Con Meo

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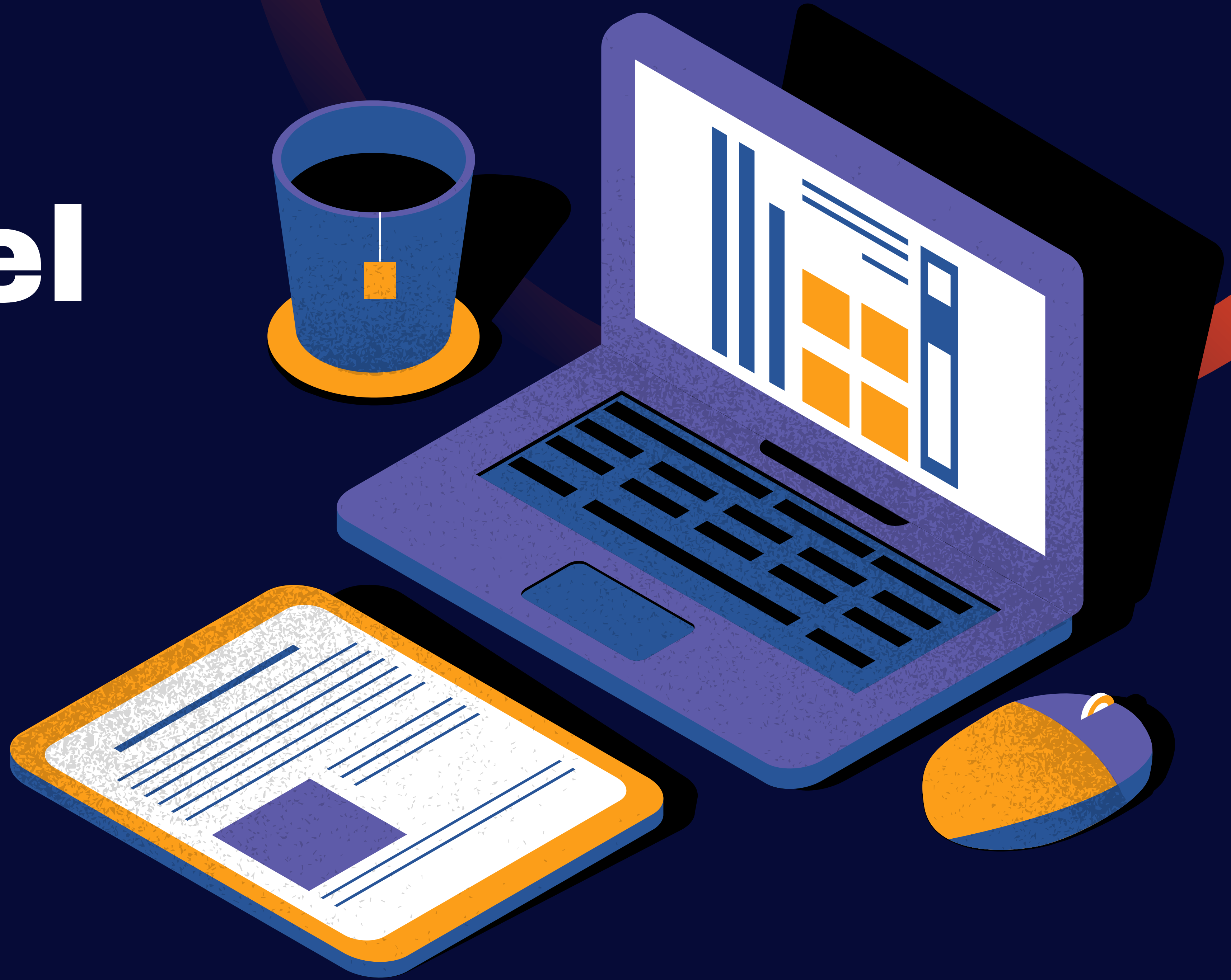
Hole Filling Model

