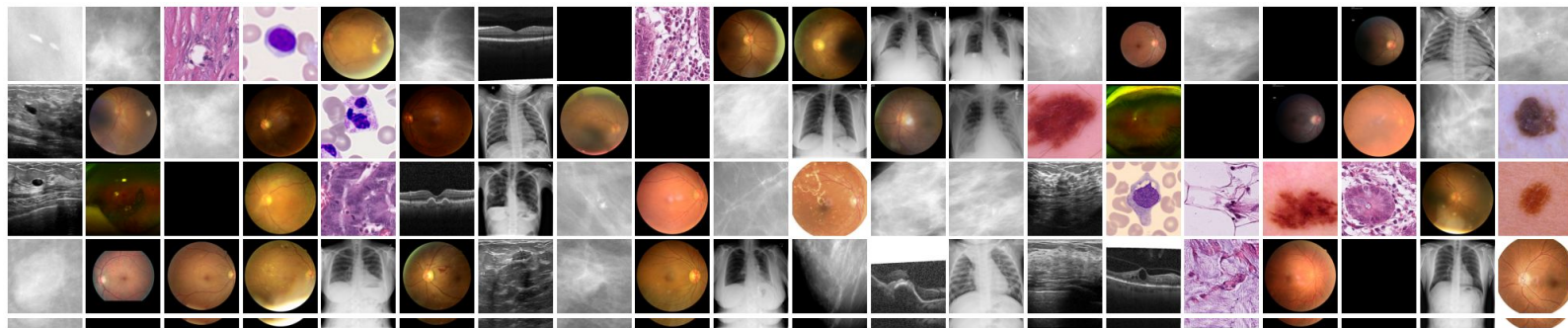


Practical Course: Machine Learning in Graphics, Vision and Language

Final presentation

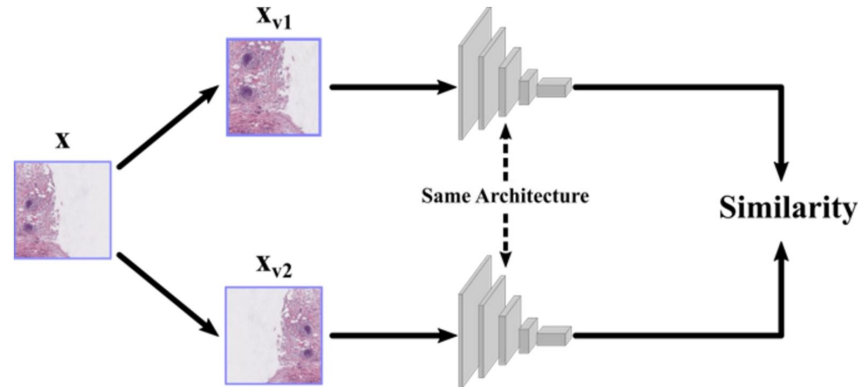
Daniela Kemp, Simon Frank, Mohamed Elsherif, Gwent Krause & Tim Rebig

