GenCAD-Self-Repairing: Feasibility Enhancement for 3D CAD Generation

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Abstract

With the advent of Generative AI, various methods and generative architectures have emerged that convert CAD images into CAD files. One such is the GenCAD model, which integrates an autoregressive transformer-based architecture with a contrastive learning framework, enhancing the generation of CAD programs from input images. However, GenCAD cannot guarantee the generation of a 'feasible' B-rep. Therefore, we propose a self-repairing pipeline that improves GenCAD's feasibility rate using **Regression** and **Guided Diffusion,** while not downgrading the accuracy of the generated geometries**.**

Introduction

- GenCAD generates CAD files from CAD images using a transformer and diffusion prior-based architecture.
- A repair pipeline is required to correct infeasible CAD sequences.
- Guided Diffusion, through classification and regression, and Regression Models can be used to generate feasible latent representations from the infeasible CAD sequences.

Objectives

- Design a self-repairing pipeline that fixes infeasible command sequences.
- Maintain accuracy of corrected CAD by comparing point clouds using Maximum Mean Discrepancy (MMD)
- Ensure similarity of latent spaces

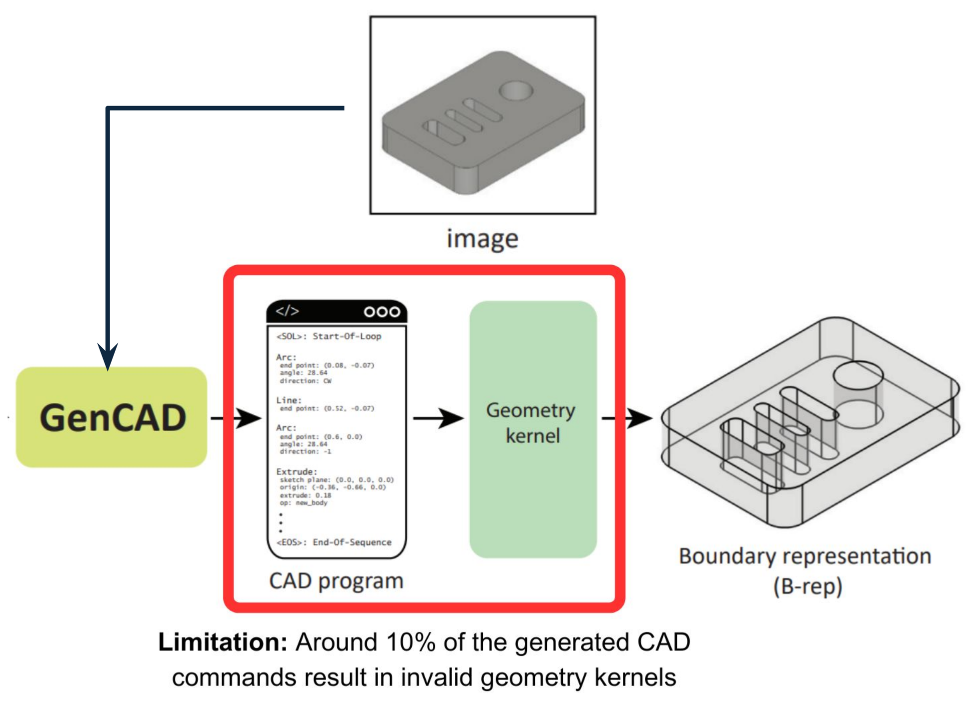


Figure 1. Limitation in GenCAD

GenCAD-Self-Repairing Dataset

GenCAD Dataset		GenCAD-Self-Repairing Dataset	
Images	840,947x448x448	Invalid Latent Representations	9,808
B-reps	168,674	Valid Latent Representations	123,809
Command sequences	168,674	Ground Truth Latent Representations	123,809

