \subset (X,Y) \mid Y \in \text{Y axis coordinates of foreground in } C_k)\end{Bmatrix}$$
Create labels $l = \{1\}^n$ for (x, y), where $n = |x| = |y|$;
end

Algorithm: Unsupervised Porosity Segmentation Framework

Input: Clustered XCT images I_k^P, Point Prompts p;
Output: Binary Masks M_i, Predicted IoU score S_i;
Steps:
Select the respective centroid images C_k for cluster k;
Generate point prompts p by Prompt generation Algorithm 2;
Input the images I_k^P from cluster k and Point Prompts p to SAM;
Set $Thresh = 0.90$;
Run SAM inference and obtain M_i, S_i where $0 \leq i \leq 2$;
for *each* M_i, S_i **do**
  Select M_1, S_1 (part);
  if $S_1 > Thresh$ **then**
    Select M_0, S_0 (subpart);
  end
end

UNCERTAINTY QUANTIFICATION BY PROMPT BOOTSTRAPPING



We calculated mean length and standard deviation of the 95\% confidence intervals of the distributions estimated by Bootstrapping using the quantiles of the estimated DSC distribution across all the samples.

Sample #	Mean length
Sample 3	0.0103 ± 0.0025
Sample 4	0.0396 ± 0.0236
Sample 5	0.0017 ± 0.0009
Sample 6	0.0153 ± 0.0034

- We performed *m* out of *n* Bootstrapping [3] on the generated prompts; where, m = sample size, n = total pixels associated with the defect area and *m* << *n*. we ran our framework on each of the samples and calculated DSC scores.
- We generated 95% confidence interval of the estimated distribution resulted from the prompt bootstrapping.

OUR CONRIBUTIONS

- Developed an end-to-end, unsupervised data-driven prompt generation strategy incorporating Segment Anything (SAM) with no fine-tuning, that addresses both the real-life challenges of lack of labeled data in domain of LAM and the overhead associated with model fine-tuning.
- Utilized different unsupervised clustering techniques for the prompt generation and provided guidelines to select the accurate predicted mask from the multi-prediction output of SAM in context of XCT imaging of inter-layer porosity.
- Performed prompt bootstrapping to quantify the uncertainty of the model's performance.

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