| Autonomous Damage Recognition in Ultrasonic Non-Destructive Evaluation Using a Semi-Supervised GAN |

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| CSCE 768 – Pattern Recognition and Classification | Final Project

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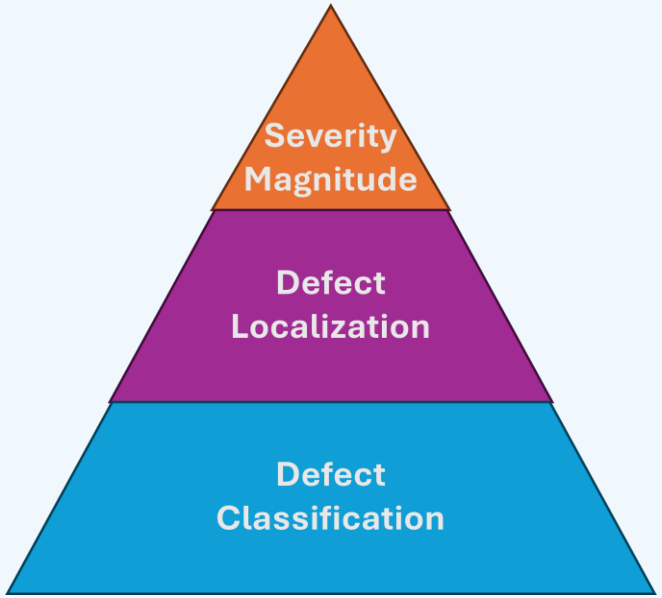
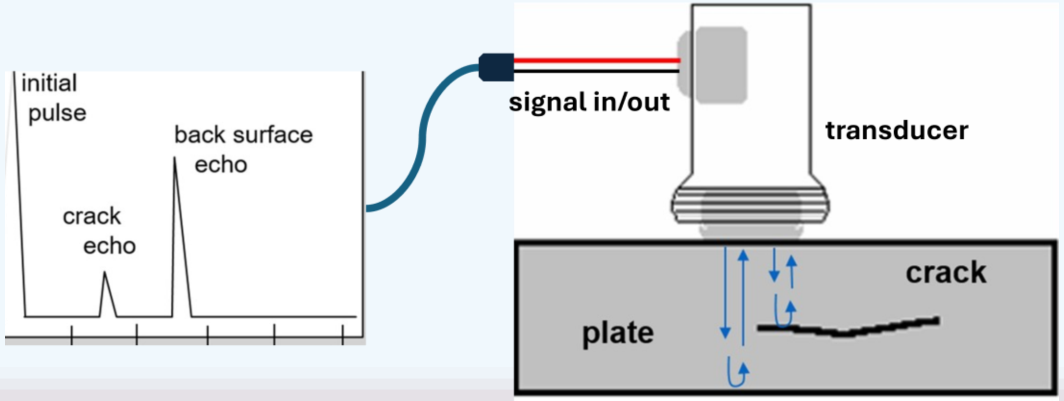
Problem Statement



- Ultrasonic C-scan inspection is widely used to detect subsurface defects in composite materials
  - Manual inspection inconsistent, time-consuming, and difficult for subtle or noisy defects
- Supervised ML methods require large labeled datasets—scarce in NDE
- **Goal:** Develop a *semi-supervised* model that:
  - Detects presence of defects
  - Localizes the spatially
  - Quantifies severity
- Approach based on SGAN reconstruction + classification



Technical Challenges

- Highly variable scan textures and noise patterns
- Very small labeled dataset; labels only indicate defect/no-defect (no segmentation)
- Need for interpretable defect localization
- GAN training instability (balancing generator & discriminator)
- Ultrasonic data requires preservation of fine-scale texture

filename	label
100MHz_2.JPG	1
24ply16plyscan10Mhz-001.JPG	1
24ply16plyscan10Mhz-002.JPG	0
24ply16plyscan10Mhz-012.JPG	1
500x_Z48323_60x60_Inside.JPG	0

Binary defect/no-defect label csv for training

Related Work

1. **Prajapati et al. (2025) -** *Semi-supervised GAN for ultrasonic defect classification*

- Related: Shows SGANs work well for low-labeled NDE data
- Different: Their generator doesn't reconstruct inputs; my SGAN produces **heatmaps + severity maps** for interpretable defect localization

2. **Schlegl et al. (2017) -** *GAN reconstruction for anomaly detection*

- Related: Introduces the idea of using **reconstruction error** as a localization tool
- Different: Their method is unsupervised and non-NDE; mine incorporates **supervision**, ultrasonic-specific preprocessing, and **quantitative severity scoring**

