Risk-Aware Decision Making for Additive Manufacturing via Conditional Diffusion Models

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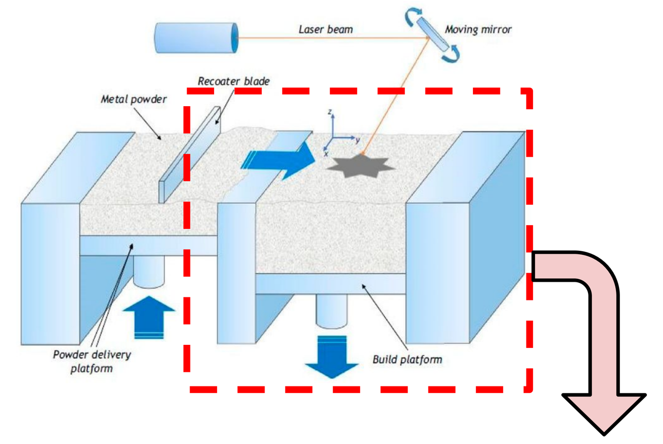
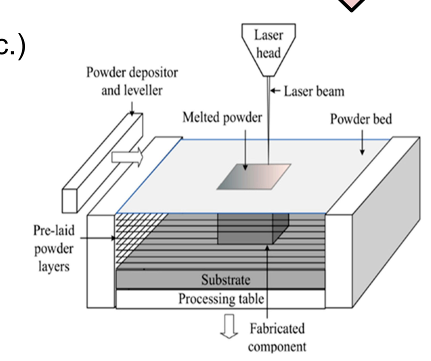
Background & Objective

Laser Powder Bed Fusion is a leading technology for production of complex metal components with high-performance, but process outcomes are highly sensitive to manufacturing conditions.



Key challenges:

- High-dimensional process parameter space
  (e.g., laser power, scan speed, chamber temperature, hatch spacing, hatch pattern, etc.)
- Stochastic defect formation
  (e.g., Recoater-related defects, incomplete spreading, swelling, debris, porosity, etc.)
- Time and cost intensive experimental validation



Existing works mainly rely on:

- Generative modeling and defect prediction in isolation
- No generative modeling has been applied on the Peregrine dataset

Our goal is to integrate generative modeling and defect prediction into a real-time decision-support framework that can:

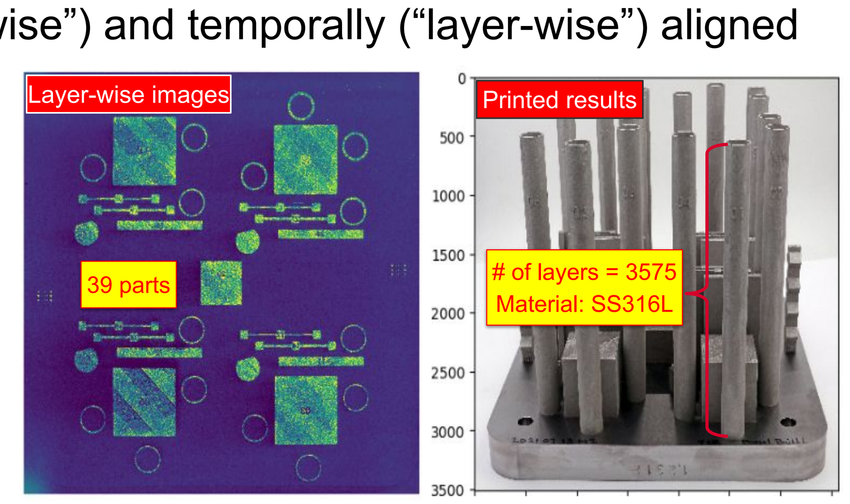
- Replace costly physical experimentation with probabilistic print forecasting
- Estimate defect distribution & support risk-aware manufacturing decisions *in situ*

Dataset

This work uses the *Peregrine dataset* released by Oak Ridge National Laboratory.
(DOI: https://doi.org/10.13139/ORNLNCCS/2008021)

