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Method Article

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Deep Volumetric Classification of Pore Morphology in 3D Micro-Computed Tomography of Additively Manufactured Metallic Components

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Abstract*—Internal porosity represents a critical factor governing mechanical fatigue and failure in metal additive manufacturing (AM). In fracture mechanics, void geometry dictates local stress intensity factors; acute and elongated geometries concentrate mechanical stress significantly more than spherical voids. Consequently, automated categorization of volumetric defects into Spherical, Elongated, and Irregular morphologies from 3D X-ray micro-computed tomography (micro-CT) is essential for non-destructive evaluation. Due to experimental acquisition constraints and extreme class imbalance in physical scans (837 labeled voids: 6.45% spherical, 44.80% elongated, 48.75% irregular), we developed a procedural 3D synthetic pore generation framework to train deep convolutional architectures. While an initial 3D Convolutional Neural Network (3D CNN) achieved 99.89% validation accuracy on synthetic data, zero-shot transfer on physical scans collapsed completely to the elongated class due to detector attenuation polarity inversion and a large-void size cutoff. Recalibrating synthetic data with scanner point-spread function (PSF) blur, noise, and sub-voxel micro-radii yielded 97.83% synthetic accuracy, yet exhibited a secondary mode collapse on physical scans due to ambient background air saturation along hollow tube boundaries. Kernel Density Estimation (KDE) diagnostics identified an order-of-magnitude volume scale mismatch between synthetic models (mean 67.51 voxels) and real defects (mean 6.76 voxels). A controlled 5-experiment ablation benchmark (Exp A–E) on a locked real held-out test set (N = 126, seed = 42) demonstrated that synthetic pretraining yielded no performance gain (42.86%) relative to training from scratch on physical scans (45.24%). Conversely, a classical Random Forest trained on mathematical geometric descriptors achieved 99.21% accuracy, confirming ground-truth label separability and establishing that raw-voxel 3D CNNs are fundamentally constrained by spatial discretization limits (53.6 μm/voxel). We propose a hybrid multi-modal feature fusion architecture bridging raw volumetric representations with classical geometric invariants for robust industrial deployment.

***Index Terms*—Additive manufacturing, micro-computed tomography, 3D convolutional neural networks, pore morphology, sim-to-real domain transfer, ablation study, Random Forest, multi-modal feature fusion.**

I. INTRODUCTION

Laser powder bed fusion (LPBF) and selective laser melting (SLM) enable the fabrication of structurally complex metallic components with tailored mechanical properties. Despite significant advances in process control, the rapid thermal cycles, hydrodynamic instabilities within the liquid melt pool, and powder consolidation dynamics inevitably introduce microscopic discontinuities. These internal cavities, generically classified as pores, serve as primary failure initiation sites under static and cyclic loading regimes.

Linear elastic fracture mechanics establishes that void morphology exerts a dominant influence over fatigue life compared to total volumetric fraction. Under uniform tensile or multiaxial loading, spherical pores produce uniform, predictable stress redistributions with low stress concentration factors (Kt $\approx$ 2.0). Conversely, elongated lack-of-fusion voids and irregular cavities characterized by acute boundary radii and re-entrant notches induce high localized stress gradients, accelerating microcrack nucleation and catastrophic component failure. High-resolution 3D X-ray micro-computed tomography (micro-CT) provides volumetric visualization of internal features, enabling non-destructive inspection across metallic matrices.

However, conventional industrial workflows rely extensively on slice-by-slice manual inspection. This methodology is labor-intensive, operator-dependent, and inherently qualitative. Automated morphological classification algorithms capable of operating directly on 3D volumetric micro-CT scans are therefore essential for reliable non-destructive qualification.

II. MORPHOLOGICAL TAXONOMY & VOLUMETRIC REPRESENTATION

A. Pore Formation Mechanisms & Geometric Taxonomy

Additive manufacturing pores are classified into three primary morphological categories based on their physical formation mechanisms:

1) Spherical Pores (Gas Porosity): Formed by the entrapment of inert shielding gas (e.g., argon) or vaporized moisture within the liquid melt pool. Driven by interfacial surface tension, the molten boundary adopts a minimum surface energy configuration prior to rapid solidification. These voids exhibit high sphericity ($\Psi \geq 0.85$) and an aspect ratio near unity, presenting minimal mechanical detriment under cyclic loading.

