Addressing Part Variability in Disassembly using Point Cloud-based Machine Learning

Marc A. Ahrens

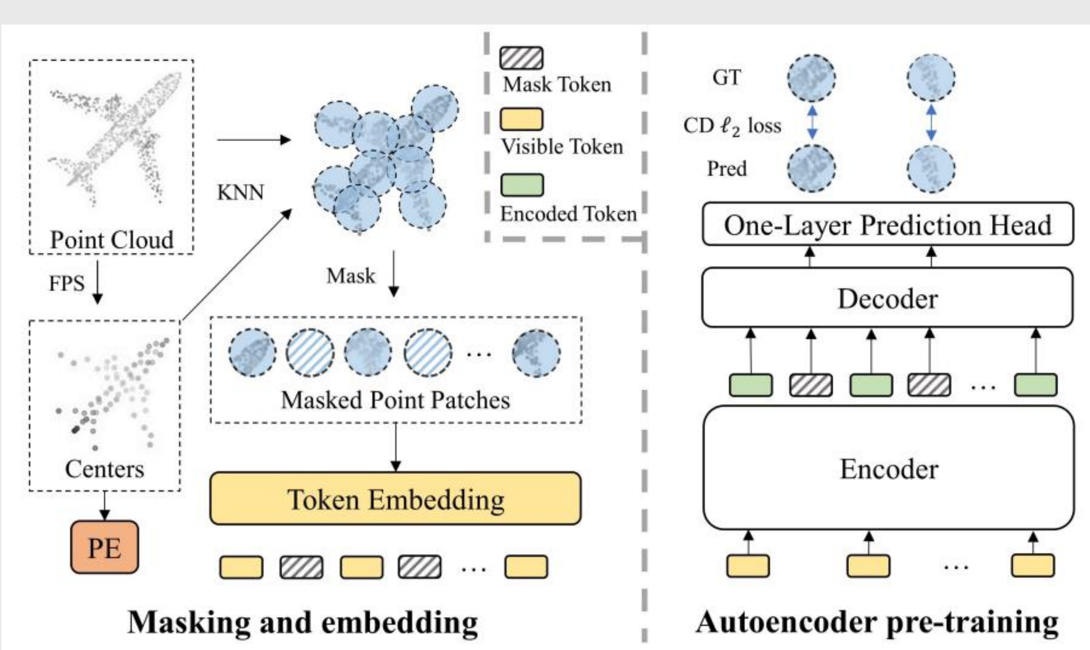
marc.ahrens@hs-aalen.de

Introduction

- Disassembly presents unique challenges that often make it economically unviable in industrial applications [1][2]. In order to profitably recirculate parts and cores, remanufacturers and other circular actors need to be able to process different core variants with the same disassembly line [3].
- This significantly increases the burden of differentiating between and tracking similar components of different variants that are not interchangeable
- To overcome these challenges, point cloud models offer a compelling alternative to image-based models by focusing on the geometric features of components, rather than their surface appearance.
- Geometric features exhibit significantly less variance across different samples, efficiently reducing the amount of training data needed [4]
- This study investigates whether a pretrained foundation model can be effectively fine-tuned using limited geometric data to support accurate component classification in disassembly. In doing so, it seeks to evaluate the feasibility of a more data efficient framework and scalable ML approach for the operational realities of circular manufacturing.

Model Architecture

- The model used was Point-MAE as developed by [5]
- Point-MAE is a transformer model utilising masked autoencoding pretrained on ShapeNet
- A predefined amount of centroids, depending on point-cloud size, are selected through farthest point sampling. A k-Nearest-Neighbour algorithm is then applied to create local point patches around the centroids.
- All patches are given positional information and some are masked, removing all information
- The model is trained to reconstruct the missing point patches, effectively having more training opportunities per point-cloud

