Reconstruction-free Anomaly Detection with Attention-based Diffusion (RADAR)

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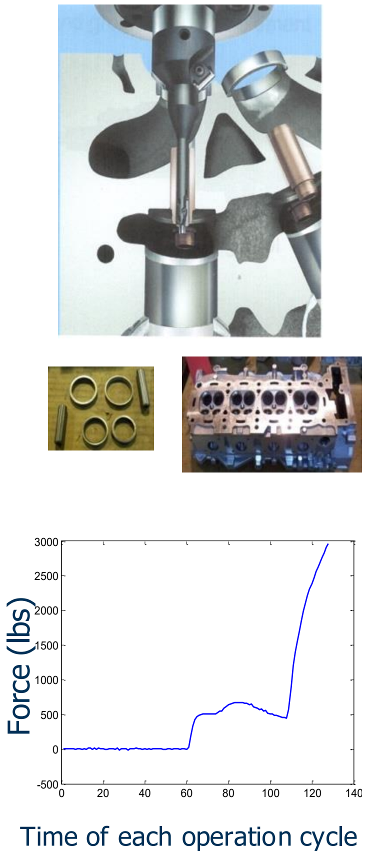
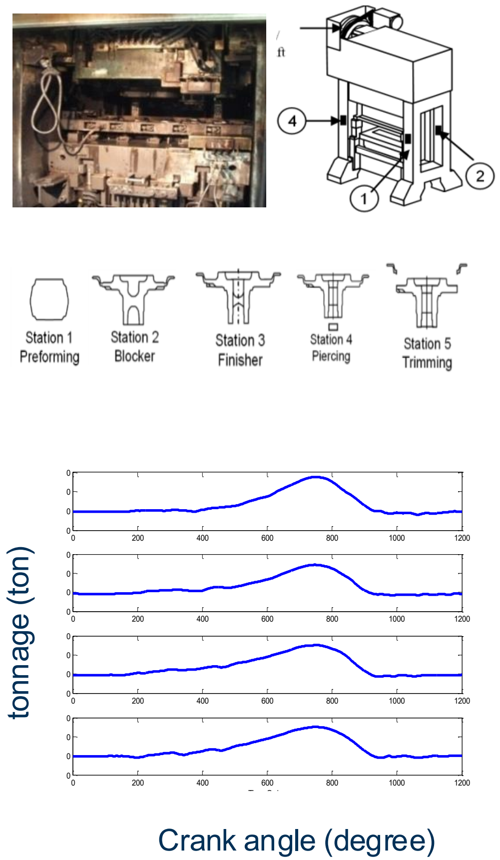
Georgia Tech

Motivation

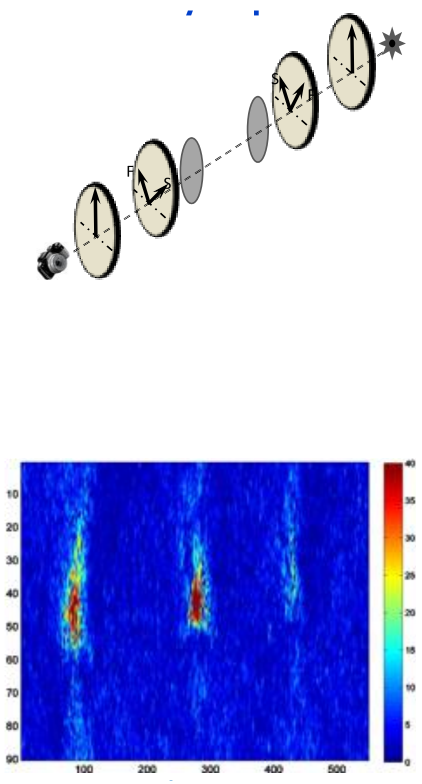
Valve Seat Assembly



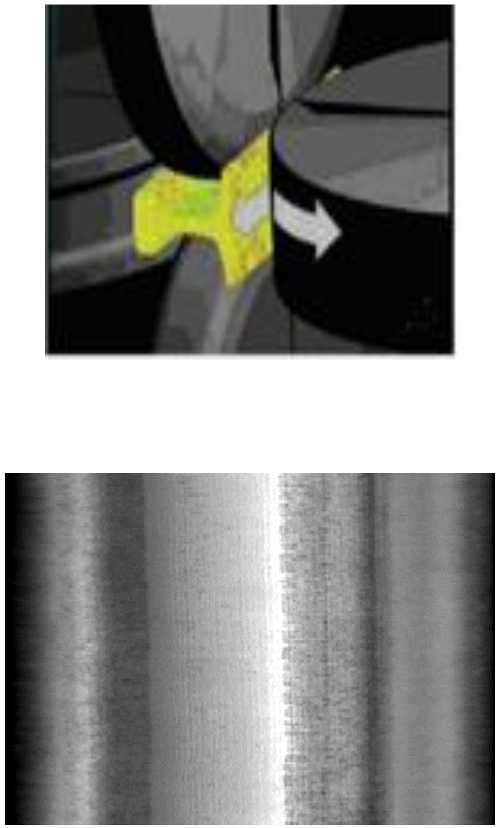
Forging



Semiconductor



Rolling

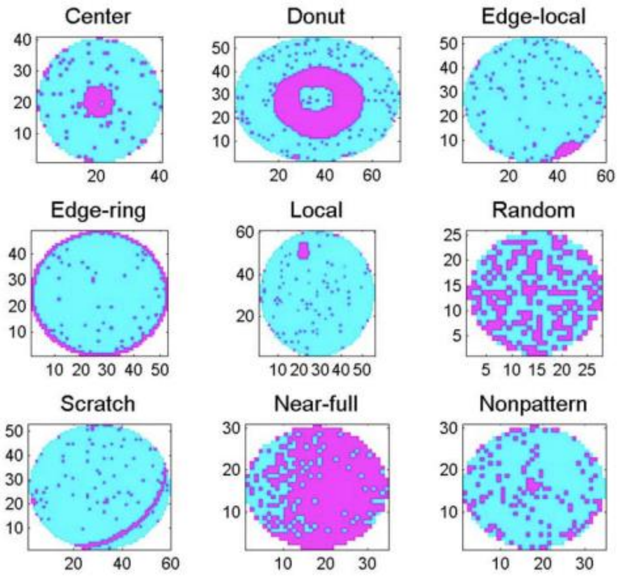


Anomaly Detection in HD Data has wide applications in different domains.