Self-Supervised Learning for Medical Image Analysis

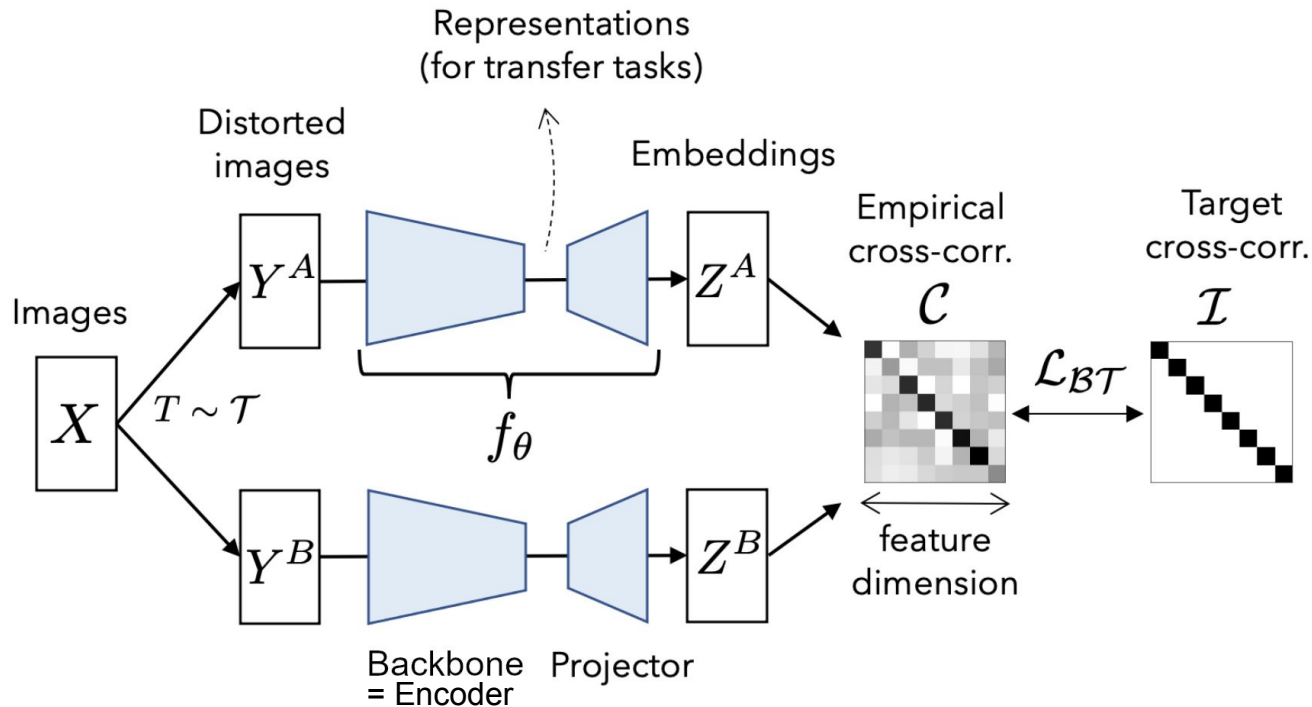


Self-Supervised Learning for Medical Image Analysis

- Classical data labeling requires expert knowledge making it expensive
- Need to reduce the necessity for annotated data
- Contrastive Learning:
 - SimCLR and MoCo dominant approaches, but hardware intensive
- Barlow Twins SOTA-method underexplored in the medical domain



Pre-training Method: Barlow-Twins



Barlow-Twins Architectures

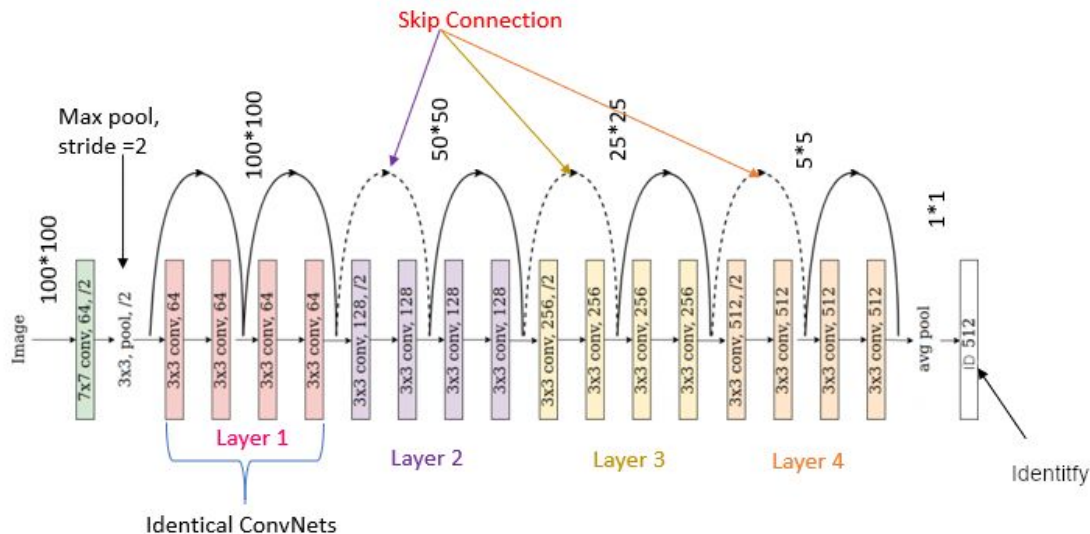
Trainable Parameters: 20.6 mio

- Resnet18 11.2 mio
- Projection Head 9.4 mio

Projection Heads:

- FC layer, batchnorm, ReLU
- FC layer, batchnorm, ReLU
- FC layer

Read-out head: MLP

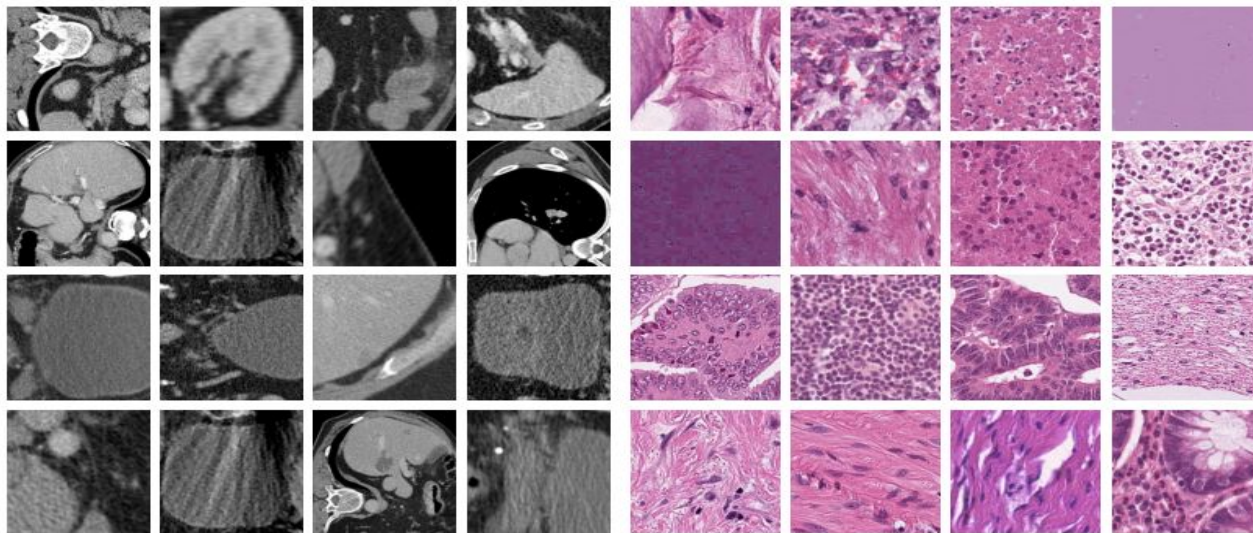


ResNet-18 Architecture

Curating medical datasets

MIMeta datasets and toolbox

- Multiple medical domains
- Provides a unified interface for loading data sets
- Images standardized to 224 x 224 pixels
- Standardised data splits