Baselines from Literature

Baseline Model	Supported By (Reference)	What It Does	Limitations Compared to My SGAN
Supervised CNN Classifier	Prajapati et al. 2025 (Ref [1])	Learns defect vs. no-defect classification from labeled data only	No localization; needs large labeled datasets; weaker performance in low-label NDE
Autoencoder (AE)	Schlegl et al. 2017 (Ref [5])	Reconstructs input and uses residuals for anomaly detection	Reconstructions are smooth; residual maps are less precise; no supervised classification
AnoGAN (Unsupervised GAN)	Schlegl et al. 2017 (Ref [5])	GAN-based anomaly detection using latent optimization	Slow inference; no supervised branch; weaker localization vs. UNet generator
Semi-Supervised GAN (SGAN baseline)	Salimans et al. 2016 (Ref [4])	Joint real/fake learning + classification	Not designed for reconstruction → cannot produce heatmaps or severity scores
Physics-Informed Neural Networks (PINNs)	Raissi et al. 2019 / Karniadakis et al. 2021 (Refs [6,7])	Encode wave physics for modeling ultrasonic propagation	No image reconstruction; no residual maps; heavy computation; requires PDE knowledge

ResNet50 + Memory Bank (Original baseline)

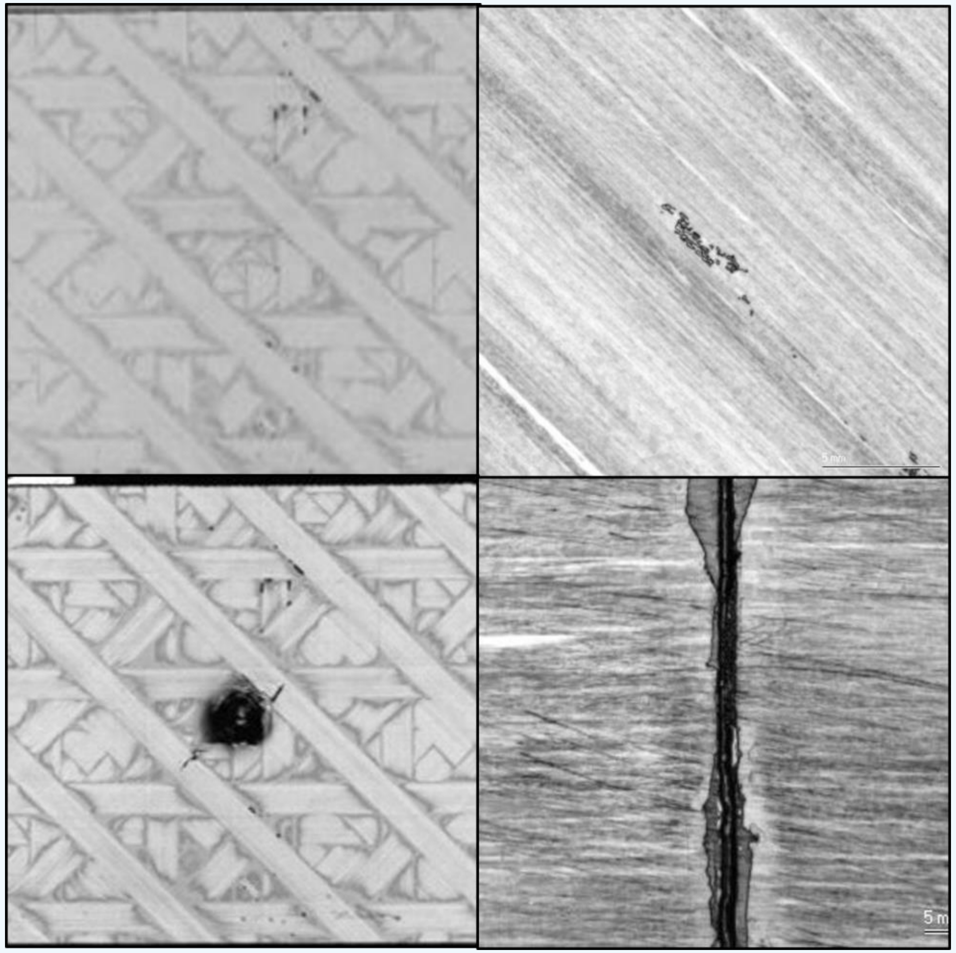
- Initial approach used unsupervised anomaly-detection pipeline
  - ResNet50 feature extraction
  - Nearest-neighbor memory bank

- Models “normal” composite behavior
  - Stores feature patches from defect-free images
  - Flags anomalies based on feature-space distance

- While it could detect strong defects the model:
  - struggled with spatial precision
  - was sensitive to noise and texture variation
  - produced inconsistent severity scores