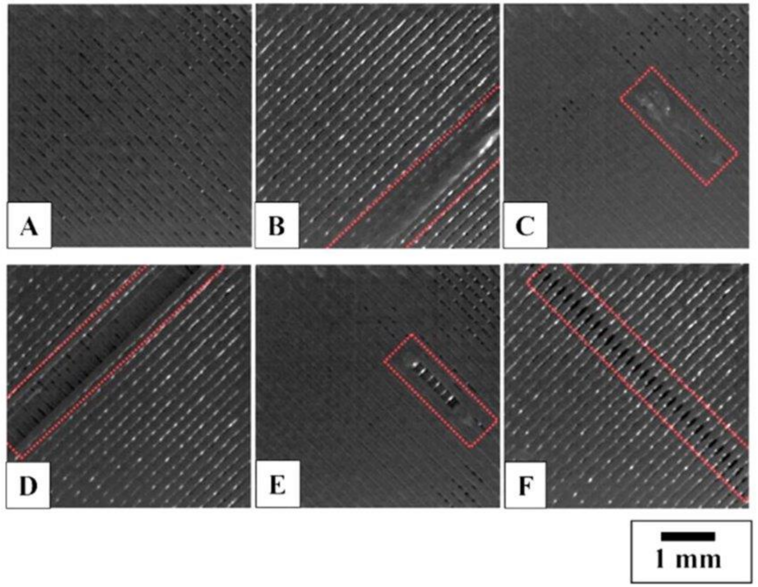
Common Methods for Anomaly Detection in HDD

- SPC-based Methods (ST-SSD and Stochastic Textured Surface)
  - Do not require large training data, but they cannot deal with complicated patterns.
  - Application specific and need to be modified for each application.

- Low-rank Decomposition Methods (e.g., RPCA [1] and SSD [2])
  - Do not require large training data, but they cannot deal with complicated patterns.
  - Low-rank (linear projection to LD space) or smoothness assumptions may not be valid.



Wafer failure map in semiconductor man. [11]

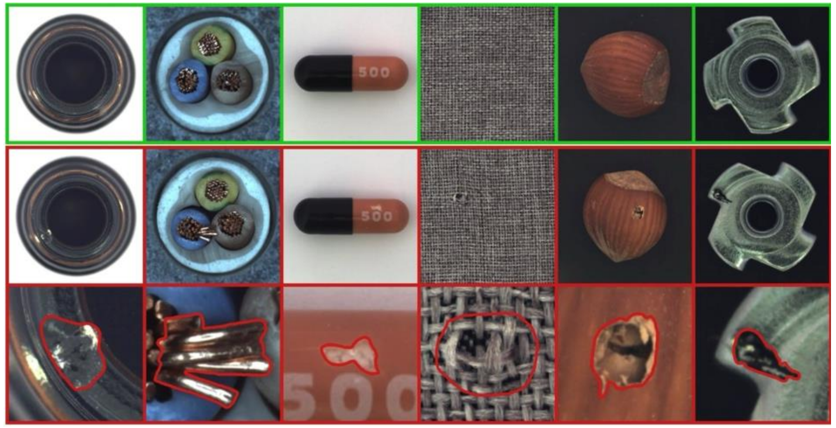


Additive manufacturing printed layers [8]

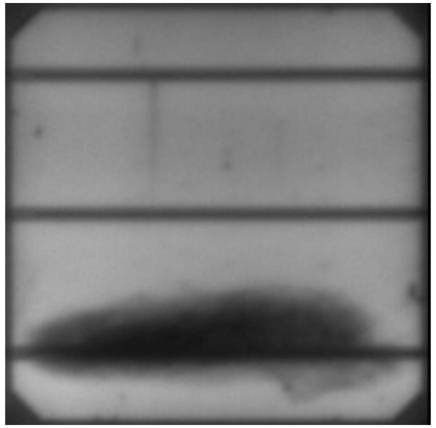
Common Methods for Anomaly Detection in HDD

- Deep Learning Approaches
  - Needs large datasets to train
  - In some cases, labeled data can be very expensive to collect

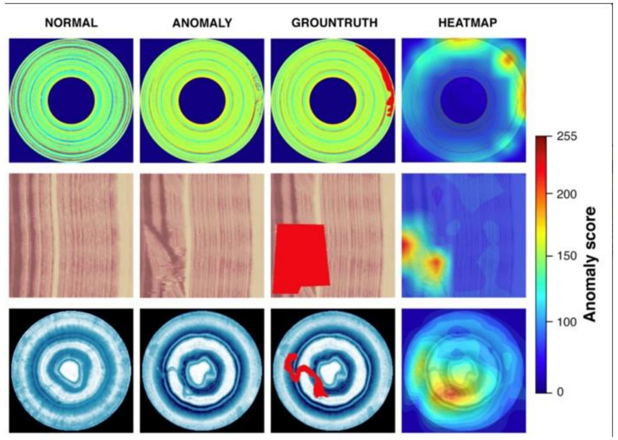
- Generative AI Approaches (e.g., VAE, GAN, DDPM)
  - Needs large datasets to train, otherwise overfits very easily
  - GANs are often unstable
  - DDPM Reconstruction-based methods cannot detect subtle defects



MVTec anomaly detection dataset [5]



ELPV data sets: solar cells
Picture of a mono crystal cell [4]

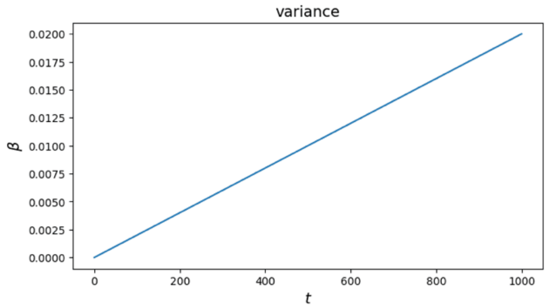


BTAD: industrial anomaly data set [10]

Review: Denoising Diffusion Probabilistic Models (DDPM [6])

- In DDPM:
  - Noise is added in a predefined Markovian chain to turn the data into pure Gaussian noise
  - Backward conditional distribution is learned as a Gaussian distribution based on MLE using neural networks.

$$p_\theta(x_{t-1} \mid x_t) = \mathcal{N}\left(x_t; \mu(x_t, t), \Sigma(x_t, t)\right)$$



$$q(x_t \mid x_{t-1}) = \mathcal{N}\left(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t\mathbf{I}\right)$$

$q(x_t|x_{t-1})$: Forward diffusion process. β_t: predefined noise schedule.