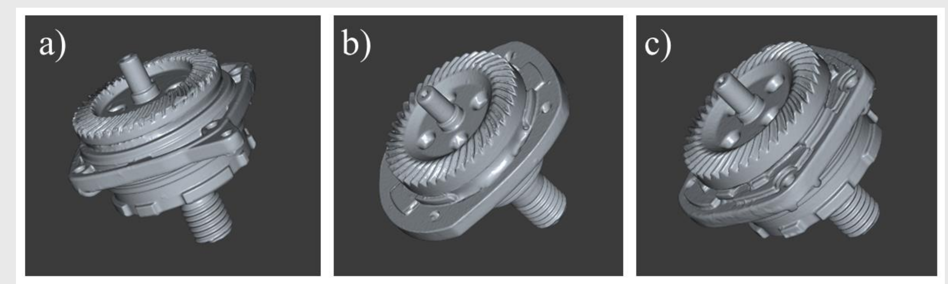


Point-MAE model architecture [5]

- After which the model is fine-tuned for the needed classification task
- Masking can significantly reduce model overfitting, and promote learning features of objects. Additionally, Point-MAE was published in 2022, and the entirety of their model code has been made accessible and is thoroughly documented

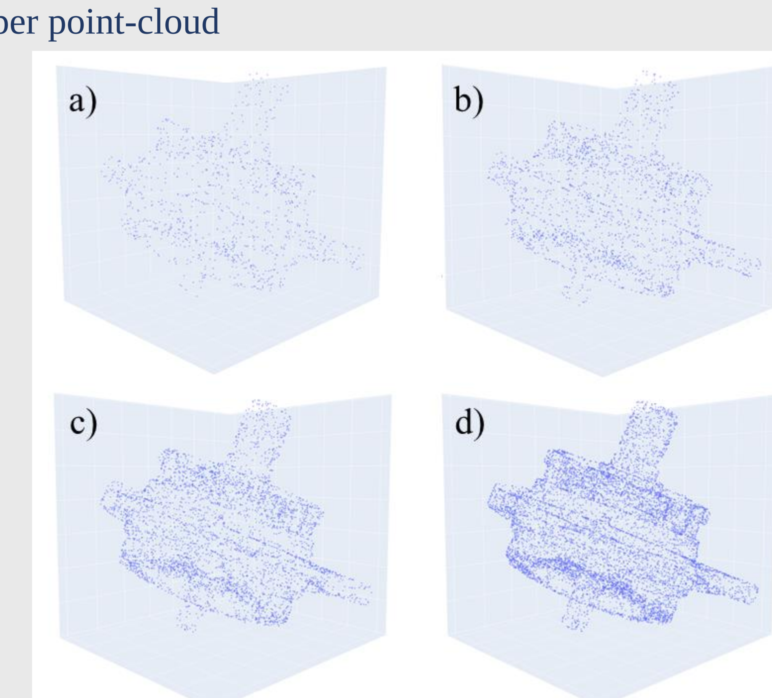
Dataset and Model Variations

- The bevel gear transmissions from three different variants of angle grinders produced by Fein GmbH were selected as exemplary components



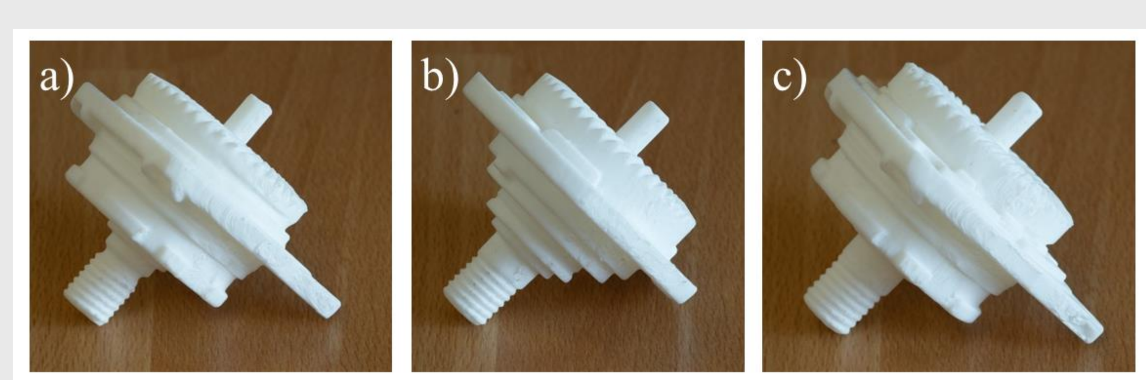
meshed models of bevel gears – a) Gear 1 b) Gear 2 c) Gear 3