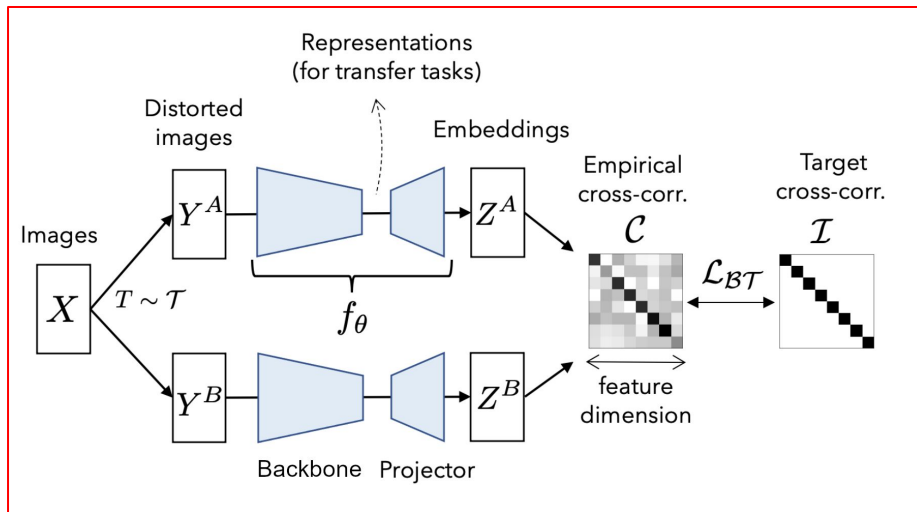
Axial organ slices

Colorectal cancer

Chosen datasets for experiments

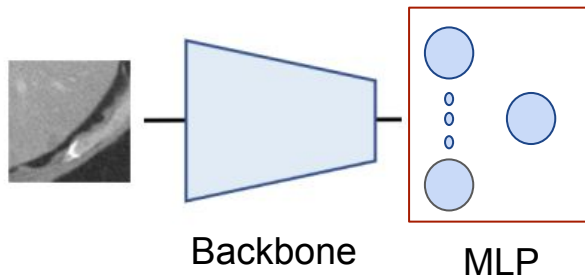
Barlow-Twin Pretraining

- Datasets: Axial Organ Slices, Coronal Organ Slices, Sagittal Organ Slices (similar domains) (3.948 images in the training set)
- Wrapper for the MIMeta Data loader to load multiple datasets
- Hyperparameters:
 - epochs: 1000
 - batch size: 256
 - learning rate: 0.03
 - optimizer: Adam



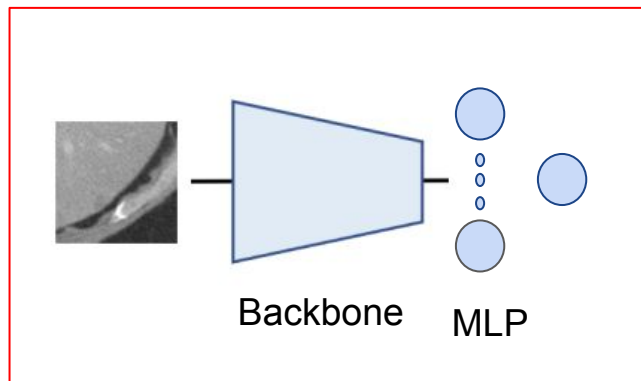
Fine-tuning Setup

- Imagenet pre-training as comparison
- Two different training method
 - Freeze Backbone train only linear Read-out head with 5.6k parameter



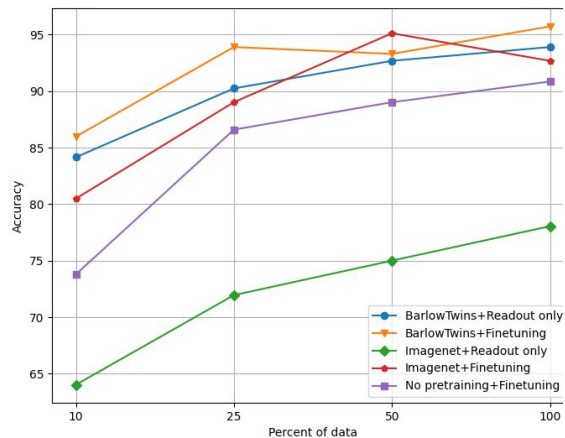
Fine-tuning Setup

- Imagenet pre-training as comparison
- Two different training method
 - Freeze Backbone train only linear Read-out head with 5.6k parameter
 - Train the whole model

