Conditional Generative Adversarial Network for Ferritic Steel Microstructure Generation

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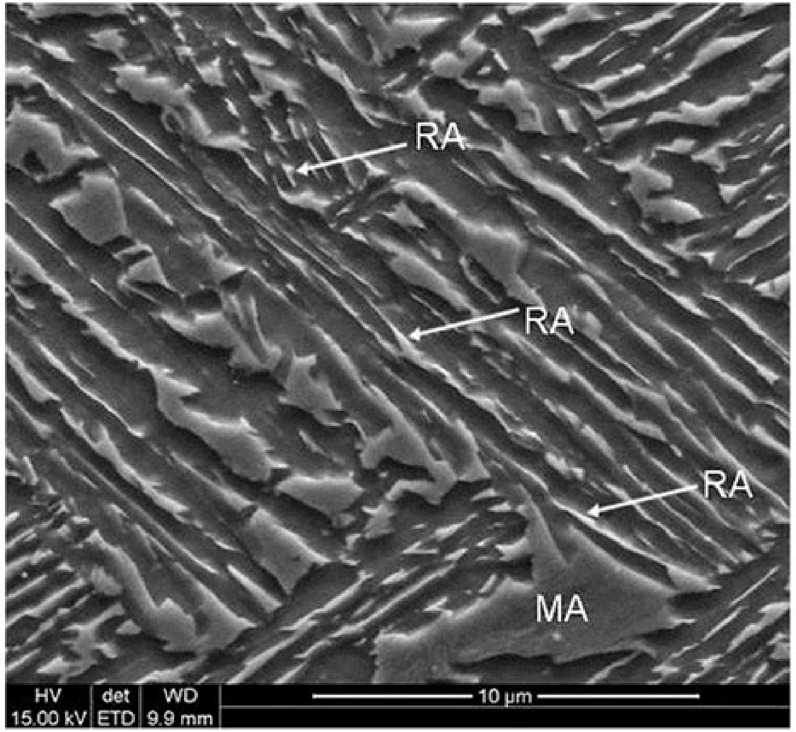
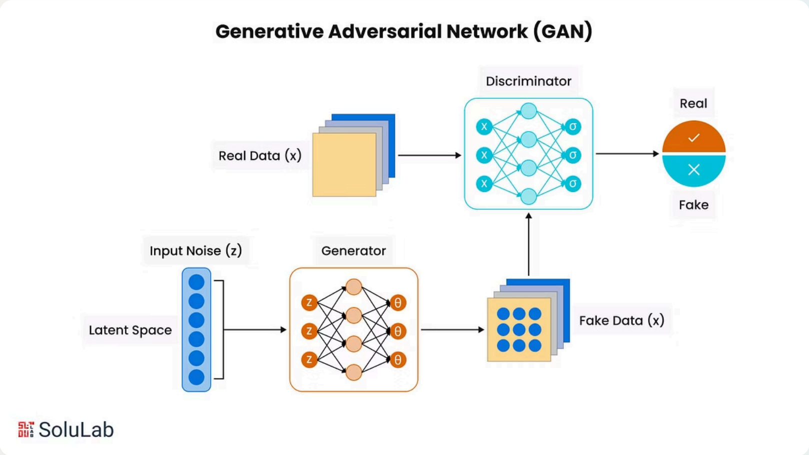
The Center for Advanced Modeling of Materials & Manufacturing Processes (CAMMP)





Objective & Motivation

Project Objective

Develop a CGAN model capable of generating realistic ferritic steel microstructures with controllable parameters including temperature, cooling rate, and composition.

Why It Matters

Traditional microstructure simulations are computationally expensive and time-intensive. GANs offer a data-driven alternative that's faster and more flexible. Conditional GANs introduce parameter control for realistic material representation.