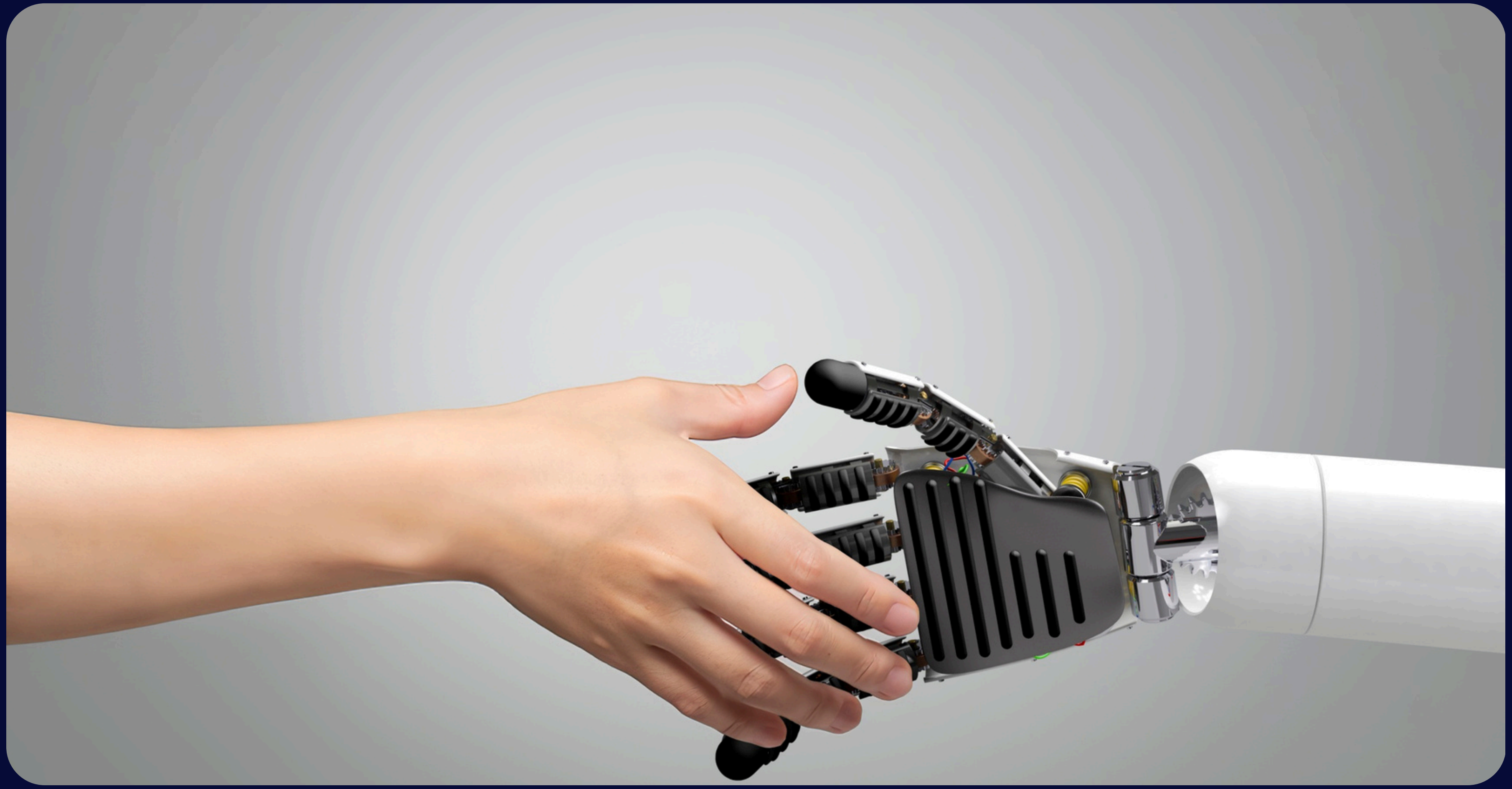
Computer Graphics



INTRODUCTION

This project addresses the challenge of point cloud completion: given a partial 3D scan with missing regions, the system must predict the missing geometry and reconstruct a complete, coherent point cloud. This is a complex problem that requires understanding both local geometric details and global shape structure.