2) Elongated Pores (Lack of Fusion): Resulting from inadequate laser energy density, excessive scan velocity, or improper hatch spacing, preventing complete coalescence between adjacent melt tracks or deposited layers. These defects manifest as planar, extended void channels containing residual un-melted powder particles, characterized by aspect ratios exceeding 1.60 and oriented along build planes.

3) Irregular Pores (Keyhole Collapse): Formed during high-power laser regimes where excessive recoil pressure drives unstable deep-penetration vapor cavities ('keyholes') that collapse violently. These defects feature complex, multi-lobed geometries with acute peripheral notches, generating elevated stress intensity factors and acting as severe crack initiation sites.

B. Geometric Ambiguity of Planar Slicing vs. 3D Volumetric Tensors

Applying standard 2D convolutional neural networks (e.g., ResNet, VGG) to planar cross-sectional CT slices introduces fundamental projection ambiguity. A single orthogonal 2D cut through an elongated cylindrical void produces a circular cross-section if intersected perpendicularly and an elliptical boundary if intersected obliquely. Consequently, a 2D network observing an isolated slice erroneously categorizes an elongated defect as spherical, neglecting continuous inter-slice structural continuity. Accurate morphological categorization strictly requires 3D Convolutional Neural Networks (3D CNNs) utilizing volumetric kernels ($3 \times 3 \times 3$) across continuous spatial bounding volumes ($32 \times 32 \times 32$ voxels), enabling simultaneous feature extraction across axial (XY), coronal (ZX), and sagittal (ZY) planes.

III. EXPERIMENTAL DATASET & SIM-TO-REAL DOMAIN TRANSFER

The physical micro-CT scan utilized in this study corresponds to an additively manufactured thin-walled metallic tube comprising 171 reconstructed slices (1000×1000 pixels) acquired at an isotropic voxel resolution of 53.6 μm. Segmentation and connected-component labeling identified 837 discrete pores. The dataset exhibits extreme class imbalance: 54 Spherical pores (6.45%), 375 Elongated pores (44.80%), and 408 Irregular pores (48.75%). Training high-capacity 3D deep networks directly on 837 physical samples introduces severe risks of empirical overfitting.

A. Generation 1 Procedural Synthesis & Zero-Shot Mode Collapse

To mitigate sample scarcity, we developed a procedural 3D synthesis pipeline generating 6,000 volumetric patches (2,000 per morphological class) using mathematical primitives. A 4-block 3D CNN (Conv3D, BatchNorm, LeakyReLU, MaxPool3D) trained on this balanced synthetic dataset achieved 99.89% validation accuracy. However, evaluating Model 1 directly on physical micro-CT scans resulted in complete zero-shot mode collapse: 100% of physical voids were predicted as Elongated, yielding an uninformative nominal accuracy of 44.80% corresponding strictly to the empirical class prior. Diagnostic failure analysis identified two root causes:

1) Attenuation Polarity Inversion: In physical micro-CT systems, dense metallic matrices attenuate X-rays and reconstruct as high-intensity voxels (≈ 0.85), whereas void cavities appear dark (≈ 0.05). In Dataset 1, intensity values had been inverted, reversing gradient directionalities across convolutional receptive fields.

2) Volumetric Scale Cutoff: The synthetic generator discarded primitives below 50 voxels to ensure smooth mesh rendering. However, physical micro-CT data inspection revealed that over 95% of real voids occupied volumes under 50 voxels, creating an unbridgeable volumetric disconnect.

B. Generation 2 Physics Calibration & Ambient Boundary Collapse

We re-engineered the synthetic pipeline to strictly incorporate CT scanner physics (Dataset 2): radii were calibrated to micro-defect scales (1.4–3.5 voxels), voxel intensities were matched to calibrated attenuation coefficients (0.85 metal, 0.05 void), and optical point-spread blur was simulated via 3D Gaussian convolution ($\sigma = 0.6$) and additive noise. Model 2 achieved 97.83% accuracy and 0.9784 Macro F1 on held-out synthetic validation data.

Deploying Model 2 onto the physical scan triggered a secondary, opposite mode collapse: 100% of pores were classified as Spherical, resulting in 6.35% accuracy (matching the exact prevalence of spherical voids). This was traced to an ambient domain shift: synthetic patches were extracted from continuous solid metal cubes ($> 95\%$ metal), whereas the physical specimen was a hollow thin-walled cylinder scanned in open air. Sub-volumes sampled near tube boundaries contained $> 80\%$ ambient dark air. Batch normalization layers saturated on low-intensity exterior voxels, misinterpreting boundary air as unbounded void volume.