- Seven different meshed scans were created of each gear, with a resolution of 136 $faces/mm^2$ resulting in a total of 2.5Mio. faces per meshed scan
- Each scan was sampled between 200-300 times using farthest point sampling creating point-clouds each consisting of 8,192 points, before being rotated along one of its axes by a random degree
- Four different models were trained with access to differing number of points per point-cloud



Sampled point-clouds – a) 1k points b) 2k points c) 4k points d) 8k points

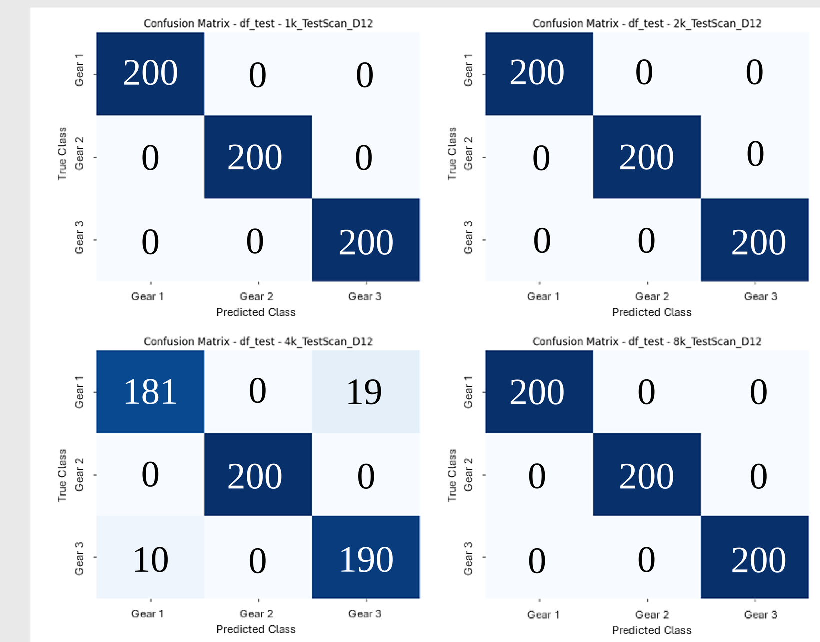
- Two different datasets were created for the model to be trained and tested with. The first was trained and tested on point-clouds sampled from the meshed scans, resulting models are named TestScan. The second was trained on meshed point-clouds sampled from the meshed scans and tested on a 3D-printed dataset, named TestPrint.
- These printed copies contained obvious surface defects and the point-clouds were created with the same procedure as all other point-clouds



3D-printed bevel gears – a) Gear 1 b) Gear 2 c) Gear 3

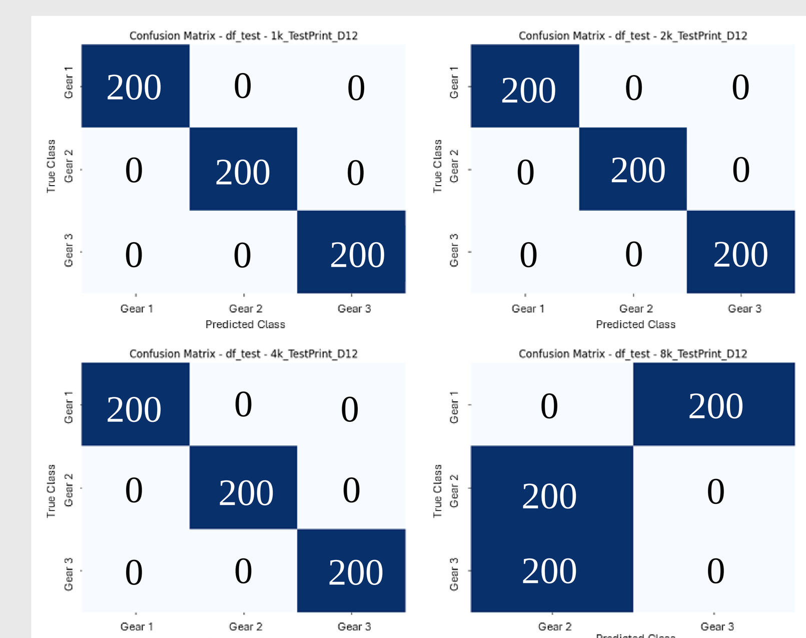
- We also train a separate model with a reduced depth of eight opposed to 12, to observe the effects of a reduction in model capacity