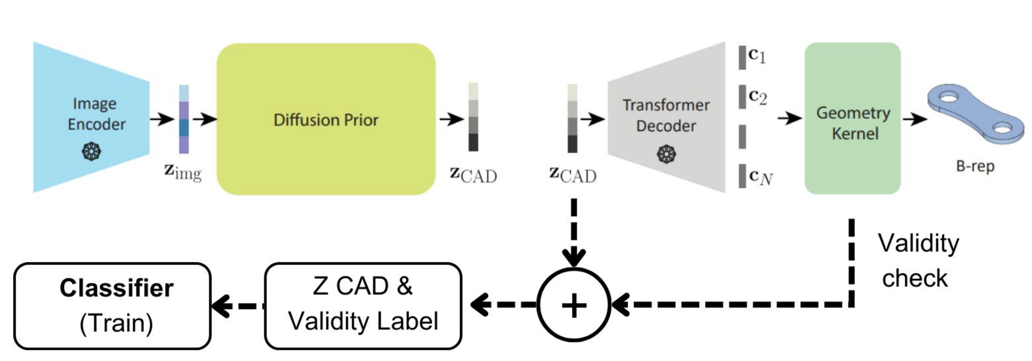


Figure 2. Dataset generation pipeline and classifier training

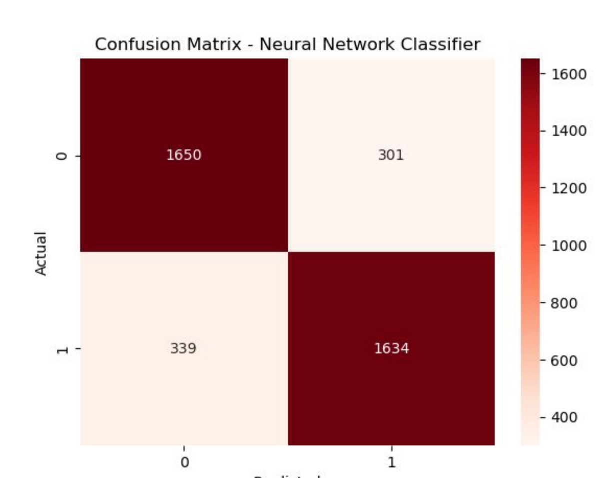


Figure 3. MLP Confusion Matrix

Methods

GenCAD-Repair Dataset is created by adding labels to the feasible and infeasible command sequence latent representations. Using this dataset, an Multi-Layer Perceptron Classifier **(MLP)** was trained with an **F1 score of 0.84 and accuracy of 0.84**, demonstrating the separability of the classes.

Additionally, two linear regression models are trained. **Regression 1**, which takes invalid image representations and predicts valid image representations, and **Regression 2**, which predicts feasible image representations from ground truth representations.