OBJECTIVES



01 Implement a deep learning-based point cloud completion model capable of predicting missing geometry from partial scans

02 Reconstruct high-quality triangle meshes from completed point clouds for visualization and downstream applications

03 Evaluate performance quantitatively using established geometric metrics including Chamfer Distance (CD), repulsion loss, and density metrics

Visualize results comprehensively by comparing partial inputs, predicted completions, and ground truth data

METHODOLOGY

01 Dataset

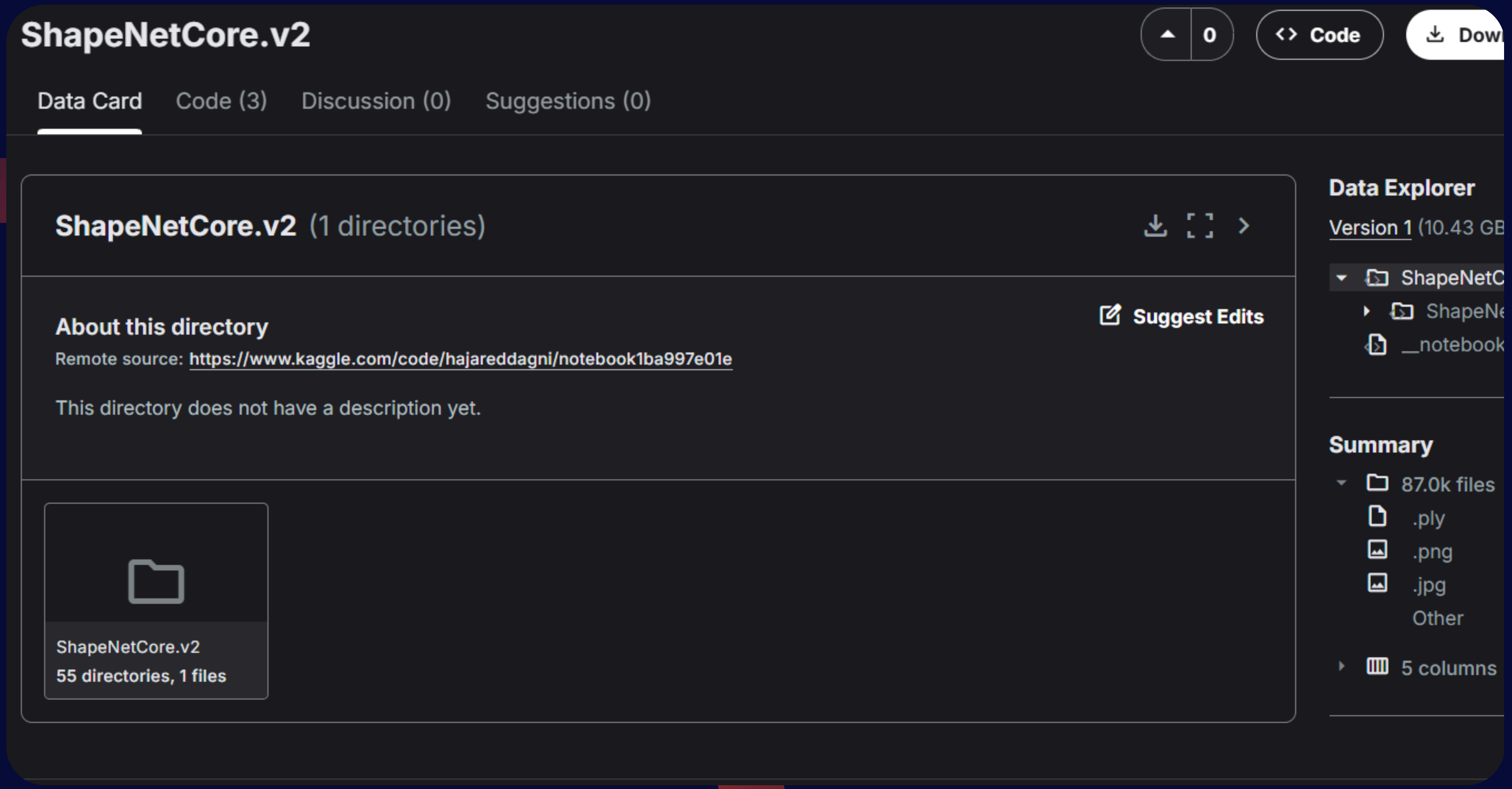
02 Preprocessing

03 Model Architecture

03 Loss Function & Optimization

04 Mesh Reconstruction

Dataset



ShapeNetCore.v2 -HAJAR EDDAGNI

The project utilizes the ShapeNetCoreV2 dataset, a large-scale repository of 3D CAD models spanning multiple object categories. The dataset preparation involves:

- Locating PLY mesh files from the ShapeNetCore hierarchy
- Limiting the dataset to 20,000 meshes to balance training time and diversity
- Processing each mesh to create paired partial-complete point cloud samples

Preprocessing

01

Mesh Processing

- Mesh repair (fix normals, winding order, fill existing holes)
- Normalization (center at centroid, scale to unit size)
- Point cloud sampling (generate 2048 uniformly sampled surface points)

02

Partial Point Cloud Generation

- Create synthetic holes using create_hole_in_pointcloud
- Randomly pick a center point → remove a spherical region (20–50% hole ratio)
- Remaining points form the partial observation
- Enforce minimum point count to avoid sparse clouds

03

Normalization

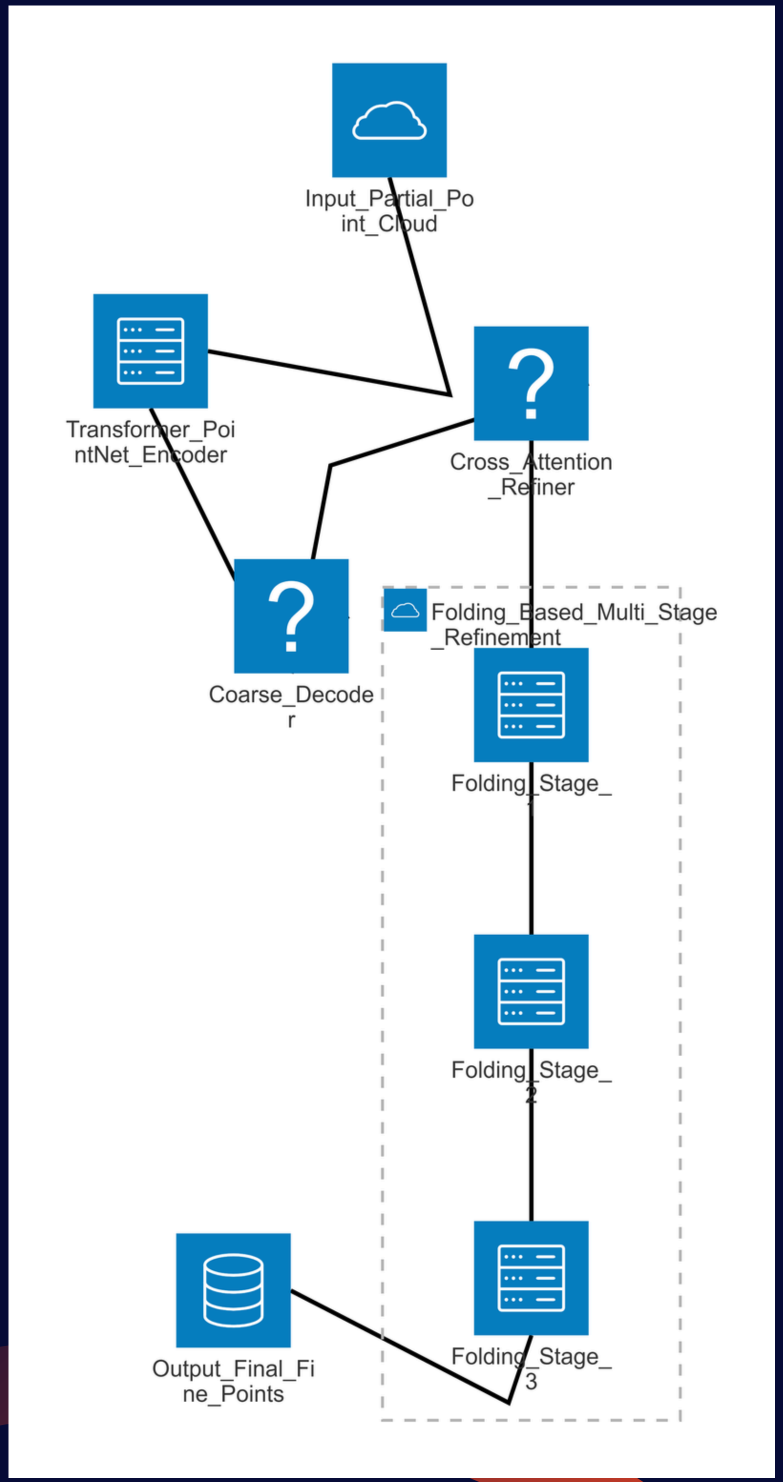
- Normalize partial & complete clouds together
- Center using the complete cloud's centroid
- Scale using the maximum radius of the complete cloud
- Ensures consistent alignment and scale