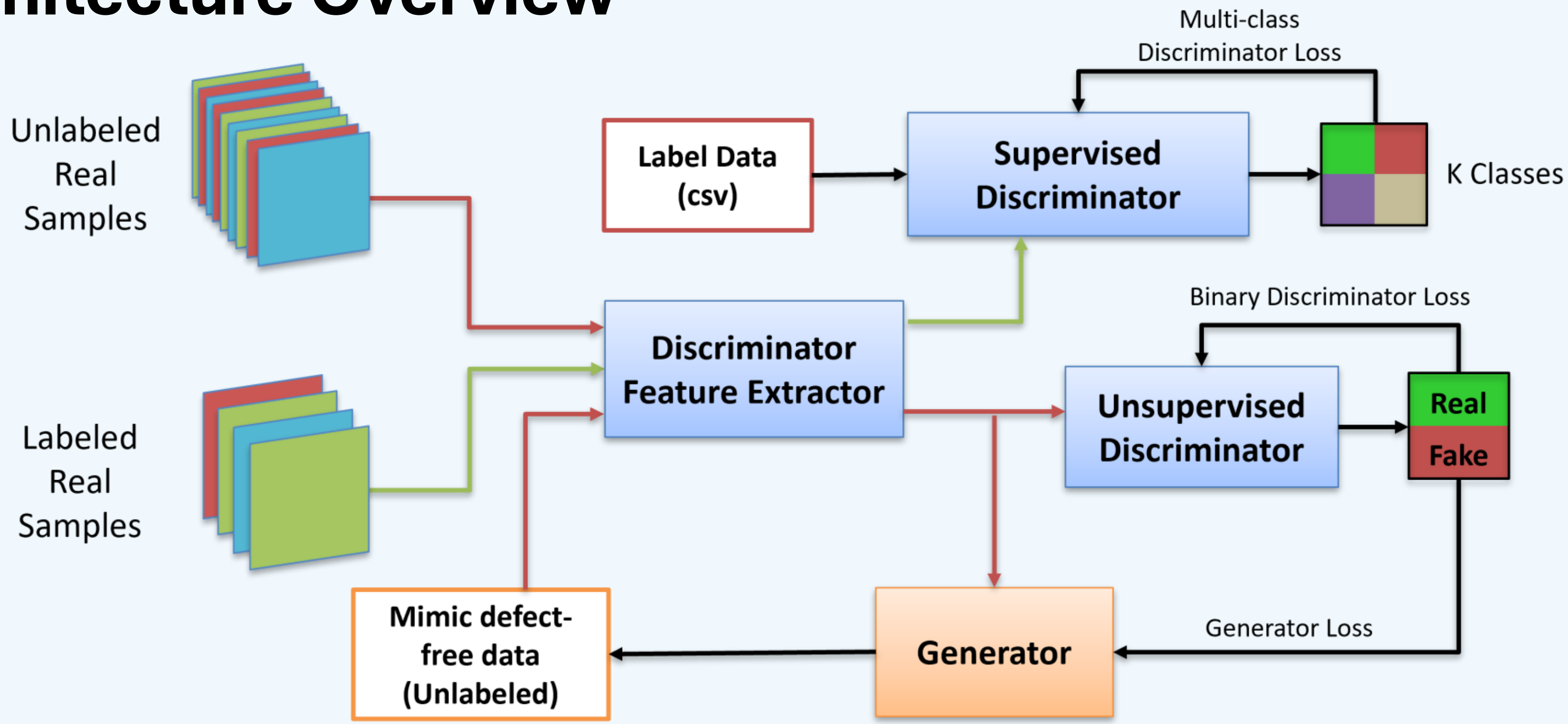
Dataset

- Ultrasonic C-scan images of CFRP composite laminates
- Files labeled as 0 = healthy, 1 = defective
- Preprocessing (from *data.py*):
  - Grayscale → 256×256
  - Random rotation (±5°), horizontal flip
  - Normalize to [-1, 1]
  - Tensor conversion



C-scan examples illustrating structural variations and typical defect modes present in the dataset

SGAN Architecture Overview



Generator (UNet-based)

- Learns to reconstruct defect-free version of input
- Skip connections preserve spatial detail
- Produces output used to compute spatial residual heatmaps

Discriminator

- Dual-headed:
  - Real/Fake discrimination
  - Defect/No-defect classification
- Enables semi-supervised learning

Training Loss Functions

Discriminator Loss

- Real/Fake BCE
- Supervised CE for defect classification
- Fake recognition for reconstructions