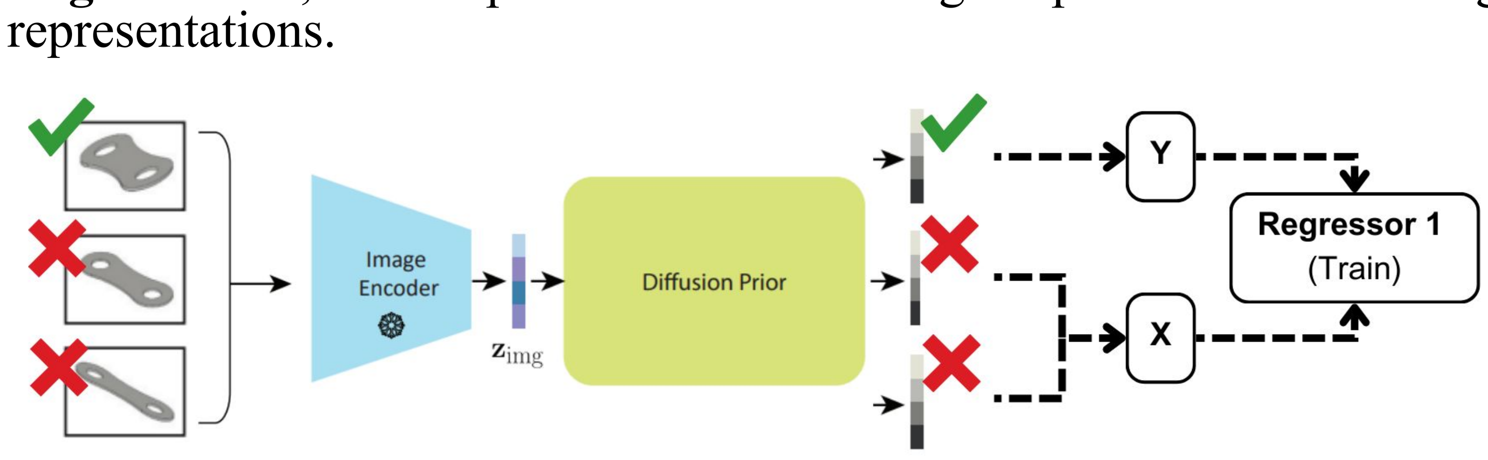


Figure 4. Regressor 1 training

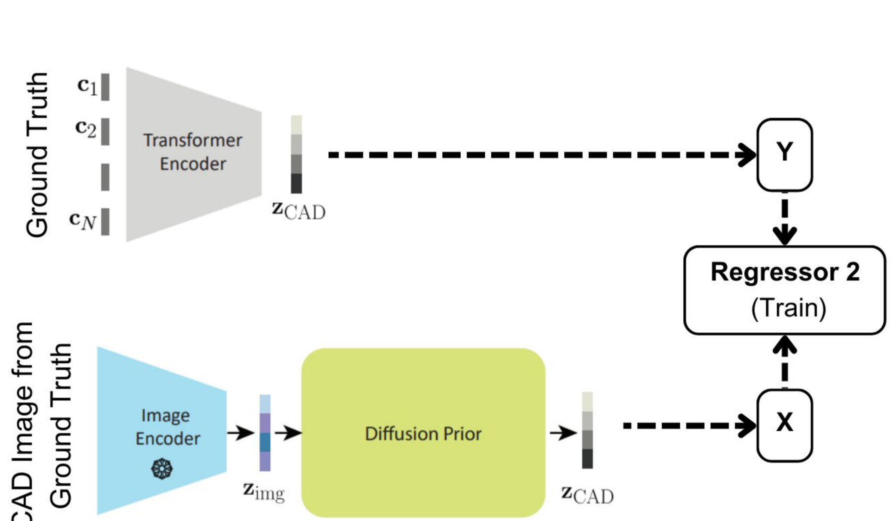


Figure 5. Regressor 2 training

Proposed Repair Model

Guided Diffusion using a Classifier and Regressor. We guide using a combination of the Classifier's infeasibility probability and the mean squared error (MSE) loss between the image and the Regression output, with a scaling factor of 10. Applying regression on the latent representations that are still infeasible