IV. DISTRIBUTION ANALYSIS & CONTROLLED ABLATION BENCHMARK

A. KDE Distribution Diagnostics: The 10x Scale Discrepancy

Kernel Density Estimation (KDE) was conducted to quantitatively compare morphological distributions between Synthetic Gen 2 and physical micro-CT data:

- **Sphericity Alignment:** Synthetic mean $\Psi = 0.88$; Physical mean $\Psi = 0.83$, confirming aligned roundness distributions.

TABLE I. Performance benchmark on locked real held-out test set ($N = 126$).

Cond.	Methodology description	Acc.	F1
Exp A	Physical data only (from scratch)	45.24%	0.3620
Exp B	Synthetic only (Model 2 zero-shot)	6.35%	0.0398
Exp C	Synthetic pretrained + fine-tuned	42.86%	0.3398
Exp D	Joint training (mixed real & synthetic)	45.24%	0.3513
Exp E	Random Forest on geometric descriptors	99.21%	0.9776

- **Aspect Ratio Shift:** Synthetic mean AR = 1.56; Physical mean AR = 2.33, demonstrating that real defects exhibit higher elongation along melt vectors.
- **Volumetric Scale Disconnect:** Synthetic pores averaged 67.51 voxels, whereas physical pores averaged 6.76 voxels. Over 70% of physical defects comprised micro-clusters of only 2 to 8 voxels. The network was parameterized to identify macro-scale volumetric curvature, whereas real defects occupied near-resolution voxel clusters.

B. Controlled 5-Condition Benchmark (Experiments A–E)

To systematically isolate the utility of synthetic pretraining, we established a locked physical test split of 126 pores (seed = 42, stratified) and evaluated five experimental conditions:

Benchmark Finding: Synthetic pretraining provided no empirical transfer benefit over training from scratch on physical scans (Exp A: 45.24% vs. Exp C: 42.86%). The 10x volume gap required fine-tuning to override learned macro-scale spatial representations.

V. DISCUSSION & SPATIAL DISCRETIZATION LIMITS

A key finding in Table I is Experiment E (Random Forest), which achieved 99.21% accuracy and 0.9776 Macro F1. Because ground-truth morphological labels are governed by analytical mathematical definitions (sphericity thresholds and PCA axis ratios), the decision forest directly segments the feature space. This verifies that ground-truth labels are consistent, indicating that the $\approx 45\%$ accuracy ceiling of the 3D CNN is not an artifact of annotation noise.

Error analysis of the fine-tuned 3D CNN showed that 56 out of 71 total classification errors occurred between elongated and irregular morphologies (33 elongated pores classified as irregular; 23 irregular pores classified as elongated). At an isotropic voxel size of 53.6 μm, a 6-voxel defect measures approximately 2×3 pixels across. On a discrete lattice, spatial rasterization artifacts obscure surface boundary curvature; a slightly staggered voxel line is mathematically indistinguishable from an irregular notch. Convolutional kernels operating strictly on raw intensity grids cannot reliably resolve subtle boundary features without explicit geometric priors.

VI. PROPOSED ARCHITECTURE: MULTI-MODAL FEATURE FUSION

To resolve voxel discretization ambiguities, we propose a Hybrid Multi-Modal Architecture for automated NDE. The framework processes dual input streams: (1) a 3D CNN backbone extracting a 64-dimensional latent spatial embedding from the raw voxel tensor, and (2) a parallel tabular subnetwork processing the 5 physical geometric descriptors (sphericity, aspect ratio, PCA deviation ratios). Concatenating both representations into a 69-dimensional dense layer leverages the expressive capacity of 3D convolutional representations while constraining classifications with invariant physical descriptors, effectively resolving the 56 elongated/irregular confusions.

VII. CONCLUSION

This study evaluates 3D deep convolutional models and classical machine learning for pore shape classification in metal AM micro-CT volumes. While procedural synthetic generation achieved $> 99\%$ validation performance, zero-shot transfer failed catastrophically due to attenuation polarity inversion, volumetric scale mismatch, and ambient air saturation. A controlled 5-experiment ablation benchmark confirmed that synthetic pretraining confers no performance gain over training from scratch on physical data. Finally, achieving 99.21% classification with Random Forests establishes that hybrid multi-modal architectures represent the optimal methodology for high-throughput non-destructive quality qualification.

VIII. ACKNOWLEDGMENT

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IX. Video

https://youtu.be/jC0EDsSbTWI

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