Generator Loss

- Adversarial loss (fool D)
- L1 reconstruction loss ($\lambda = 20$)
- Classification-forced healthy label

$$\mathcal{L}_{D,\text{real}} = -\left[0.92 \cdot \log(D_{\text{adv}}(x)) + (1 - 0.92) \cdot \log(1 - D_{\text{adv}}(x))\right]$$

$$\mathcal{L}_{D,\text{cls}} = -\sum_{c=0}^{1} \mathbf{1}_{[y=c]} \log\left(\text{softmax}(D_{\text{cls}}(x))_c\right)$$

$$\mathcal{L}_{D,\text{fake}} = -\left[0 \cdot \log(D_{\text{adv}}(G(x))) + 1 \cdot \log(1 - D_{\text{adv}}(G(x)))\right]$$

$$\mathcal{L}_D = \mathcal{L}_{D,\text{real}} + \mathcal{L}_{D,\text{cls}} + \mathcal{L}_{D,\text{fake}}$$

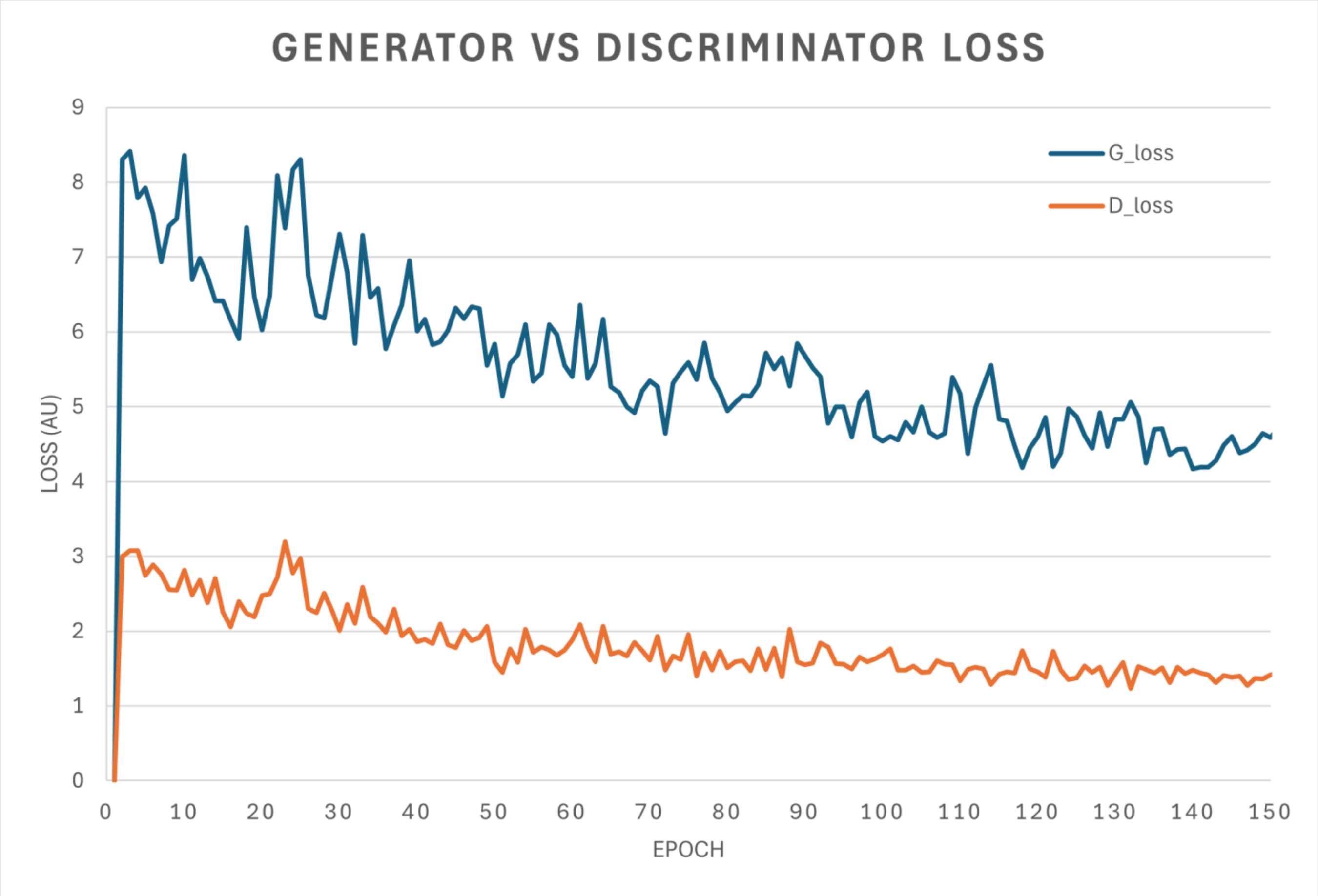
$$\mathcal{L}_{G,\text{adv}} = -\left[0.92 \cdot \log(D_{\text{adv}}(G(x))) + (1 - 0.92) \cdot \log(1 - D_{\text{adv}}(G(x)))\right]$$

$$\mathcal{L}_{G,\text{rec}} = \|G(x) - x\|_1$$

$$\mathcal{L}_{G,\text{sup}} = -\log\left(\text{softmax}(D_{\text{cls}}(G(x)))_0\right)$$

$$\mathcal{L}_G = \mathcal{L}_{G,\text{adv}} + \lambda \mathcal{L}_{G,\text{rec}} + \gamma \mathcal{L}_{G,\text{sup}}$$