$p_\theta(x_{t-1}|x_t)$: Backward conditional distribution. $p_\theta(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}, \mu_\theta(x_t, t), \sum_\theta(x_t, t))$

$$\mu_\theta(x_t, t) = \frac{1}{\sqrt{\alpha_t}}(x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(x_t, t)) \Rightarrow x_{t-1} = \frac{1}{\sqrt{a_t}}(x_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}}}\epsilon_\theta(x_t, t)) + \sqrt{\beta_t}\epsilon$$

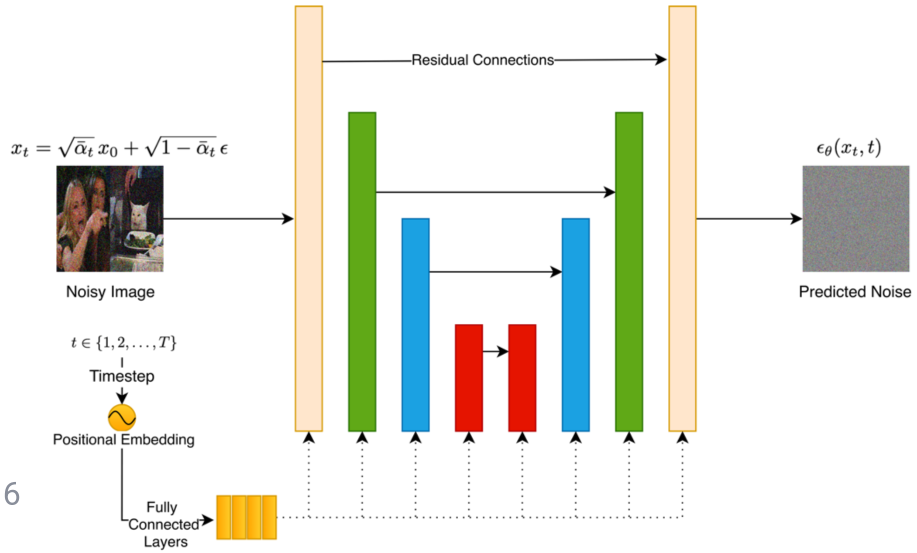
DDPM Training Algorithm [6]

- Denoising Diffusion Probabilistic Models (DDPM) using noise prediction models

$$x_{t-1} = \frac{1}{\sqrt{a_t}}(x_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}}}\epsilon_\theta(x_t, t)) + \sqrt{\beta_t}\epsilon$$

- In each training iteration:
  - Sample a data point, a time step in forward diffusion process (T is usually 1000) and a Gaussian noise and construct the noised data based on forward diffusion process
  - Apply gradient descent algorithm on the L2 norm of noise prediction error

- The architecture used is usually UNet an autoencoder with skip connections



Algorithm 1 Training

1: **repeat**
2: $\quad \mathbf{x}_0 \sim q(\mathbf{x}_0)$
3: $\quad t \sim \mathrm{Uniform}(\{1, \ldots, T\})$
4: $\quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: $\quad$ Take gradient descent step on
$$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$$
6: **until** converged

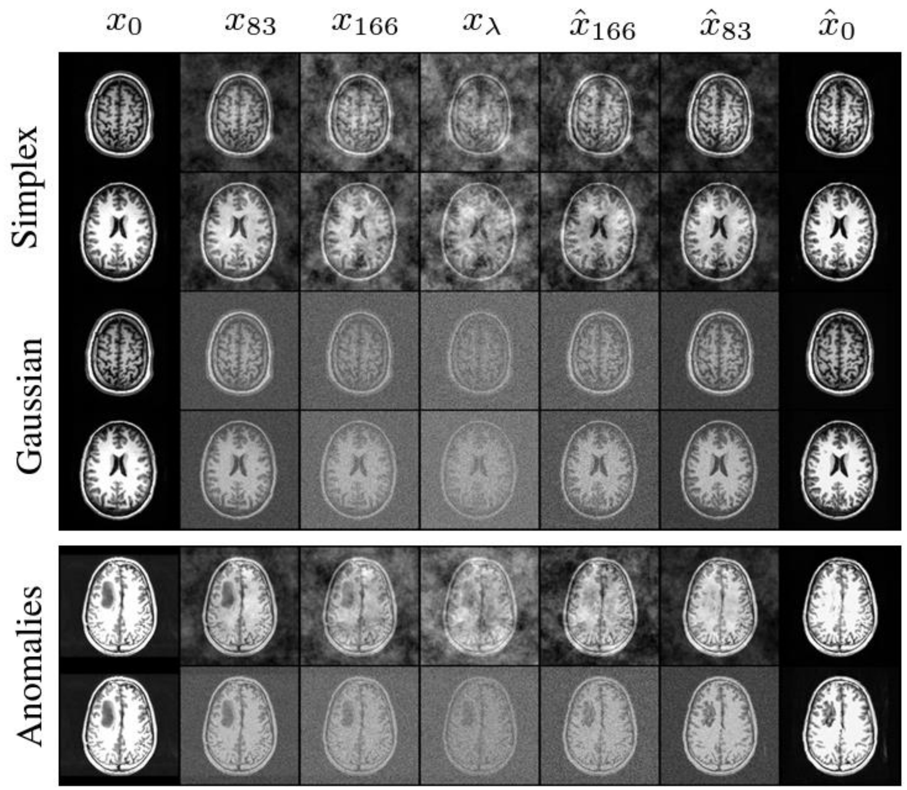
Algorithm 2 Sampling

1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
2: **for** $t = T, \ldots, 1$ **do**
3: $\quad \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
4: $\quad \mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)\right) + \sigma_t \mathbf{z}$
5: **end for**
6: **return** $\mathbf{x}_0$