04

Data Augmentation

- Apply random rotation around the z-axis to both clouds
- Improves rotational invariance during training

Model Architecture



01

Transformer PointNet Encoder

- Extracts global + local features from the partial point cloud.
- Backbone: 4× Conv1d layers (3→64→128→256→512) + BatchNorm + ReLU.
- Self-attention module (8 heads) with residual connection refines per-point features.
- Outputs:
- Local features: (B, N, 1024)
- Global feature: (B, 1024) via Conv1d + max pooling.

02

Coarse Decoder

- Generates coarse point set from the global feature.
- 3× fully connected layers (with LayerNorm + ReLU).
- Output: (B, num_coarse, 3) — initial coarse shape.

03

Attention-Based Refinement Module

- Uses cross-attention between coarse points (queries) and local features (keys/values).
- Predicts an offset (delta) via a small MLP → coarse_refined = coarse + delta.
- Aligns coarse prediction with the observed partial cloud.

04

Folding-Based Multi-Stage Refinement

- Three refinement stages (folding-based upsampling).
- Each stage inputs: global feature + point coordinates + 2D grid (1029 dims).
- Each block: Conv1d(1029→512) → Conv1d(512→512) → Conv1d(512→3) with GroupNorm + ReLU.
- Outputs: fine1 → fine2 → fine3 (final point cloud).

Loss Function & Optimization

- Chamfer Distance (CD)
- Repulsion Loss
- Density Loss
- Boundary-Aware Loss

Loss Strategy

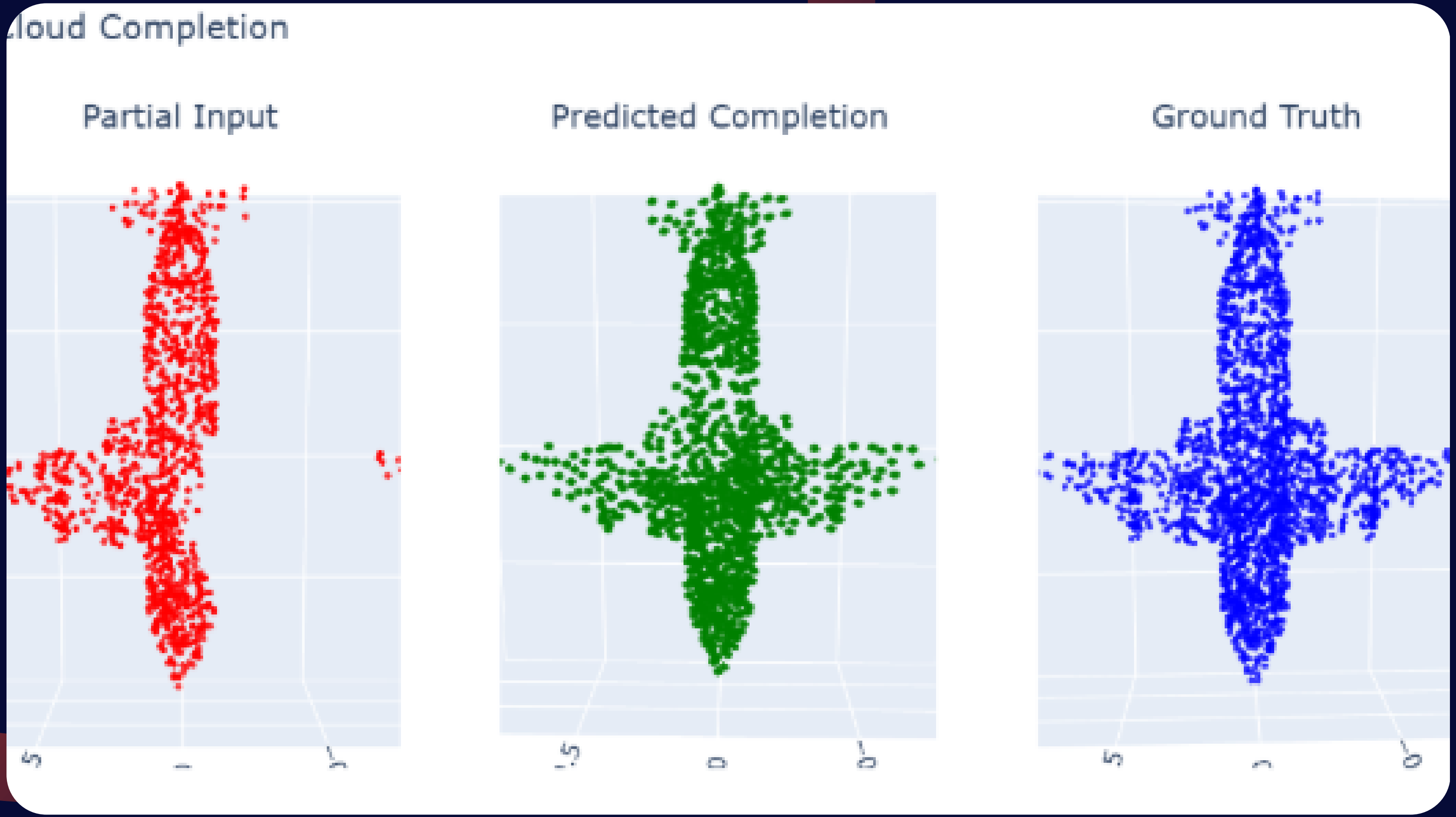
Combined Loss L_total = 1.5·L_chamfer + 1.5·L_repulsion + 0.05·L_density + 0.05·L_boundary