Training Pipeline



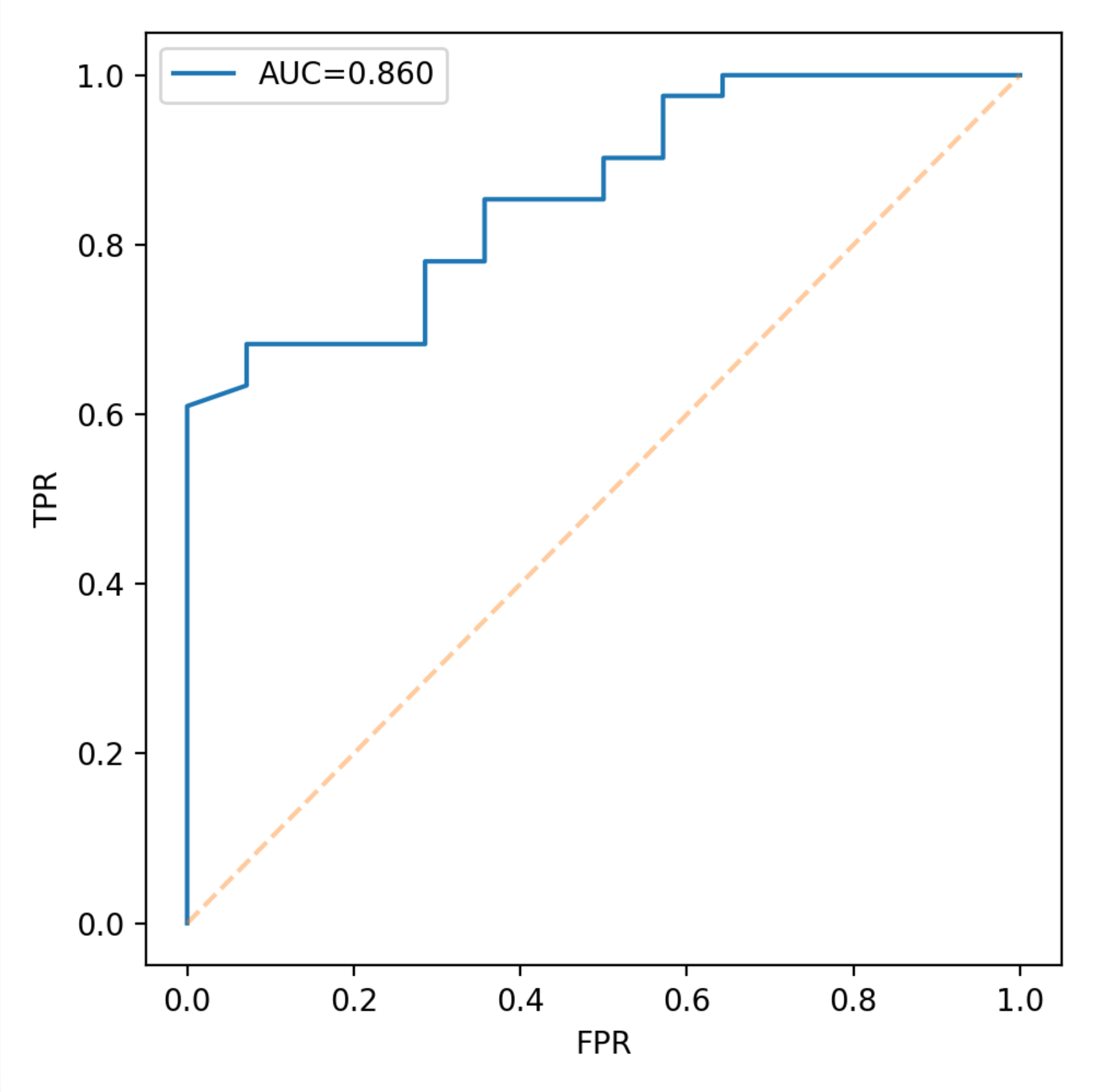
- Implemented in *trainer.py*
  - Alternating G/D updates
  - Extra G steps when D becomes too strong
  - Severity metric from top-k reconstruction error
- Optimization
  - Epochs = 150
  - Batch size = 8
  - Adam optimizers (β_1=0.5, β_2=0.999)
  - Adaptive update frequency
  - Label smoothing (0.92 real)