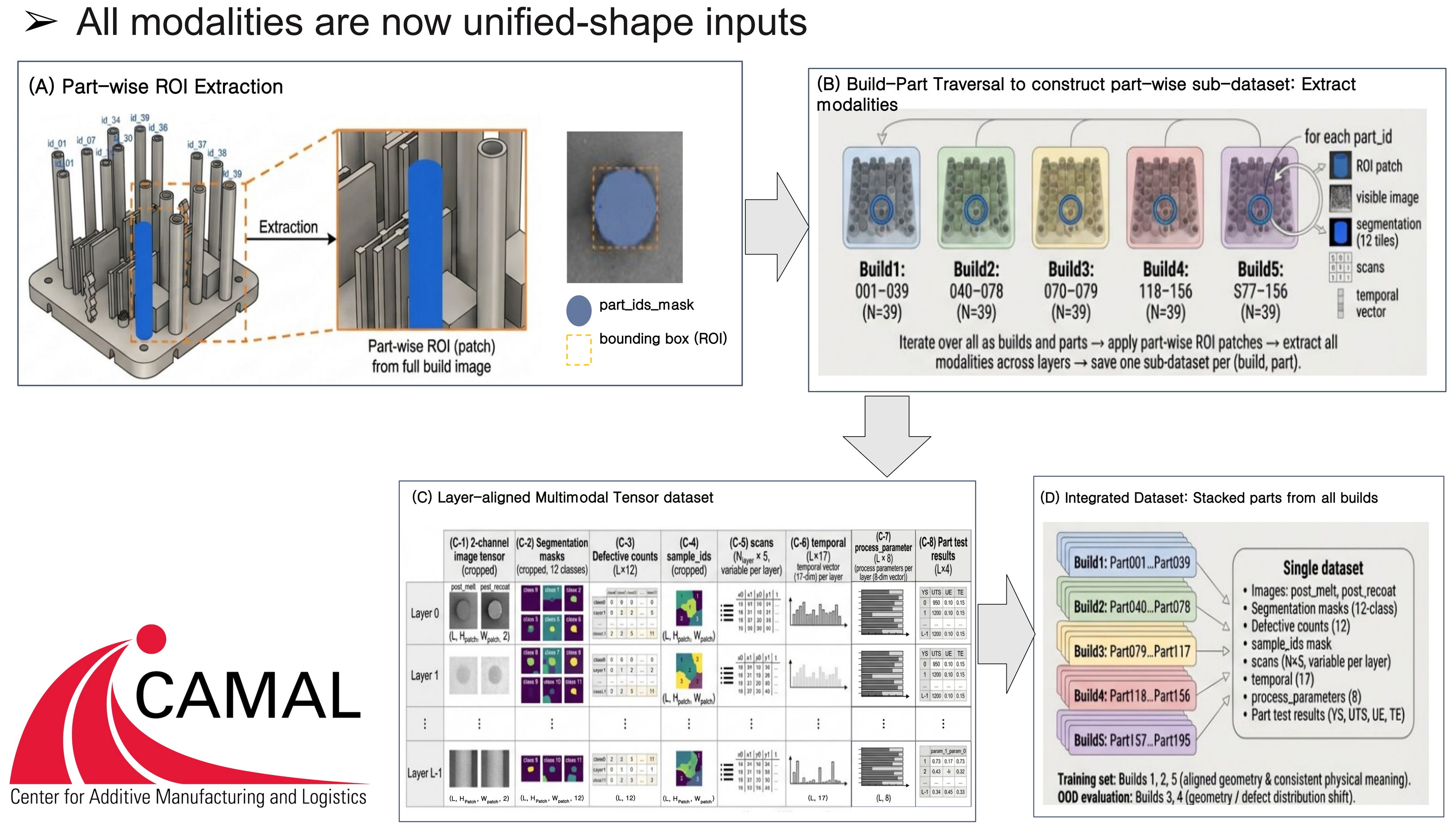
Exploratory Data Analysis:

- Consists of multimodal data from 5 different AM builds
- All modalities are spatially ("pixel-wise") and temporally ("layer-wise") aligned
  - Post-melt images
  - Post-recoat images
  - *In situ* environmental signals
  - Scan paths and part IDs
  - Machine process parameters
- Co-registered digital twin dataset



Data pre-processing

- Scan paths, part IDs, and process params converted into pixel-aligned masks
- All modalities are now unified-shape inputs

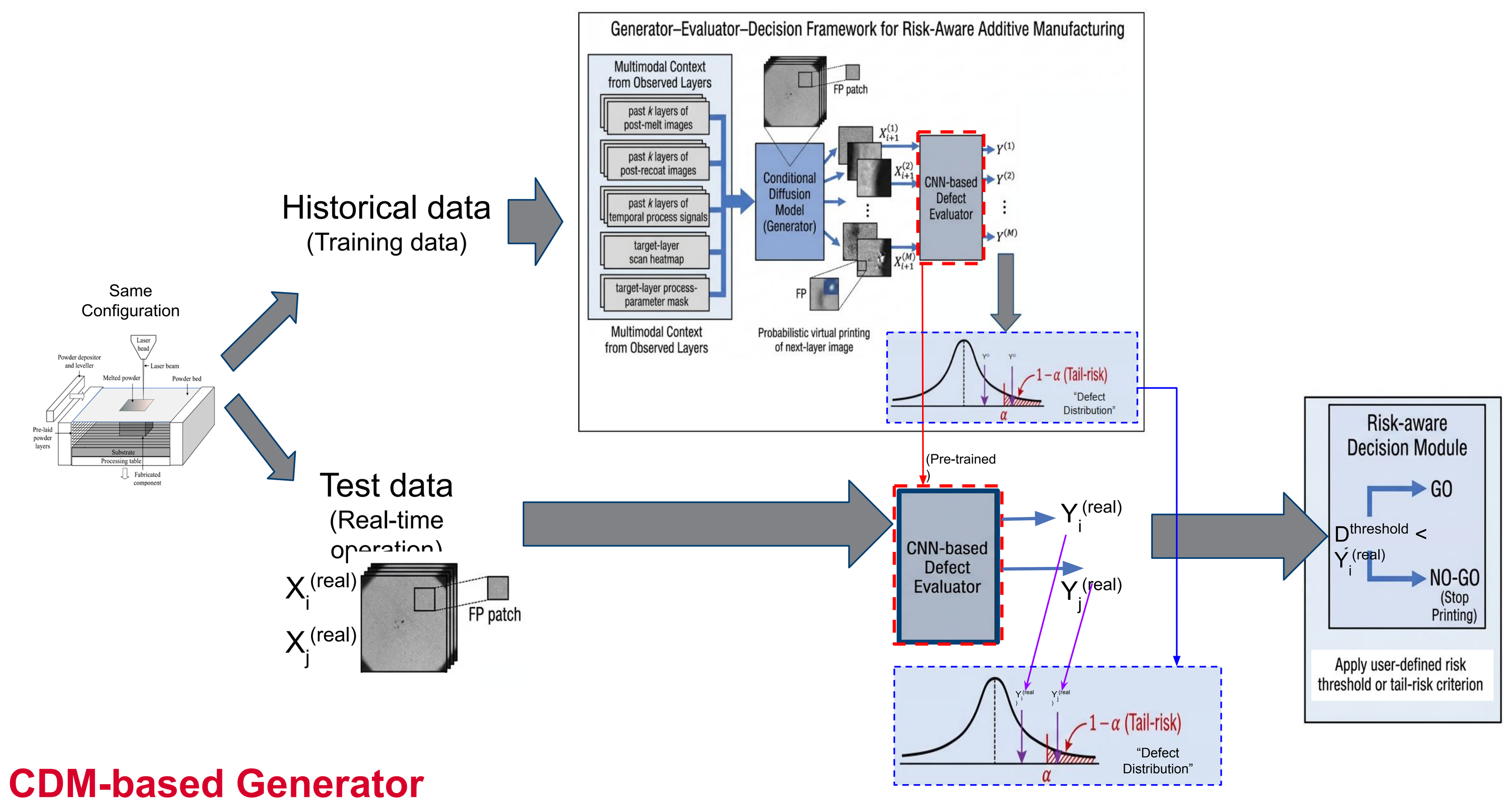


CAMAL
Center for Additive Manufacturing and Logistics

Methodology

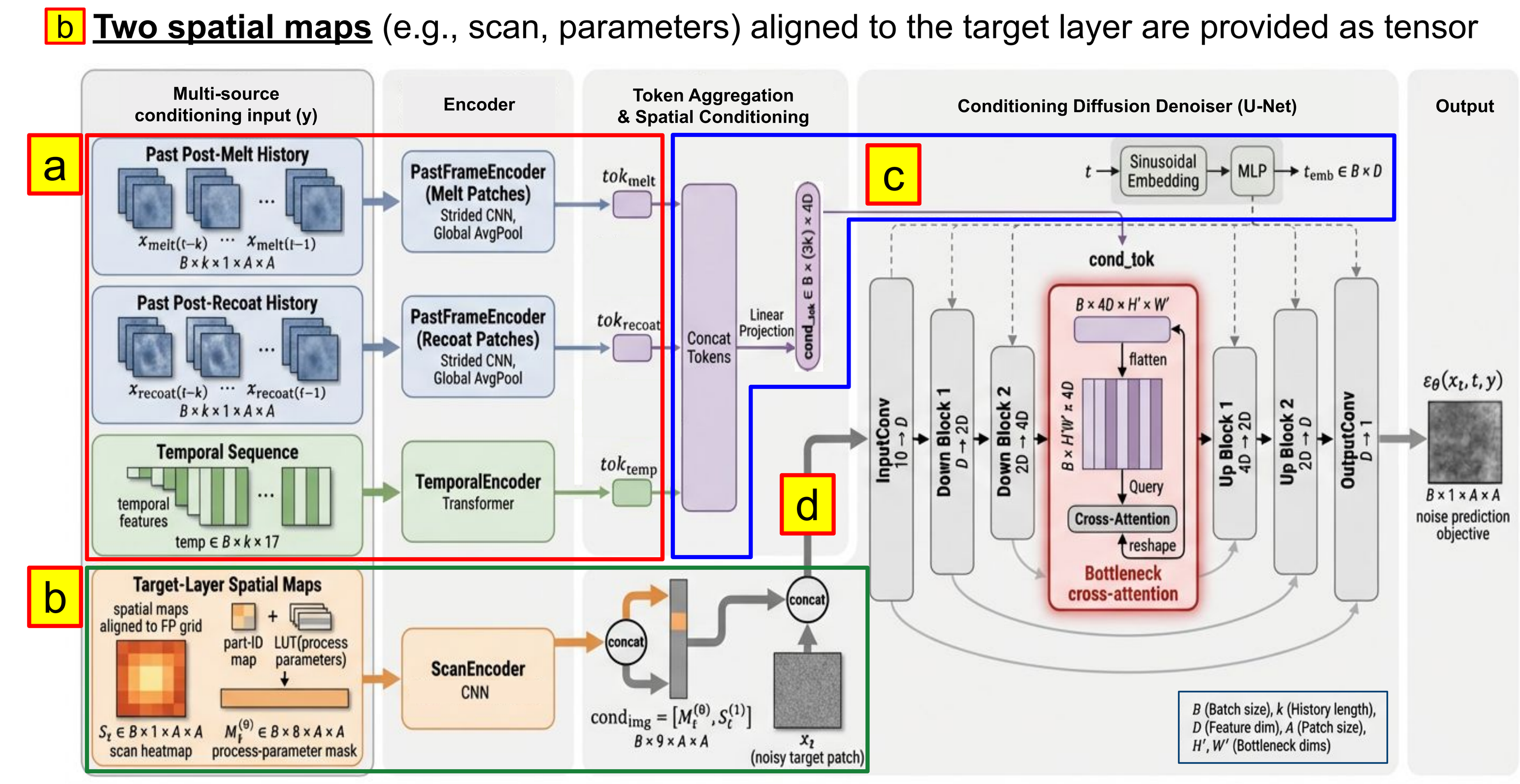
We propose a unified 'Generator-Evaluator-Decision Engine' framework, where