Anomaly detection with DDPM [7]

- First training DDPM on healthy data with 1000 steps in forward diffusion
- For a new image we noise image to λ steps (250 chosen)
- Apply sampling algorithm from noisy image to step 0 and get the corresponding healthy data point
- Find the difference between the original image and the reconstructed one.
- Reconstruction-based anomaly detection

- Needs large amount of healthy data
- Reconstruction-based method does not work for very subtle defects
- Cannot reconstruct well when random patterns exist like bright points



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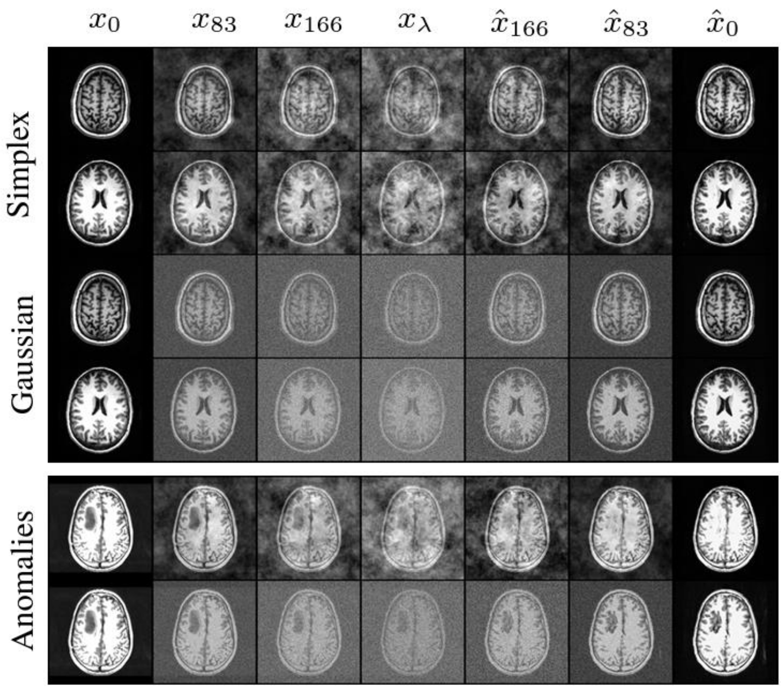
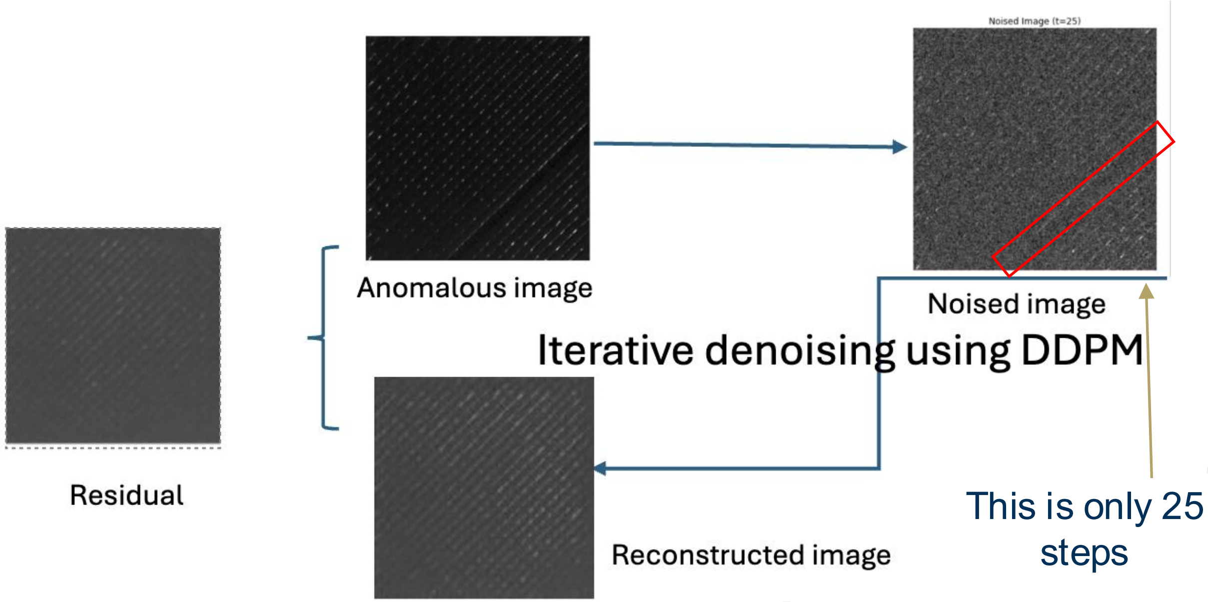