K-Fold Cross Validation

epoch	G_loss	D_loss	val_auc
1	8.305547202	2.994782854	0.698606272
2	8.417826264	3.072160465	0.757839721
3	7.789292936	3.077182584	0.677700348
4	7.922417923	2.741973568	0.527874564
5	7.576630327	2.885773747	0.766550523
6	6.93380234	2.758417169	0.724738676

Output per-epoch metric csv example

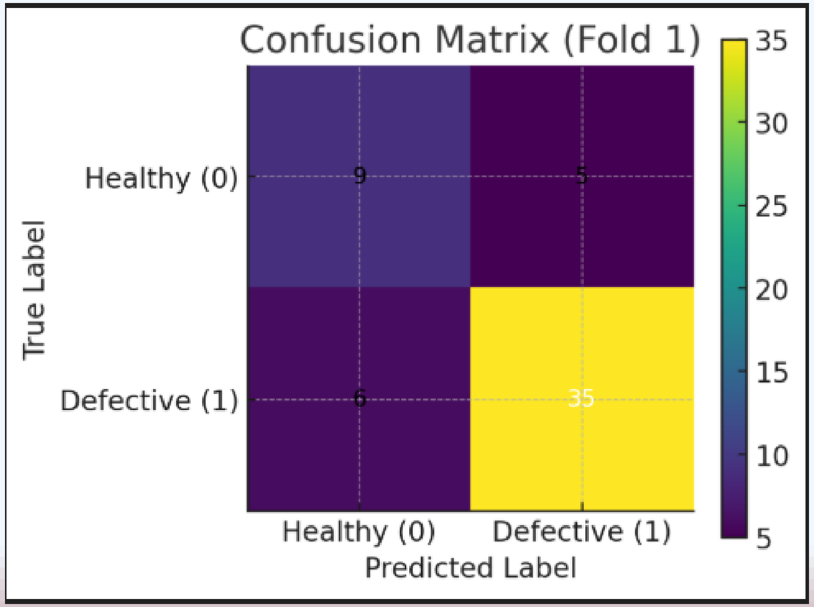
- Implemented in *train_cv.py*
  - Stratified splits
  - Per-epoch metrics: G loss, D loss, AUC
  - Saves checkpoints each epoch
  - Combined summary CSV
- Useful for small NDE datasets with label imbalance