Results



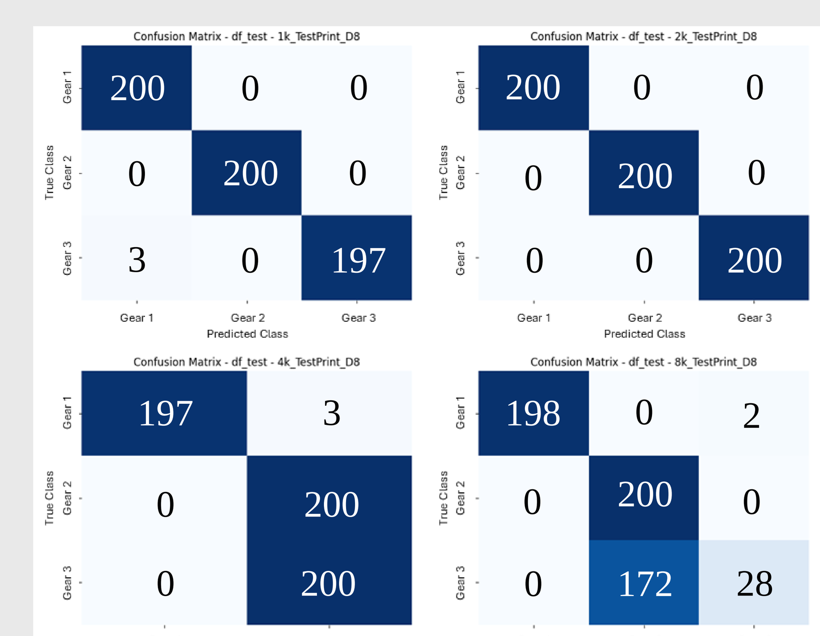
Confusion Matrix – TestScan depth 12

- The TestScan models performs well across all model variations and across all iterations of training



Confusion Matrix – TestPrint depth 12

- Most of the TestPrint models with a depth of 12 perform well, except for the model with access to all points per point-cloud



Confusion Matrix – TestPrint depth 8

- The reduction in depth lead to a decrease in performance for the 4k model and a significant increase in performance for the 8k model
- These fluctuations suggest a degree of instability in the system's predictive behaviour

Conclusions and Further Research

- The results demonstrate that accurate classification of previously unseen parts exhibiting noticeable surface defects is achievable even with a small dataset
- Prediction confidence was consistently higher for Gear 2 compared to Gear 1 and 3 across all models, a result that aligns well with the observed differences in the dimensional characteristics of the three samples.
- Across multiple training cycles, increased instability in the 8k model with a depth of 12 and both the 4k and 8k models with a depth of 8 were observed
- This instability in combination with the consistently good performance of the smaller models, suggests the presence of an upper limit in effective sampling density, beyond which models may begin to overfit
- In both well performing and subpar models, the accuracy on both the training and validation datasets were consistently high. Consequently, it remains uncertain whether the datasets employed are sufficiently complex to fully assess the capacity limits of the models.
- While the foundational model performed well in this context, it remains an open question whether such complexity is necessary for this specific application. It is conceivable that simpler, more specialized models could achieve comparable performance, particularly when computational efficiency and ease of deployment are also considered.
- Automated techniques for injecting realistic defects into test datasets, reflecting the conditions typical of end-of-life components, would enhance model robustness.
- Additionally, expanding the use of data augmentation, both in training and validation datasets, or applying thorough cross validation, could improve generalization. Experiments with adversarial training and noise injection represent particularly promising avenues.

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Aalen University
Of Applied Sciences

Beethovenstraße 1
73430 Aalen, Germany

www.hs-aalen.de