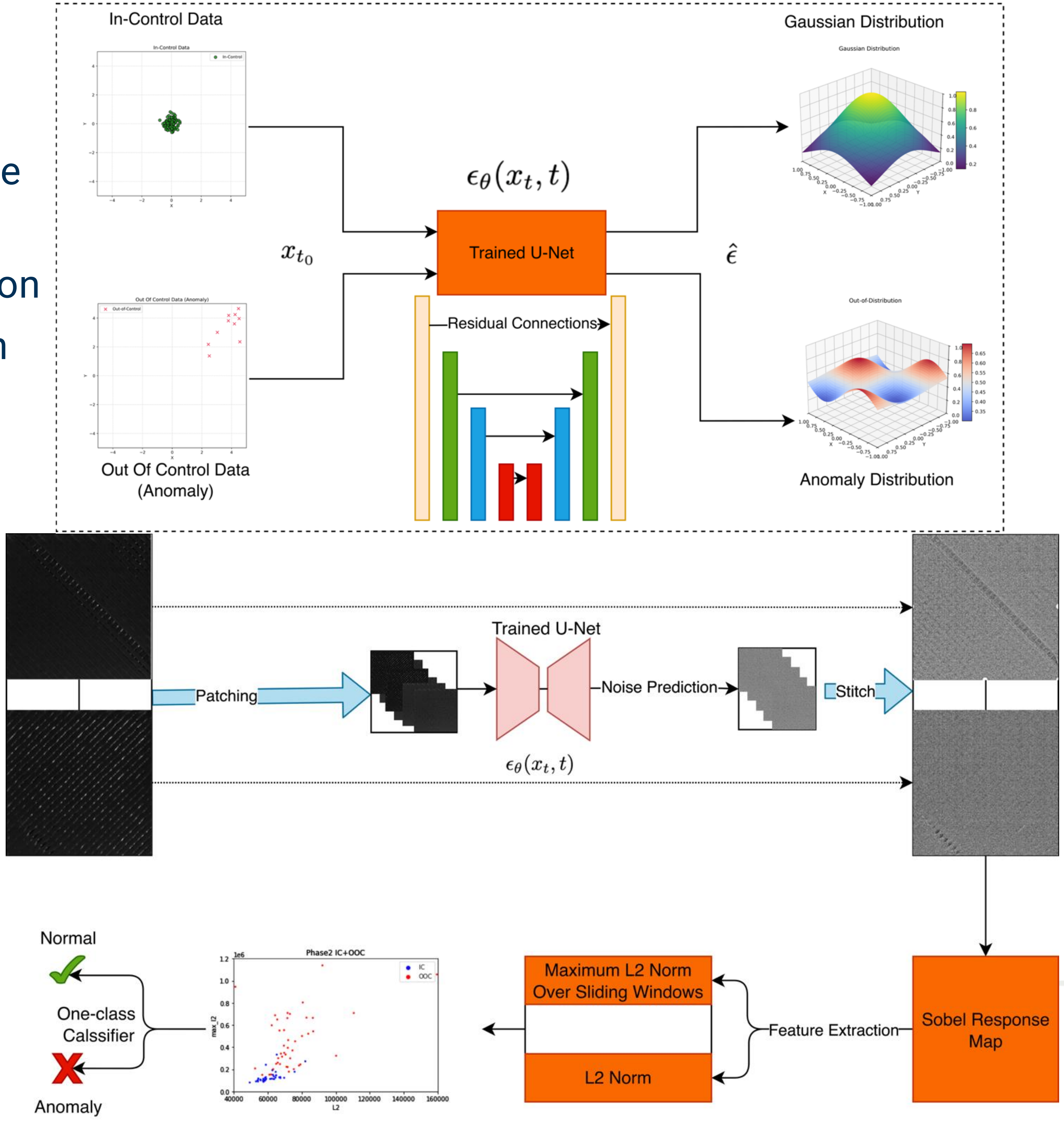
Drawbacks:

- Needs large amount of healthy data
- Reconstruction-based method does not work for subtle defects



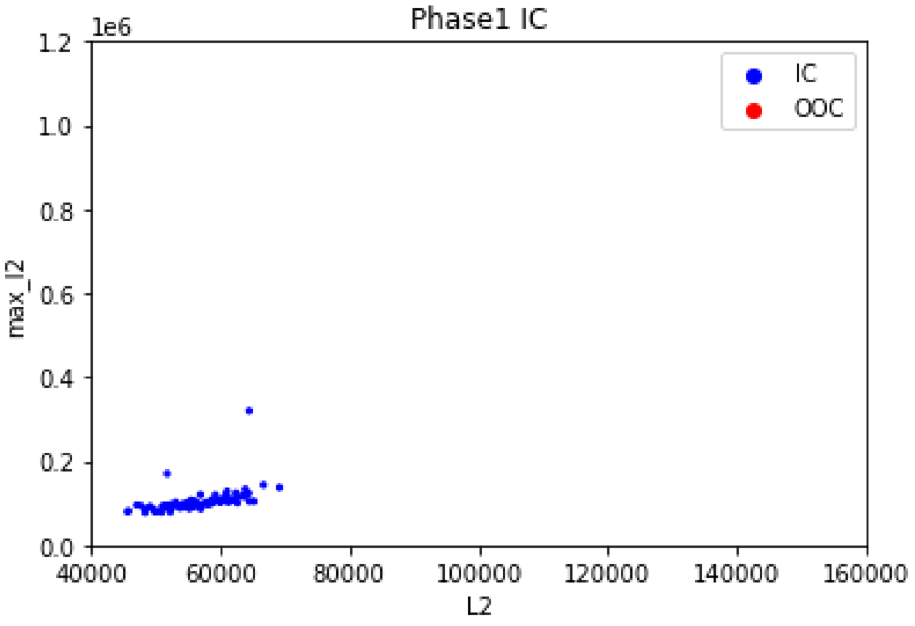
Proposed RADAR [12]

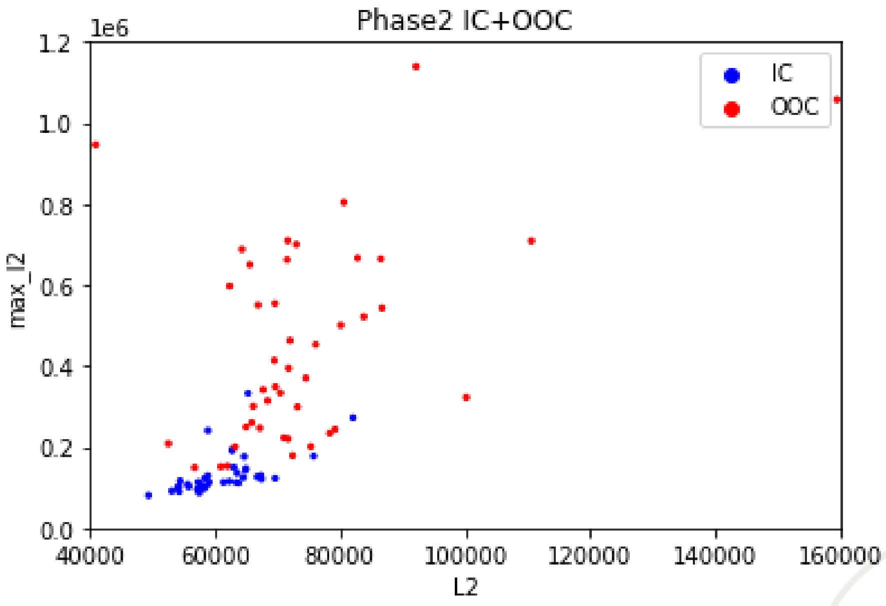
- Diffusion model is trained to predict the Gaussian noise added to the sampled image
  - In control image: approximately Gaussian prediction
  - Out of control: different distribution than Gaussian
- RADAR
  - Divide the image into patches and learn the distribution by diffusion models.
  - Significantly increases the training size
    - A 255*255 image turns into 228*228 patches of 28*28 images
    - Prevents memorization and overfitting
    - Reduces computational burden
  - In inference, noise patches in 1 step forward diffusion are predicted
  - Apply a combination of edge detection and norm-based feature extraction to extract features