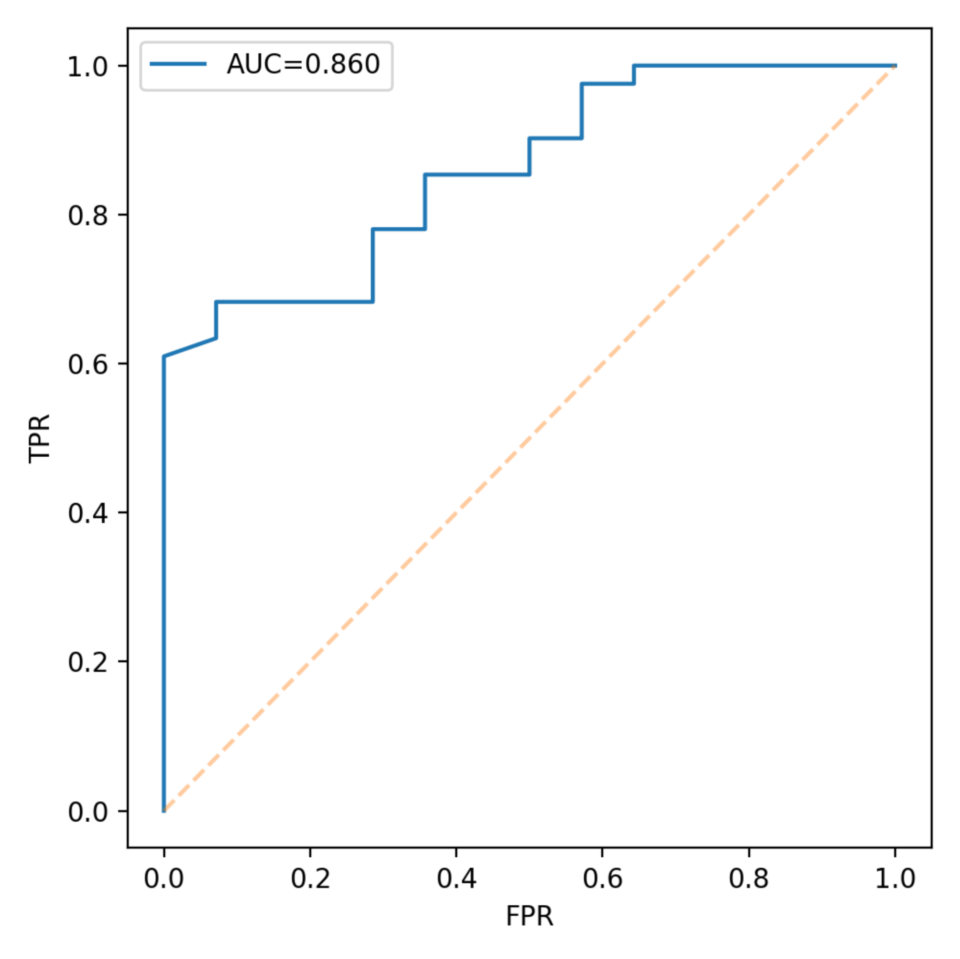


ROC curve for Fold 1 with corresponding AUC

Results: Classification

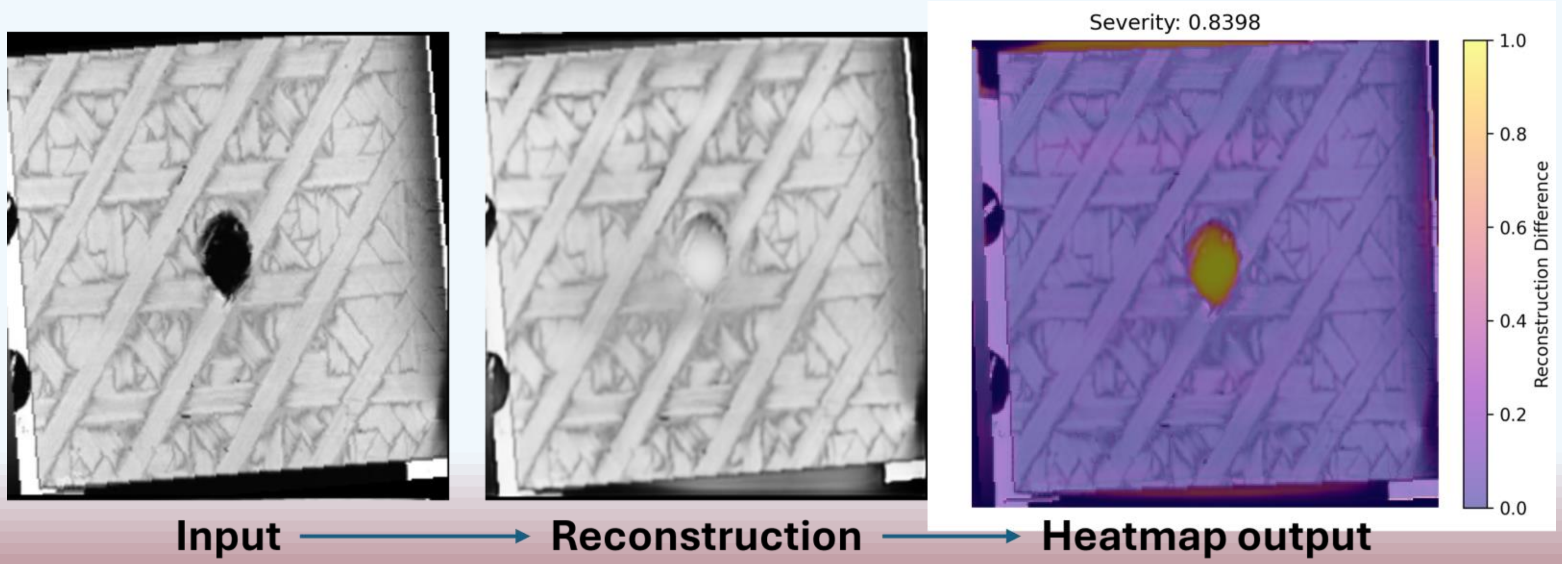
- Discriminator achieves strong separation between defective/non-defective samples
- Consistent ROC-AUC across folds
- Low cross-fold variance indicates stable generalization