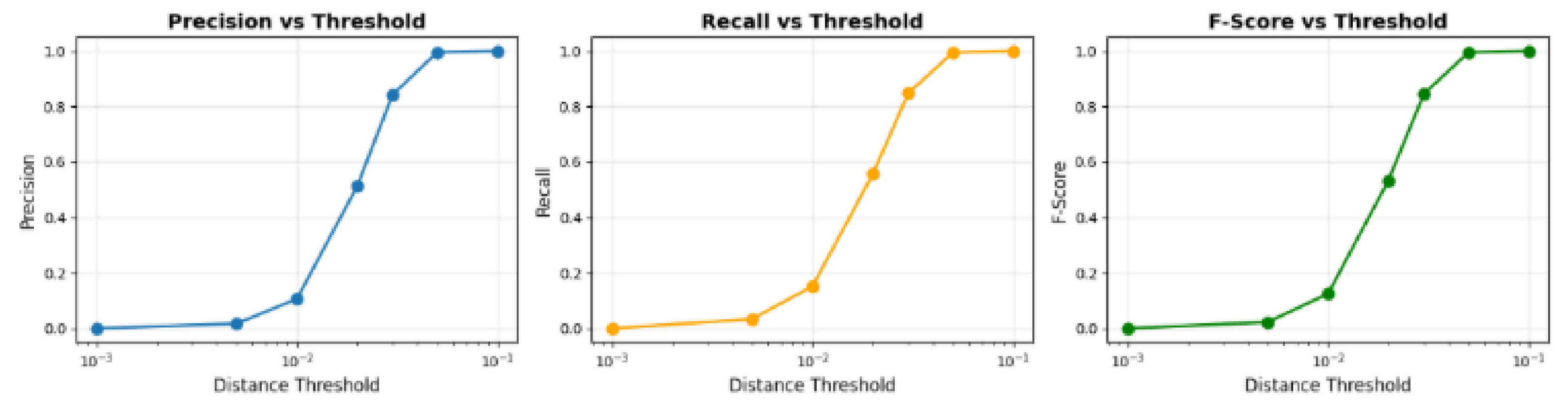
Mesh Reconstruction

- After point cloud completion, the predicted points can be converted to a triangle mesh using:
- Ball-pivoting algorithm: Connects nearby points based on a rolling ball radius
- Poisson surface reconstruction: Fits an implicit surface through the points
- Alpha shapes: Creates a shape based on point proximity

Optimization Strategy

- Optimizer: Adam with learning rate 1e-4
- Mixed Precision Training: FP16 automatic mixed precision (AMP) for faster training
- Gradient Clipping: Maximum norm of 1.0 to prevent instability
- Batch Size: 8 samples per batch
- Training Duration: 50 epochs with best model checkpointing