Feature Extraction and One-class Classification

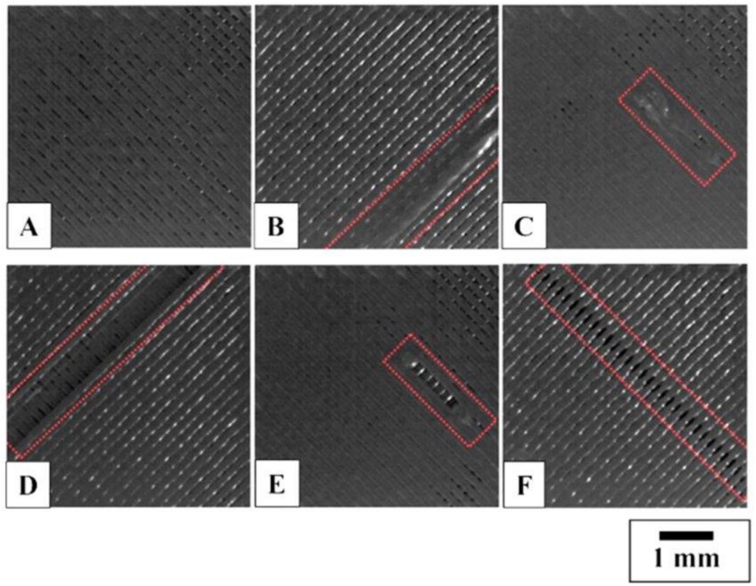
- Apply a Gaussian blur to smooth the image (kernel_size=5)
- Apply a Sobel edge detection (kernel_size=5) and extract the total L2 norm + max of L2 norm for windows with size 20 sliding 20 times in x and y axis
- For each image extract both max_L2 and L2 as two features for SPC
- Apply LOF one-class classification algorithm for anomaly detection

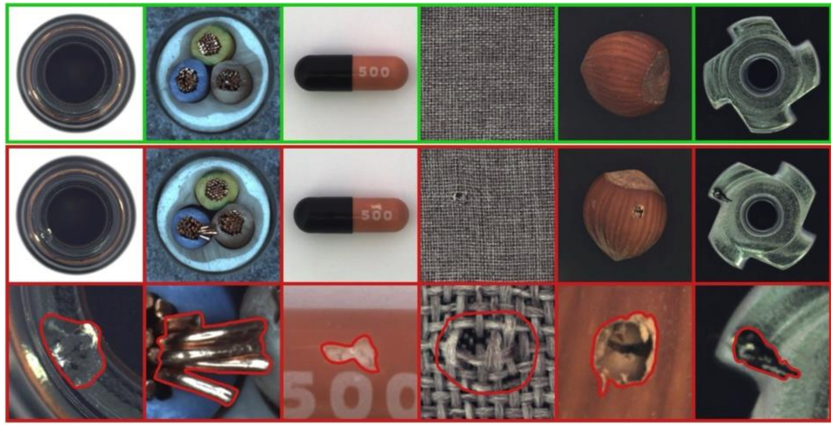




Case Study

- Dataset:
  - LPBF Additive Manufacturing Dataset (different process parameters and scan strategies)
  - MVTec-AD anomaly detection dataset: tile category
- Benchmarks:
  - State of the art diffusion models: AnoDDPM [7], DiffusionAD [9]
  - Statistical machine learning models: C&B [8], B&A [3]
  - Statistical descriptors: GLCM, Entropy, Hough Transform, SSIM
- Metrics:
  - accuracy, precision, recall, F1 score

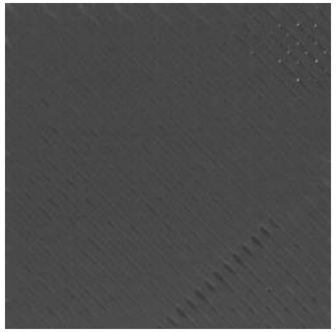




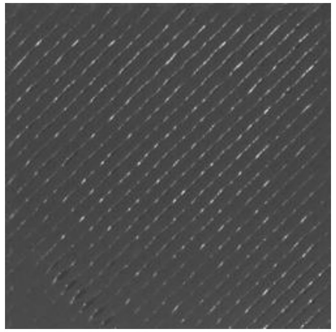
Extrusion-Based Additive Manufacturing [8]

- Phase 1 data (training): 81
  - 45 degrees orientation: 41
  - 135 degrees orientation: 40
- Phase 2 data (validation and testing): 84
  - 45 degrees in control: 21
  - 45 degrees out of control: 22
  - 135 in control: 19
  - 135 out of control: 22