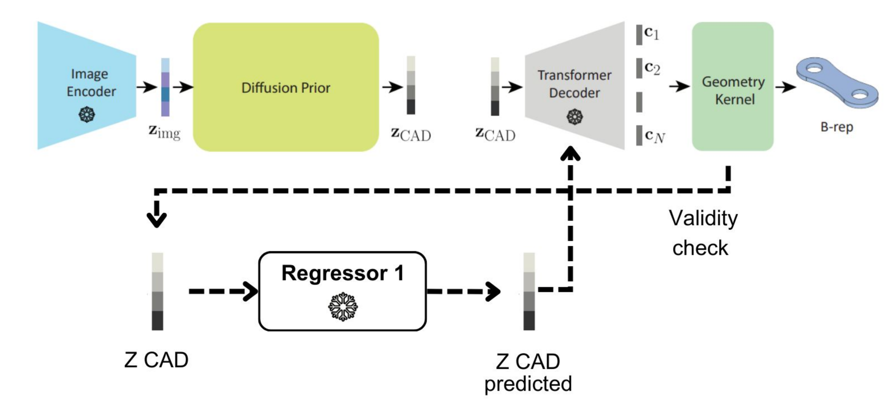


Figure 6. Use of regressor to repair infeasible sequences

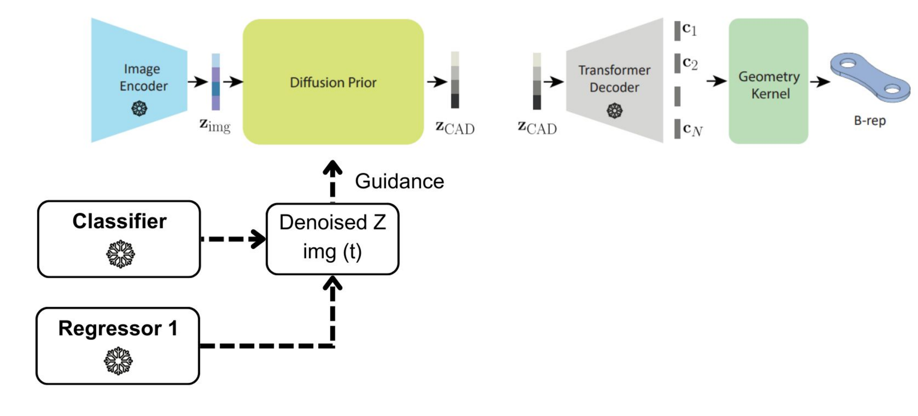
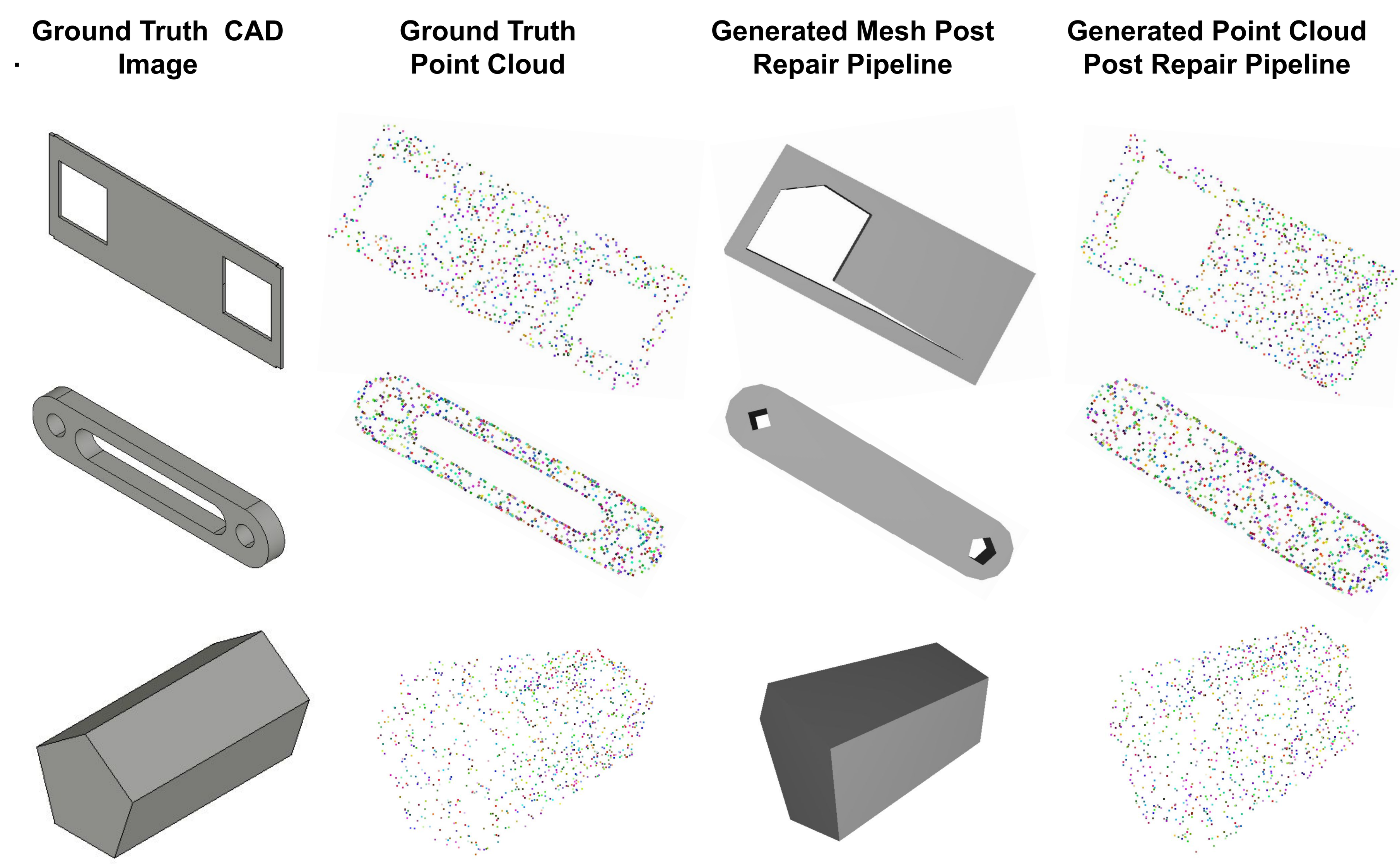


Figure 7. Use of guidance to repair infeasible sequences

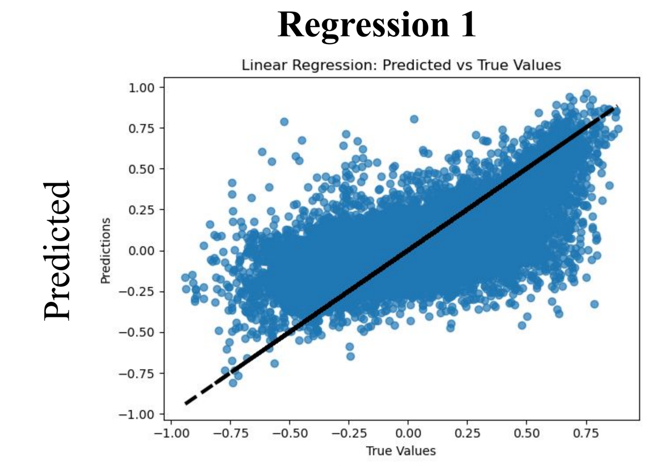
Results

We evaluated our model using a validation dataset consisting of 8,515 samples.