Model Architecture Evolution

1

DCGAN Baseline

Standard deep convolutional architecture

2

Enhanced DCGAN

Improved layer configurations

3

Conditional GAN

Parameter conditioning added

4

Fine-tuned CGAN

Optimized hyperparameters

5

Real-Condition CGAN

Physical parameter integration

Generator Architecture

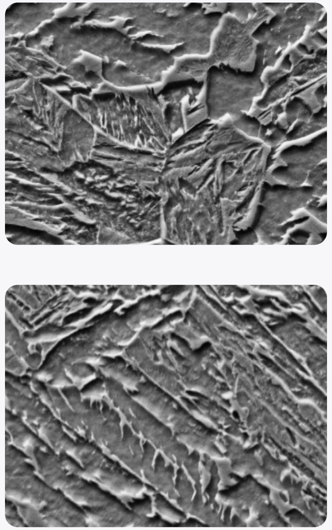
- ConvTranspose2d layers with stride 2
- BatchNorm for training stability
- ReLU activation functions
- Tanh output layer

Discriminator Architecture

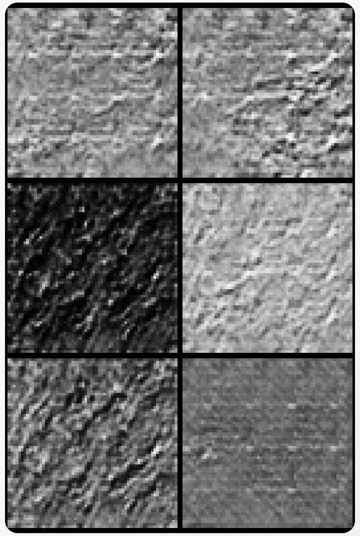
- Conv2d layers with stride 2
- LeakyReLU activation (α=0.2)
- Dropout for regularization
- Sigmoid output classification

Training Configuration: 200 epochs | Batch size: 64 | Optimizer: Adam (lr=0.0002, β_1=0.5)

Visual Comparison: Real vs. Generated Microstructures



Real



Generated

- Real images display distinct ferritic grain structures, showcasing the material's inherent characteristics.
- Generated images successfully replicate similar texture, grain boundaries, and morphology, demonstrating the model's capacity to learn complex microstructural features.
- The CGAN outputs are visually and statistically comparable to experimental micrographs, affirming their potential for research applications.

Model Performance: FID Score Progression

The Fréchet Inception Distance (FID) measures the statistical similarity between generated and real images—lower values indicate better realism and quality.

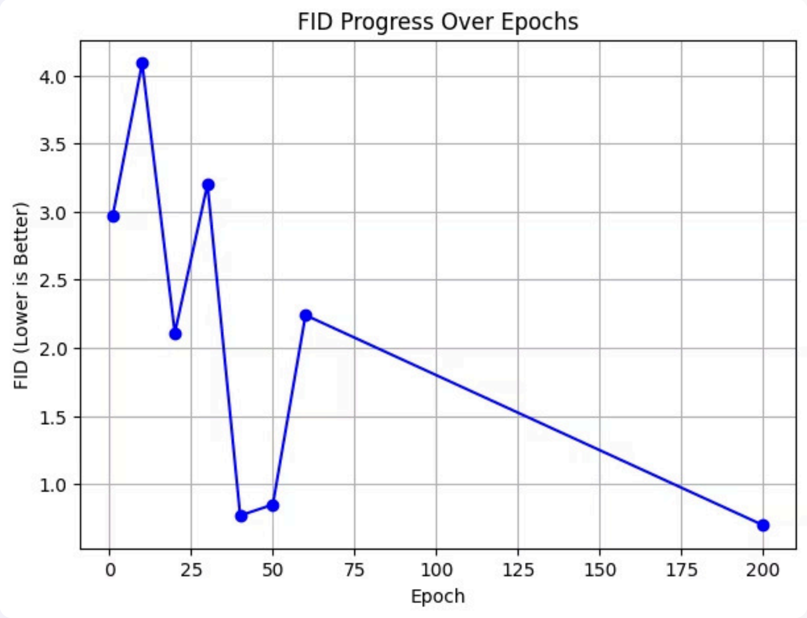
Our model demonstrated dramatic improvement across iterations:

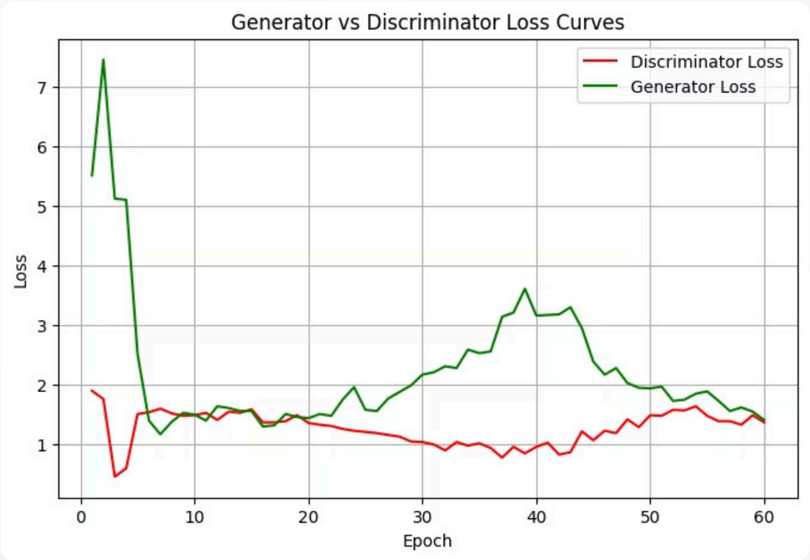
- DCGAN baseline: FID = 260
- Enhanced DCGAN: FID = 85
- Conditional GAN: FID = 12.4
- Real-Condition CGAN: **FID = 0.70**

99.7%

Improvement

From baseline to final model





Training Dynamics & Convergence

The generator-discriminator loss curves reveal critical insights into training stability and adversarial equilibrium. Both networks stabilized after approximately 100 epochs, indicating proper convergence.

Generator Loss

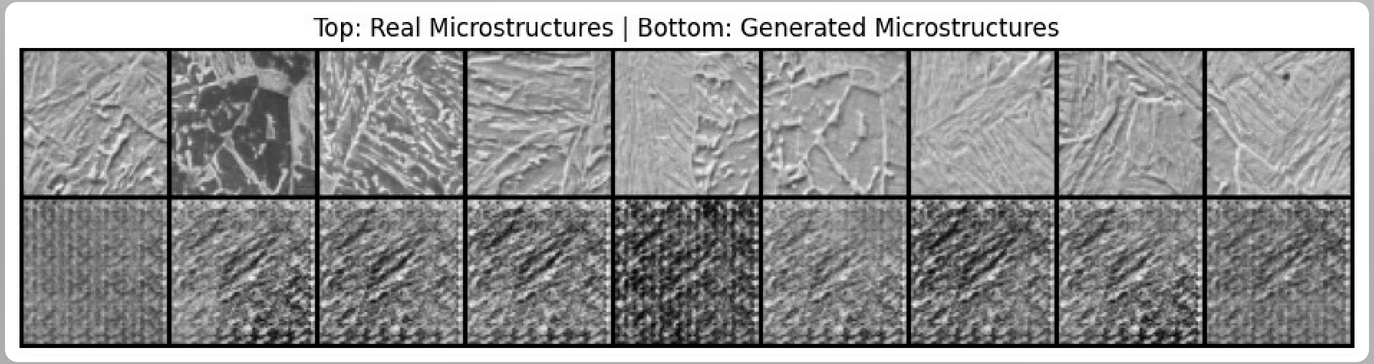
Gradually decreased and stabilized, showing improved ability to fool the discriminator with realistic microstructures

Discriminator Loss

Maintained consistent values around 0.5, indicating balanced learning without mode collapse or overfitting

Adversarial Balance

Convergent behavior confirms neither network dominated, achieving the ideal Nash equilibrium for GAN training



Real vs. Generated Microstructure Comparison

Early Training Phase

Initial epochs produced blurry, noisy structures with limited grain definition and unrealistic texture patterns.