In control data 45 degrees



Out of control data 135

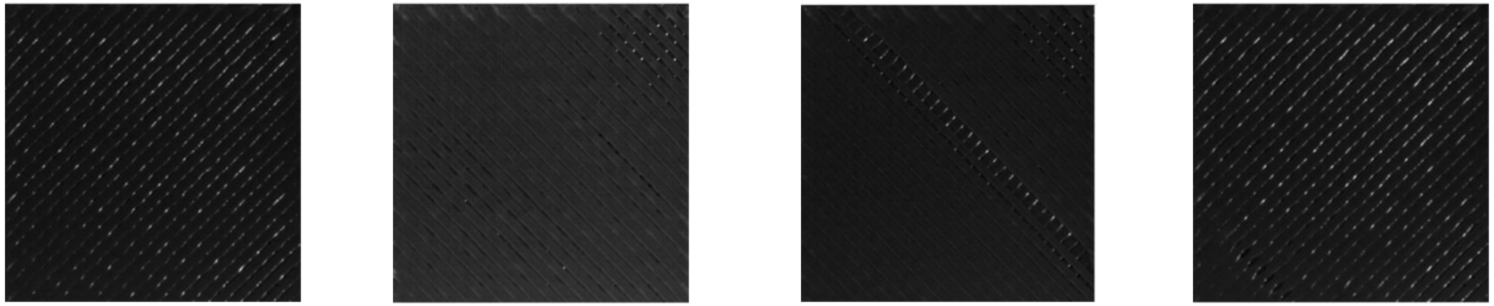


Out of control data 45

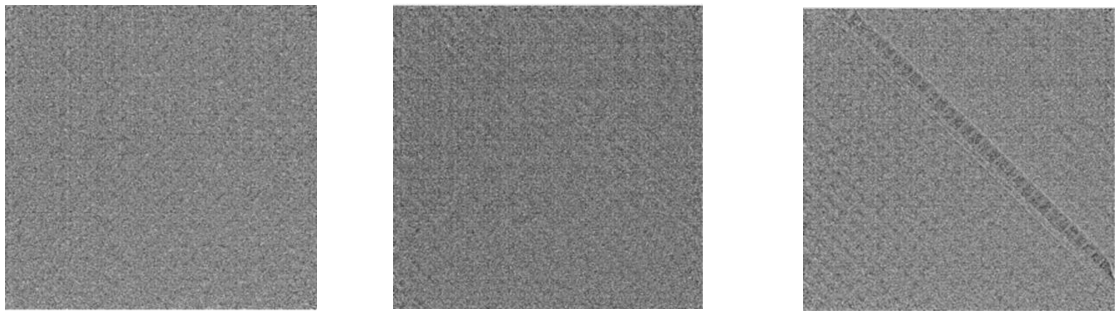
- Current State of the art: they have one model for each pattern
  - (Caltanissetta, Bertoli, & Colosimo) [8]
  - (Bui & Apley) [3]
- We train a single model for both angles

Visual Results (Precise Pixel-Level Segmentation and Image Level Anomaly Detection with Single Model)

Phase2 images



Predicted noise



Results LPBF Case Study

	B&A	C&B	DiffusionAD	AnoDDPM	DDPM	RADAR
Accuracy	0.73	0.67	0.42	0.46	0.5	**0.82**
Precision	0.77	0.70	0.39	0.45	0.6	**0.77**
Recall	0.68	0.64	0.20	0.11	0.14	**0.93**
F1 score	0.72	0.67	0.27	0.18	0.22	**0.85**

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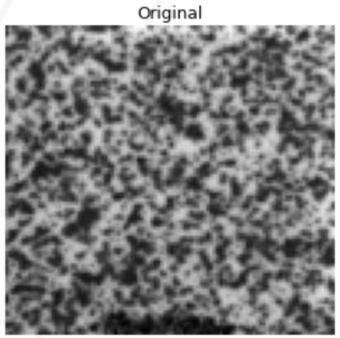
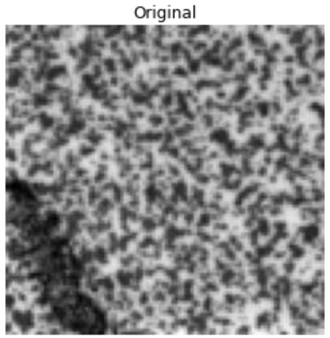
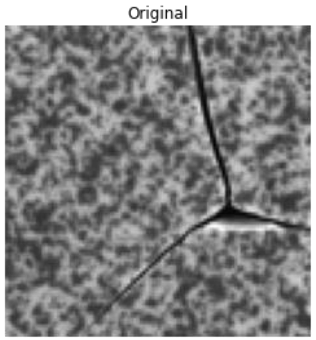
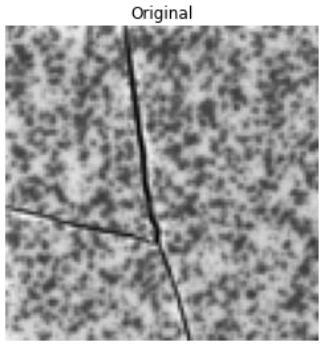
Tile Case Study