- Probabilistic print forecasting is conducted by **Diffusion-based Generator**
- Potential defects are predicted by a **CNN-based defect Evaluator** in near real-time
- **Decision Engine** tells GO / NO-GO based on defect-distribution by 6-sigma rule

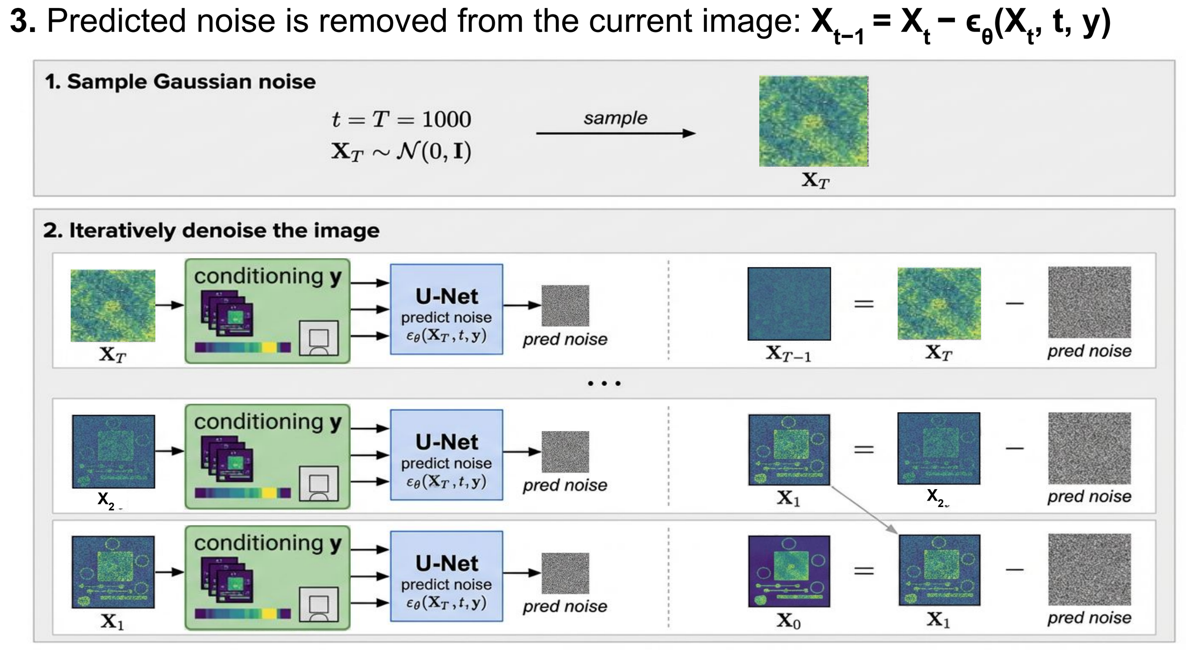


CDM-based Generator

- Given a context window of 'k' observed layers up to layer 'i', the model generates the next-layer FP patch: $P_\theta(X_{i+1}[x_0,y_0] \mid \text{context}_{i-k+1:i}(x_0,y_0))$
- Use two types of conditioning information to generate the next-layer image
  - a **Context 'k' history** (e.g., layer images, temporal sequence) are summarized into tokens
  - b **Two spatial maps** (e.g., scan, parameters) aligned to the target layer are provided as tensor



- Use two complementary conditioning pathways
  - c **Context tokens**, capturing global spatial structure, are injected to U-Net bottleneck directly
  - d **Spatial maps**, capturing local spatial structure, are injected to U-Net as extra inputs
- Generates the next-layer post-melt image via iterative denoising process
  - **Step 1.** Initialize with Gaussian noise: $X_T \sim N(0, I)$ represents a noisy image at diffusion step 'T'
  - **Step 2.** At each diffusion step 't', the noise is predicted by a denoiser: $\epsilon_\theta(X_t, t, y)$, where 'y' integrates multimodal condition contexts
  - **Step 3.** Predicted noise is removed from the current image: $X_{t-1} = X_t - \epsilon_\theta(X_t, t, y)$