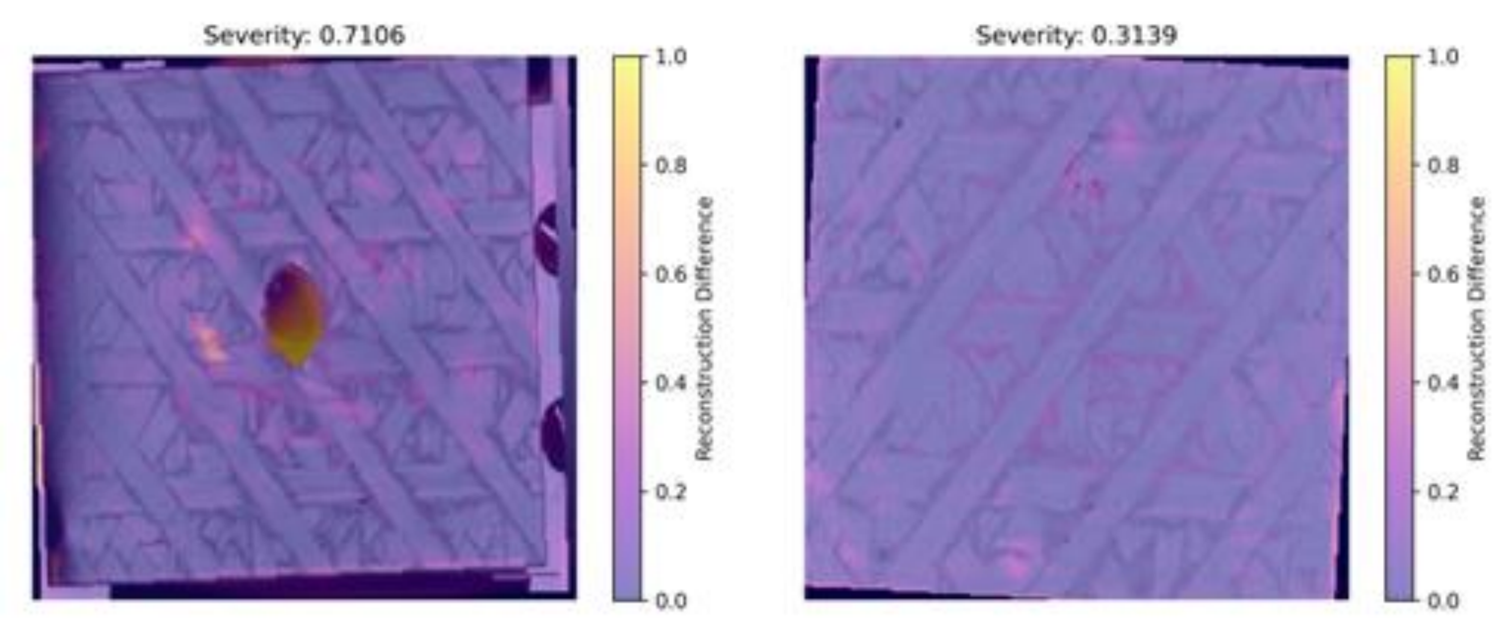
Results: Reconstruction & Localization

- Generator reconstructs smooth “healthy” structure
- Residual = |input − reconstruction| highlights local defects
- Produces intuitive heatmaps
- Severity score computed using top-k residual intensity



Results: Severity Estimation

- Top-k residual error correlates with physical defect magnitude
- High-severity vs low-severity defects clearly separated



(a) High-severity defect.   (b) Low-severity defect.

Broader Impact

Benefits:

- Automated, interpretable NDE
- Less reliance on large labeled datasets
- Provides classification + localization + severity estimation
- Extensible to other modalities (B-scan, A-scan)

Limitations:

- GAN training instability
- Severity metric empirical (not physically constrained)
- Reconstruction may blur subtle fine-scale defects

Future Work

- Add **physics-informed loss terms** incorporating ultrasonic wave propagation
  - PDE-constrained generator penalty
- Expand to multi-modal ultrasonic data
  - A-scans, B-scans, multi-frequency inputs
- Experiment with newer architectures
  - **Diffusion-based** reconstruction models
  - Vision **transformers** for discriminator
- Improve severity metric calibration using physical simulation

References

[1] K. K. Prajapati, A. Ghosh, and M. Mitra, “Semi-supervised generative Adversarial Network (SGAN) for damage detection in a composite plate using guided wave responses,” Mechanical Systems and Signal Process ing, vol. 232, p. 112686, Jun. 2025. doi:10.1016/j.ymssp.2025.112686

[2] K. K. Prajapati, “Lamb Wave-Based Structural Health Monitoring using Deep Learning Techniques,” thesis, 2025

[3] J. Hooks, ”CSCE768 Final-Project,” GitHub, Dec. 2025. [Online]. Available: https://github.com/jhooks5313/CSCE768 Final-Project.git

[4] T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen, “Improved techniques for training GANs,” in Proc. NeurIPS, 2016.

[5] T. Schlegl, P. Seeb¨ock, S. M. Waldstein, U. Schmidt-Erfurth, and G. Langs, “Unsupervised anomaly detection with generative adversarial networks to guide marker discovery,” in Proc. IPMI, 2017.

[6] M. Raissi, P. Perdikaris, and G. E. Karniadakis, “Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations,” Journal of Computational Physics, 2019.

[7] G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang, “Physics-informed machine learning,” Nature Reviews Physics, 2021.

[8] J. Hu, “Lecture 9: Generative Models,” CSCE 768 Pattern Classification, Dept. of Computer Science and Engineering, Univ. of South Carolina, 2025, [PowerPoint slides].