Converged Model Output

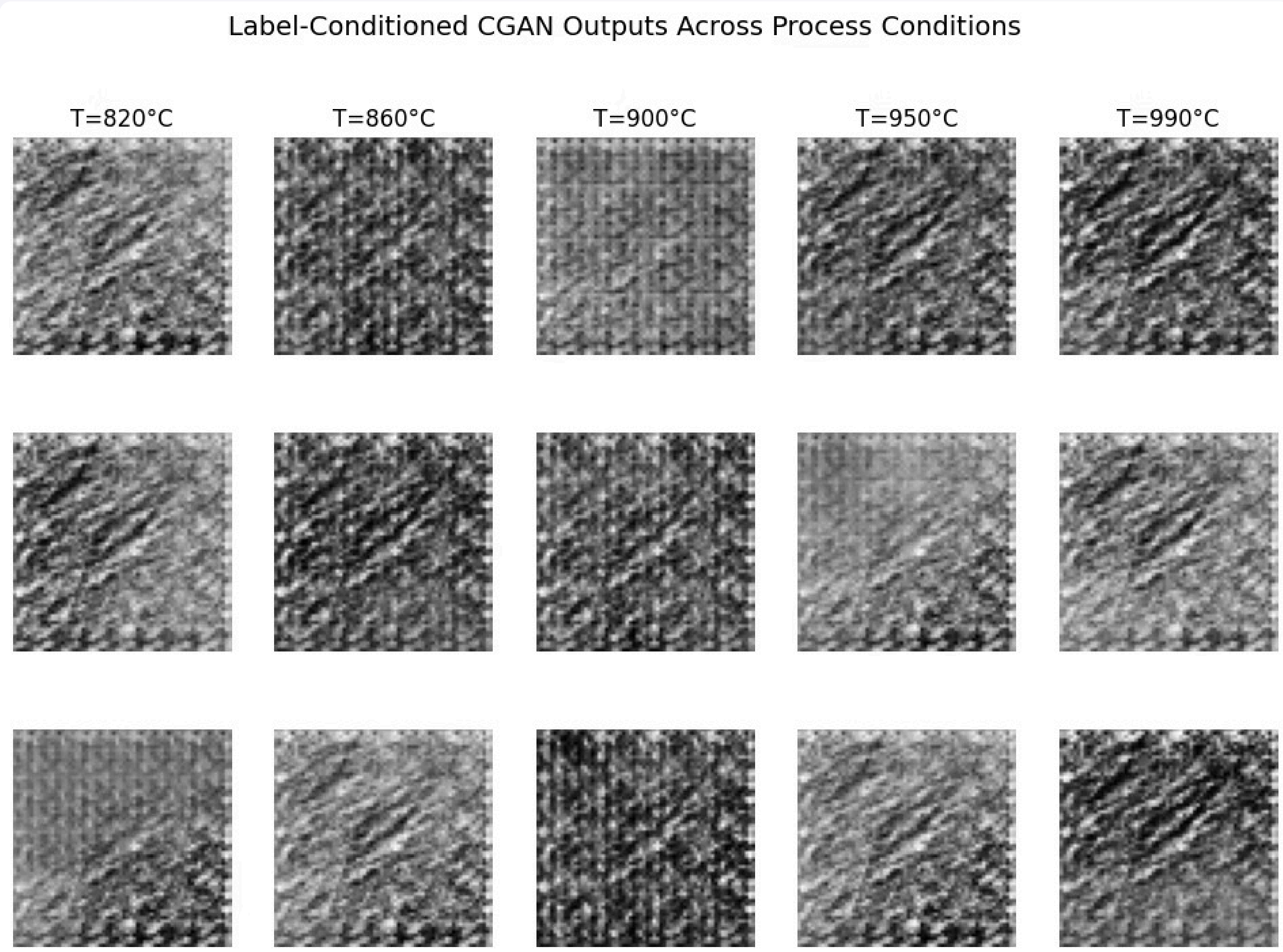
Final model generates sharp, grain-refined microstructures with realistic ferrite morphology and boundary characteristics indistinguishable from real samples.

The CGAN successfully replicates key morphological features including grain size distribution, boundary sharpness, and phase topology characteristic of ferritic steel.