Summary of Results		
Method	**Feasibility Rate (↑)**	**MMD Score (↓)**
GenCAD (Baseline)	0.931	**0.180**
Regression 1	0.961	0.183
Regression 2	0.931	0.181
Classifier Guidance	0.936	0.197
Regressor Guidance	0.926	0.198
Classifier & Regressor Guidance	0.954	0.199
Classifier & Regressor Guidance with Regression 1 **(GenCAD-Self-Repairing)**	**0.970**	0.200

Regression 1

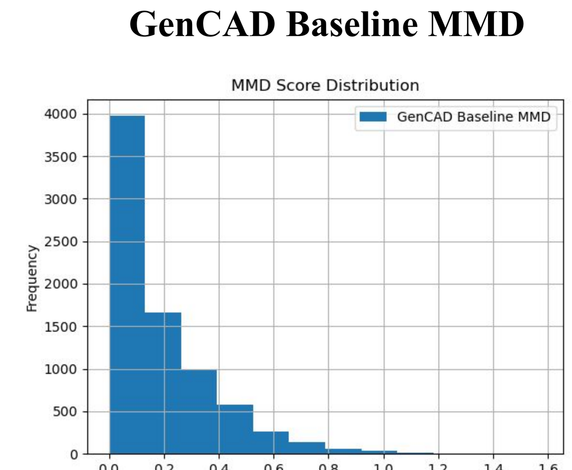


MSE: 0.021 | R^2: 0.068

Regression 2

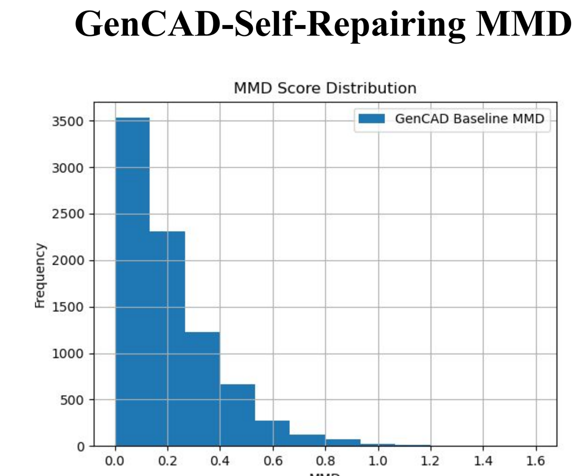
MSE: 0.004 | R^2: 0.631

GenCAD Baseline MMD



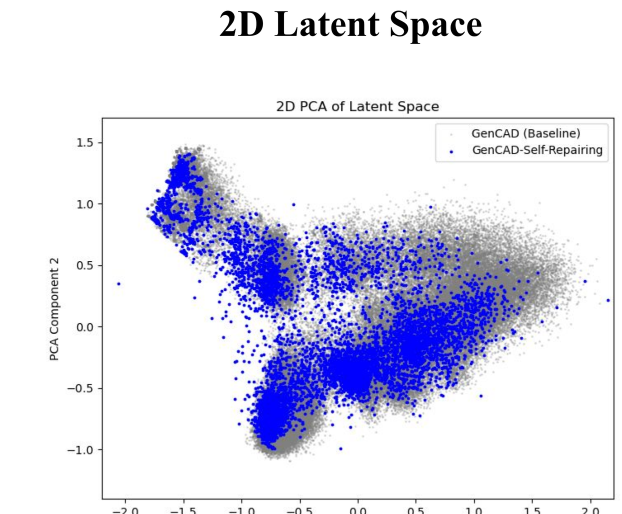
Mean MMD: 0.1802

GenCAD-Self-Repairing MMD



Mean MMD: 0.2003

2D Latent Space



Future Work

- Checking the accuracy of the generated CAD file with respect to the actual CAD file using a different metric
- Training a better regressor for better prediction of feasible latent spaces
- Using Conditional Variational AutoEncoders (VAE)

References:

Alam, Md Ferdous, and Faez Ahmed. "Gencad: Image-conditioned computer-aided design generation with transformer-based contrastive representation and diffusion priors." *arXiv preprint arXiv:2409.16294* (2024).

Acknowledgements:

We would like to thank Professor Faez Ahmed, Dr. Ferdous Alam, Lyle Regenwetter, Amin Heyrani Nobari, and Noah Bagazinski for their mentorship and advice throughout this project. Your support was truly outstanding.