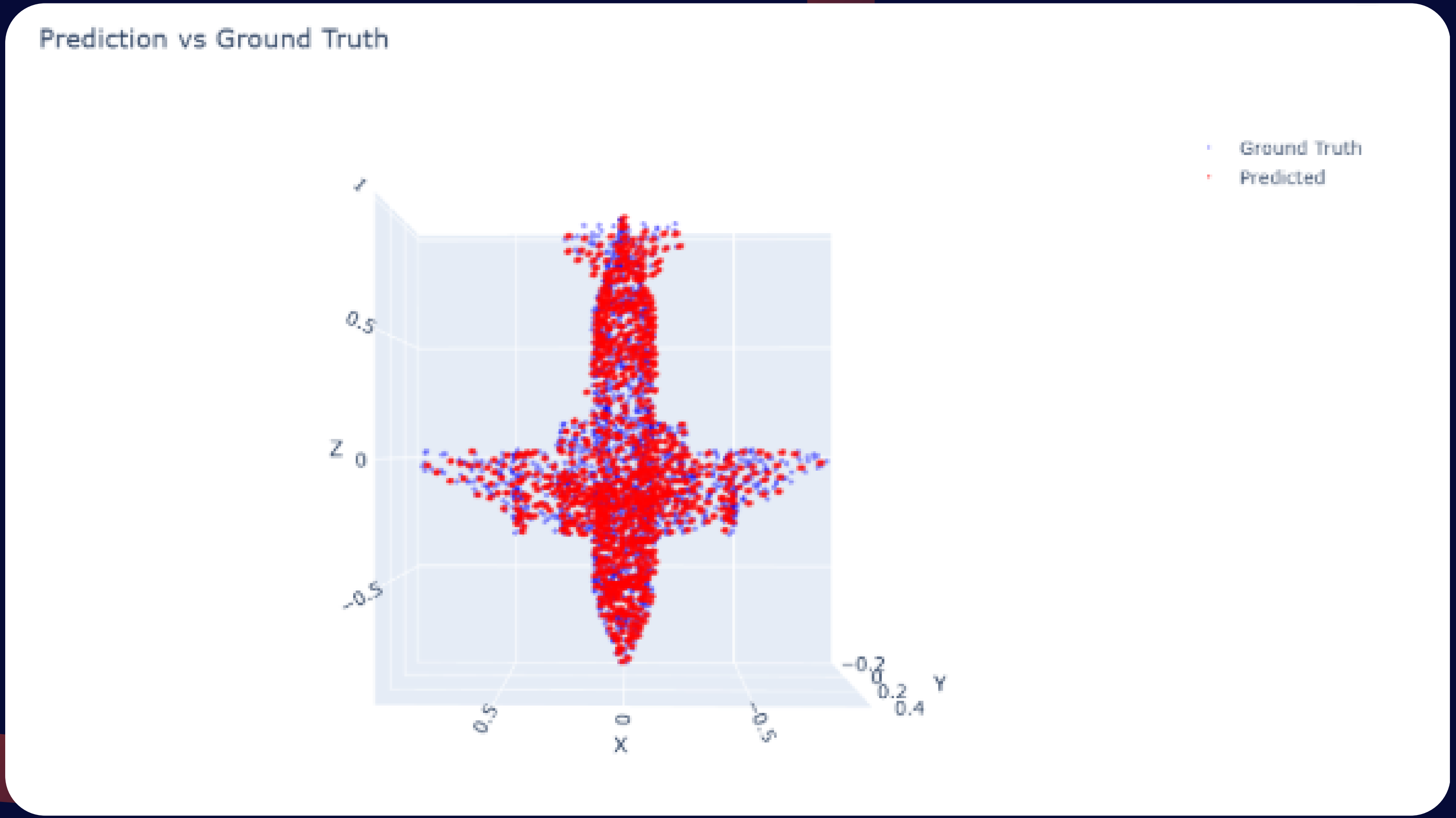


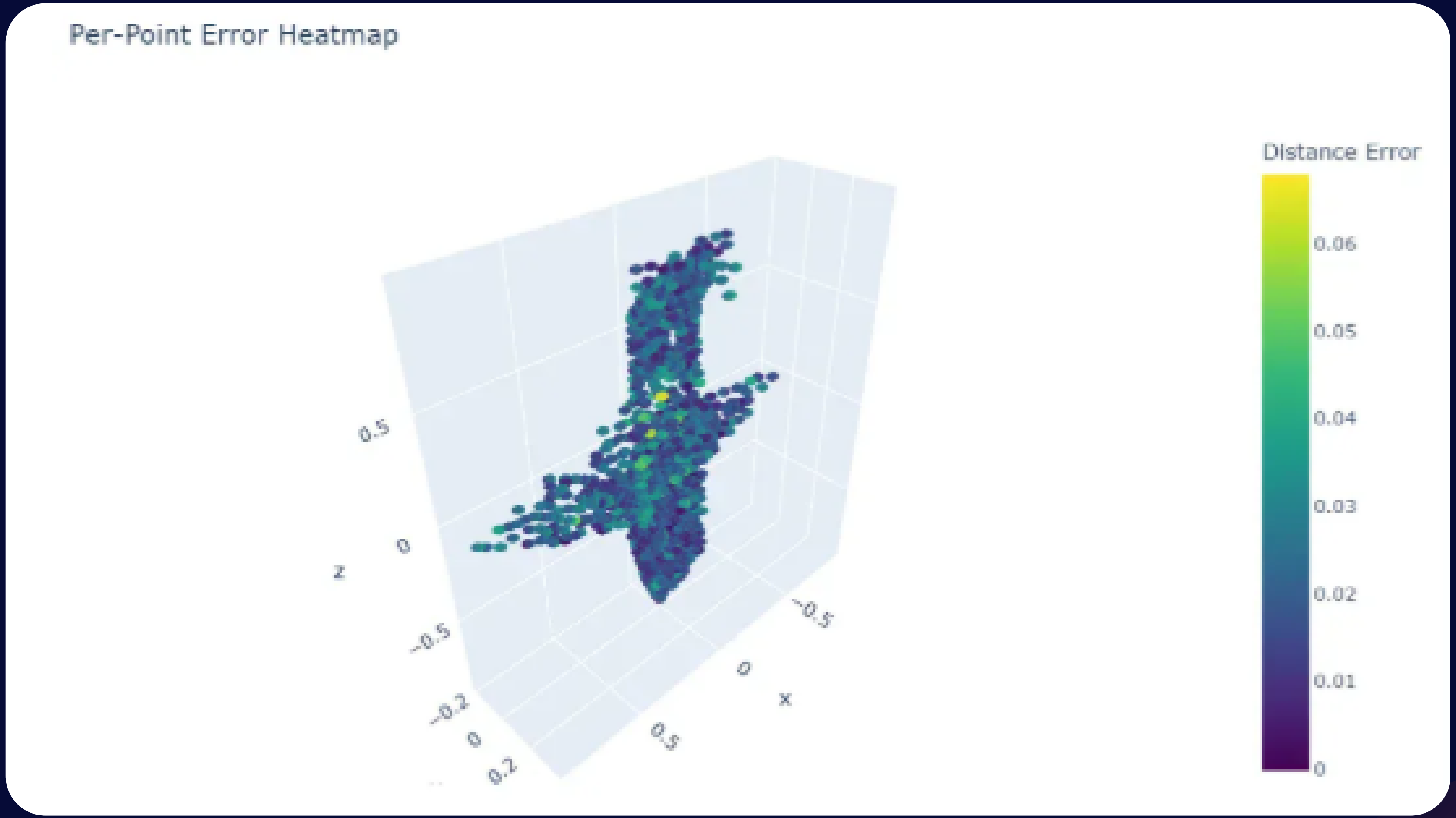


Threshold (τ)	F-Score	Precision	Recall	Interpretation
0.01 (1%)	0.1708	0.1457	0.2063	Strict evaluation
0.02 (2%)	0.5978	0.5829	0.6136	Moderate tolerance
0.05 (5%)	0.9950	0.9918	0.9983	Standard threshold

Results

- Chamfer Distance (CD): 0.0375
- Earth Mover's Distance (EMD): 0.0873
- Hausdorff Distance: 0.0719
- Maximum Mean Discrepancy (MMD): 0.0182





Results

- Mean Chamfer Distance: 0.0202
- Range: 0.020176 to 0.020319
- Variation: Less than 0.0002 between best and worst samples

DEMO

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About

Thank You For Listening