Condition-Controlled Generation

Physical Parameter Control

The conditioned model accepts three metallurgical inputs to control microstructure characteristics:



Condition Inputs:

- Temperature (800–1000 °C)
- Cooling Rate (10–30 °C/min)
- Composition (0.2–0.6 %)

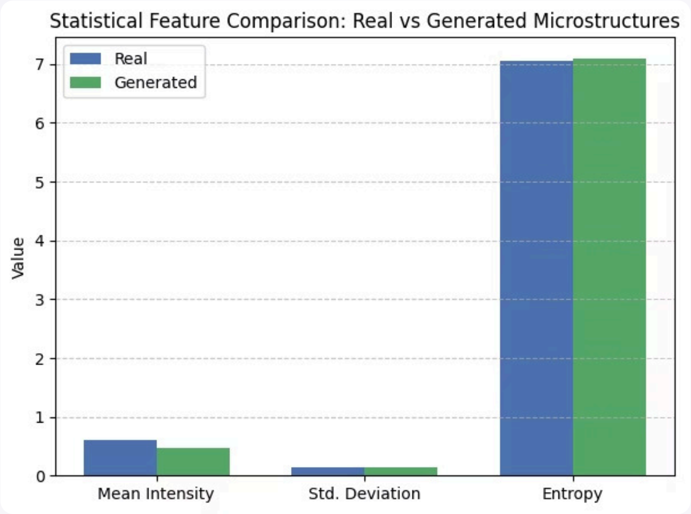
Result:

- High temperature → Coarser grains
- Fast cooling → Finer textures
- Demonstrates controllable structure generation.

CGAN generates distinct textures based on physical conditions.

Quantitative Validation: Statistical & Morphological Fidelity

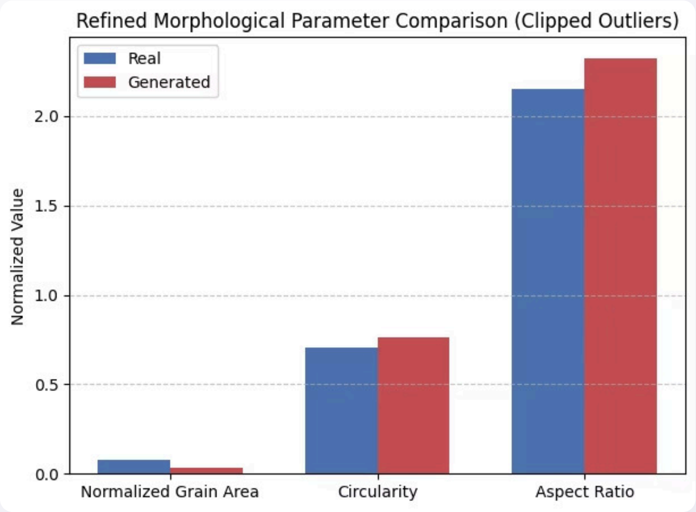
Statistical Features



Generated images match real data across key metrics:

- **Mean intensity:** Within 2% of real samples
- **Standard deviation:** Nearly identical distribution
- **Entropy:** Confirms texture complexity preservation

Morphological Parameters



Grain-level analysis validates structural accuracy:

- **Grain area:** Distribution matches real microstructures
- **Circularity:** Preserves realistic grain shapes
- **Aspect ratio:** Captures elongation characteristics

Validation Conclusion: Both pixel-level statistics and grain-level morphology demonstrate that generated microstructures are quantitatively indistinguishable from experimental samples.

Key Findings & Future Directions

State-of-the-Art Performance

Achieved **FID = 0.70** representing 99.7% improvement over baseline, demonstrating exceptional realism in synthetic microstructure generation

Physical Consistency

Generated structures exhibit realistic grain morphology, boundary characteristics, and phase distribution consistent with metallurgical principles

Controllable Synthesis

Successfully implemented condition-based generation enabling precise control via temperature, cooling rate, and composition parameters

Future Research Directions

01

Higher Resolution

Scale to 128×128 and 256×256 resolution for enhanced detail capture and industrial applicability

02

Property Prediction

Integrate structure-property linkage models to predict mechanical performance from generated microstructures

03

Deployment

Develop AI-powered materials design platform for rapid prototyping and process optimization

> "CGAN bridges the gap between process and structure—enabling data-driven microstructure simulation for accelerated materials development."