CNN-based Evaluator

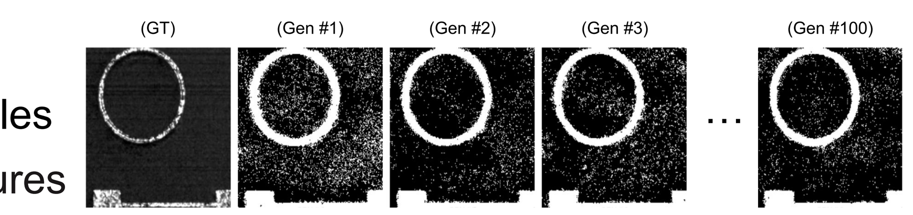
- The **Evaluator** maps generated images to defect-related outcomes: $Y^{(m)} = f_\theta(X^{(m)})$
- Form a Monte-carlo defect distribution with $\{Y^{(1)}, Y^{(2)}, \ldots, Y^{(m)}\}$

Decision Engine: Real-time decision making

- **"Keep printing"** if predicted defect risk ≤ $D^{threshold}$
- **"Stop printing"** if predicted defect risk > $D^{threshold}$ ("early termination to avoid further production cost")

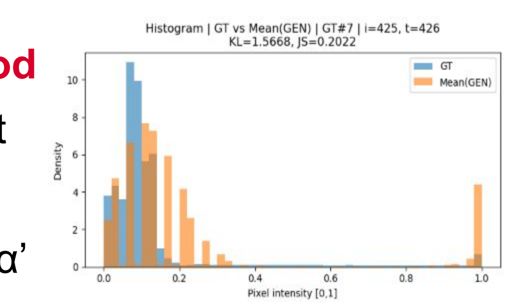
Results / Contributions

High-quality print forecasting



- CDM generate high-quality samples
- Capture both structures and textures
- Intensity distribution of the generations well-aligned with GTs

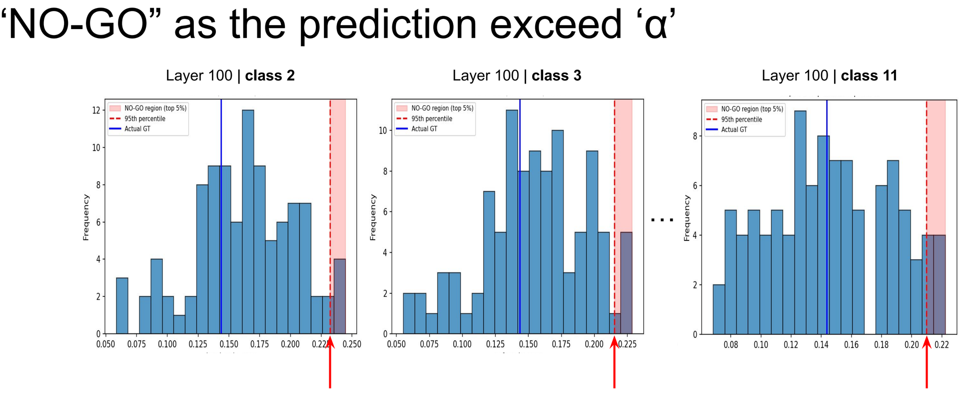
Defect distribution estimated with GT in the mean-period



- Take a tensor of **[gen post-melt, post-recoat]** as input
- Output the defect rates for 12 classes at each patch
- Decide "NO-GO" region with a user-defined threshold 'α'