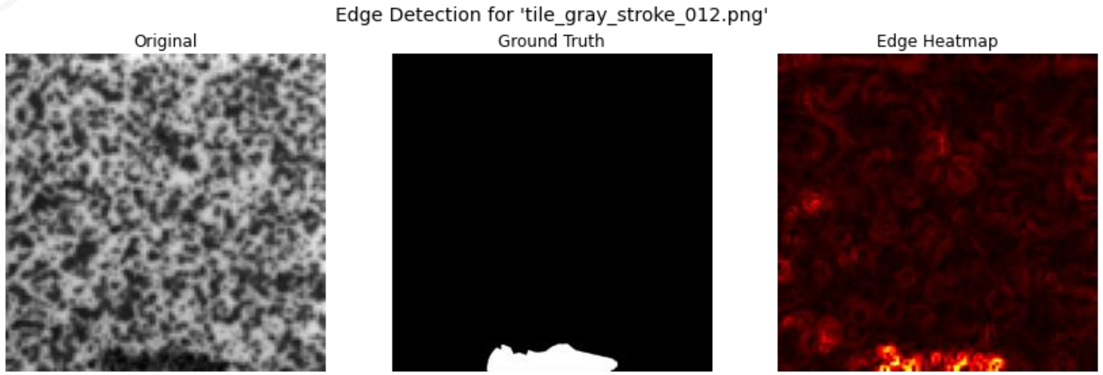


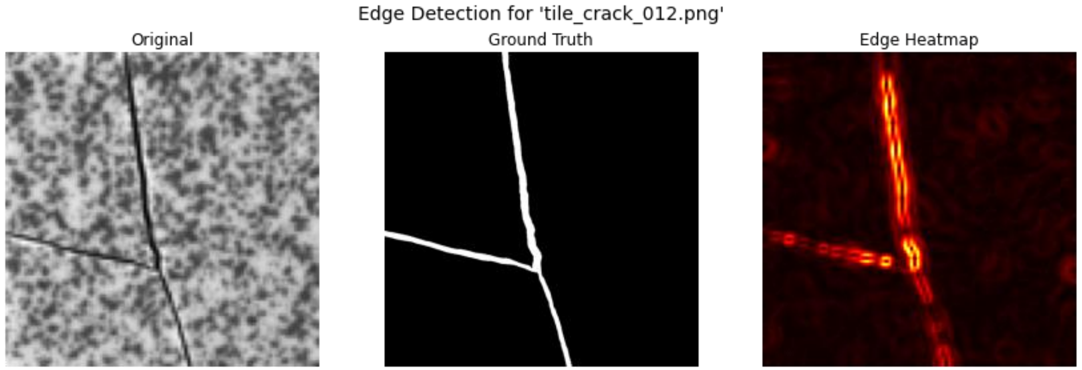


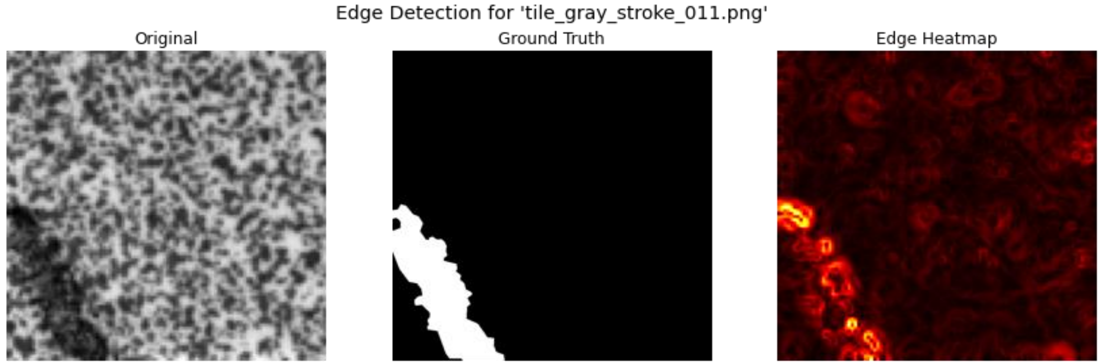
	C&B	B&A	DiffusionAD	AnoDDPM	DDPM	RADAR
Accuracy	0.36	0.51	0.35	0.47	0.43	**0.64**
Precision	1.0	0.87	0.58	0.63	0.59	**0.95**
Recall	0.07	0.35	0.20	0.57	0.57	**0.51**
F1 Score	0.13	0.50	0.30	0.60	0.58	**0.67**

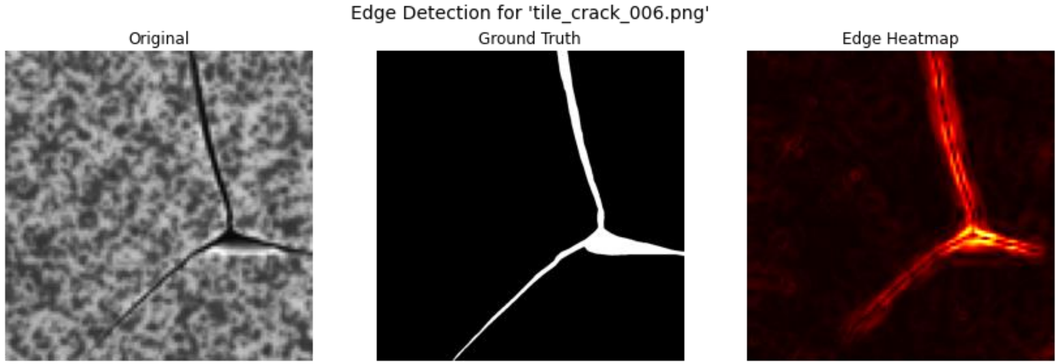
Case Study: Tile

In addition to image level anomaly detection, RADAR shows good pixel level anomaly detection for diagnosis









Ablation Study: Feature Extraction (Contamination=0.05) on the Second Case Study

	Current method	GLCM	SSIM	Hough Transform	Entropy
Accuracy	**0.64**	0.55	**0.59**	0.34	0.39
Precision	**0.95**	0.88	**0.94**	0.80	0.74
Recall	**0.51**	0.41	**0.43**	0.05	0.19
F1 Score	**0.67**	0.56	**0.59**	0.10	0.30

Conclusion

- Generative models show exceptional performance in anomaly detection and segmentation.
  - Current state-of-the-art methods require healthy training data to be effective.
  - Anomalies are localized by reconstructing a normal version of the image through hundreds of sampling steps in the backward diffusion process, followed by residual calculation.
- **Our Contributions:**
  - **RADAR**: Performs diffusion-based anomaly detection and segmentation in a *single step*, unlike reconstruction-based models that require hundreds of steps.
- **Future Work:**
  - Extend the current methods to non-stationary time-series monitoring and anomaly detection:
    - Condition training on past windows to enforce temporal relationship learning.
    - Incorporate a prediction loss to encourage the model to forecast future points.
  - Extend the model to unstructured point-cloud monitoring and anomaly detection:
    - Define patches as neighborhoods of points and train the model to learn their distribution.
    - Develop new feature extraction modules for more precise anomaly localization.

On the Job Market - *Open to Research & ML Opportunities*

Connect on Linkedin

- **Mehrdad Moradi**
  - Focused on robust generative AI for anomaly detection and vision systems
  - Ph.D. Student in Machine Learning, Georgia Tech
  - Advisor: Prof. Kamran Paynabar
  - Research focus: Anomaly Detection, Diffusion Models
- **Selected Publications**
  - **Moradi, M.**, Chen, S., Yan, H., Paynabar, K. A Single Image Is All You Need: Zero-Shot Anomaly Localization Without Training Data. (Submitted to WACV 2026) [9]
  - **Moradi, M.**, Grasso, M., Colosimo, B. M., Paynabar, K. Single-Step Reconstruction-Free Anomaly Detection and Segmentation via Diffusion Models. (ICMLA 2025) [7]
  - **Moradi, M.**, Paynabar, K. RDDPM: Robust Denoising Diffusion Probabilistic Model for Unsupervised Anomaly Segmentation. (ICCVW 2025) [8]
- **Opportunities**
  - Actively seeking Machine Learning research or applied roles (internship or full-time) starting in Spring, Summer, or Fall 2026.
- **Contact:**
  - Email: mmoradi6@gatech.edu

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