Enable real time distribution-aware "GO/NO-GO" decision making

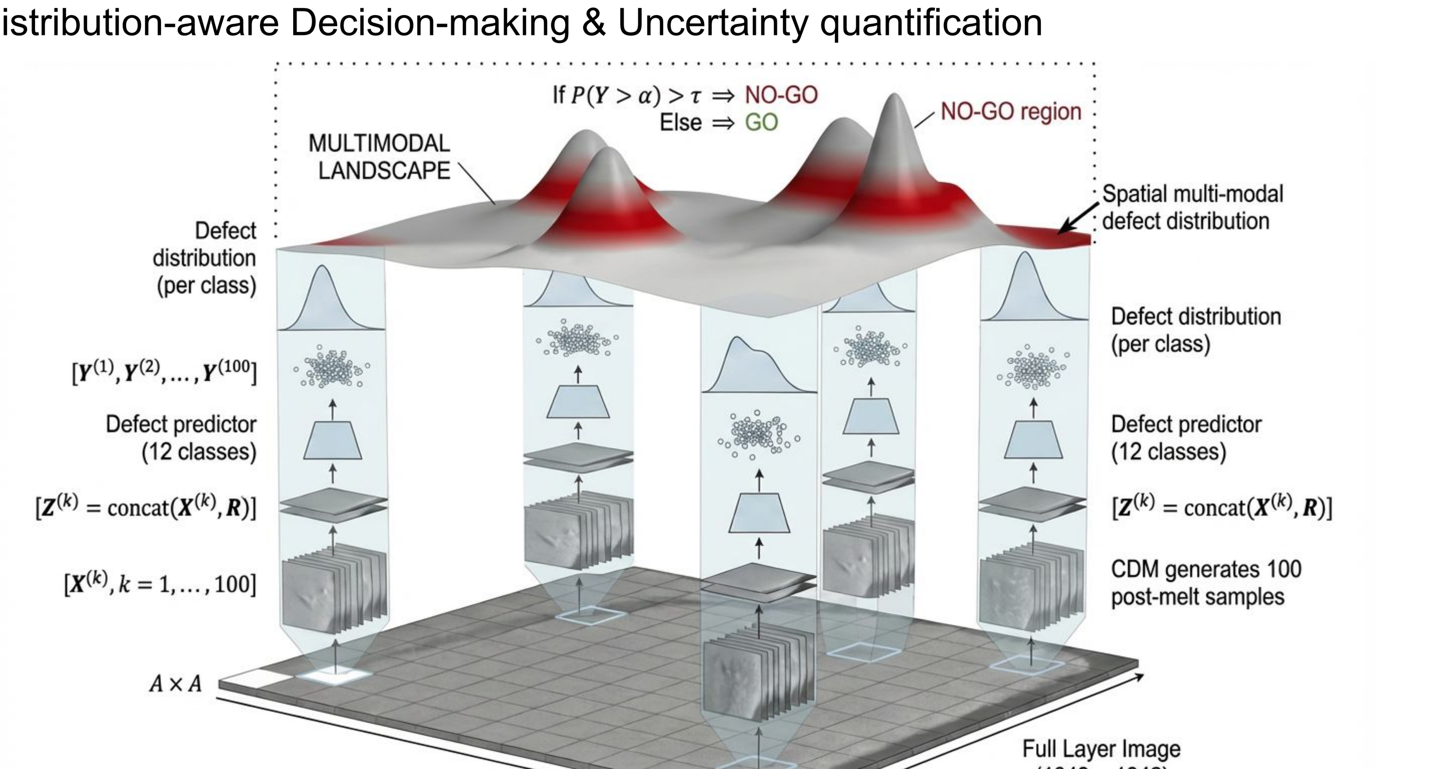
- Real-time layer images sent to the Evaluator
- Estimate defect rates for the real-time printed
- Declare "NO-GO" as the prediction exceed 'α'



"If 100th real printing yields 2nd class defect of 0.230"
⇨ Stop the printing as this defect will be propagated and make the process worse!

Contributions

- A first unified "Generator–Evaluator–Decision" framework for risk-aware LPBF monitoring
- A first multimodal Conditional Diffusion Model on the Peregrine digital twin dataset
- Distribution-aware Decision-making & Uncertainty quantification



Future works

- Generalization across builds, machines, and process settings
- From "Rule-based decisions" to Bayesian optimized & cost-aware decision policies
- Investigate and forecast how defect propagation will affect the final part quality
- Investigate methods and tolerance rates for controlling defects