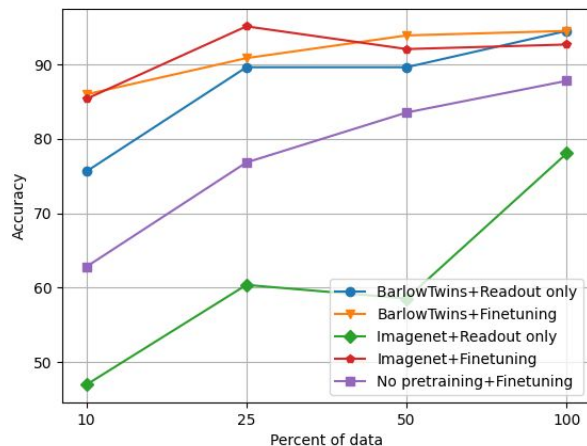


Accuracy: Comparison

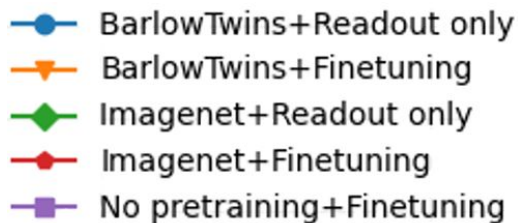
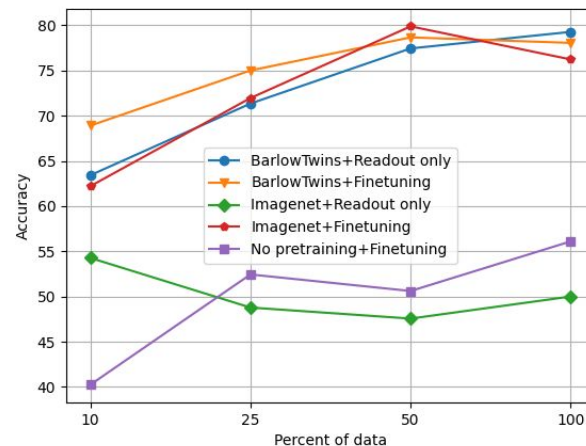
Axial



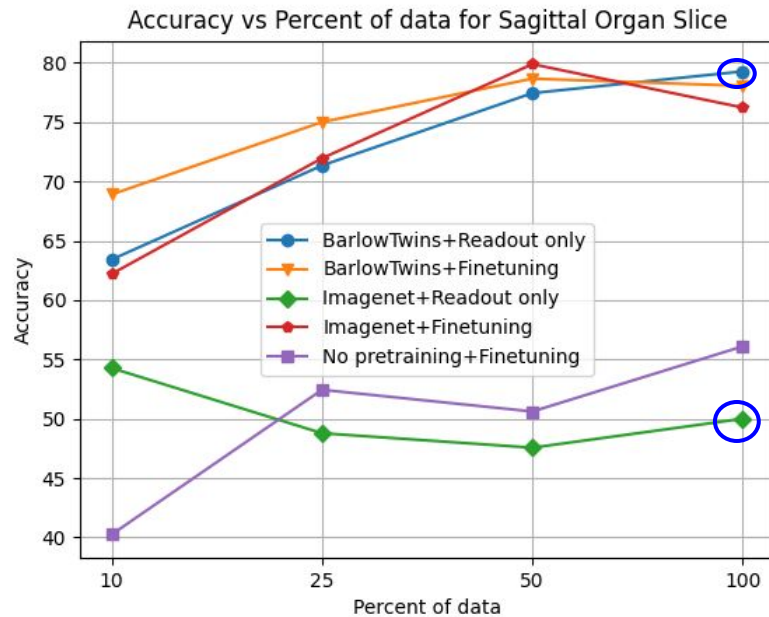
Coronal



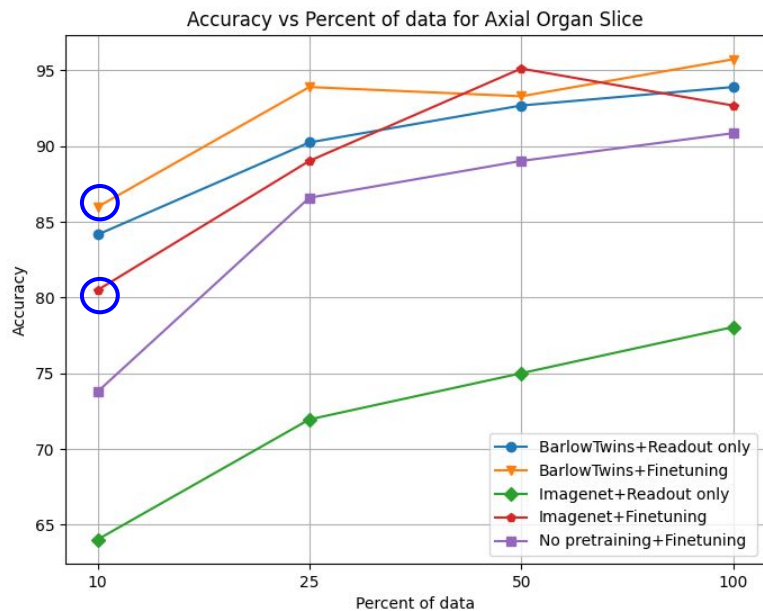
Sagittal

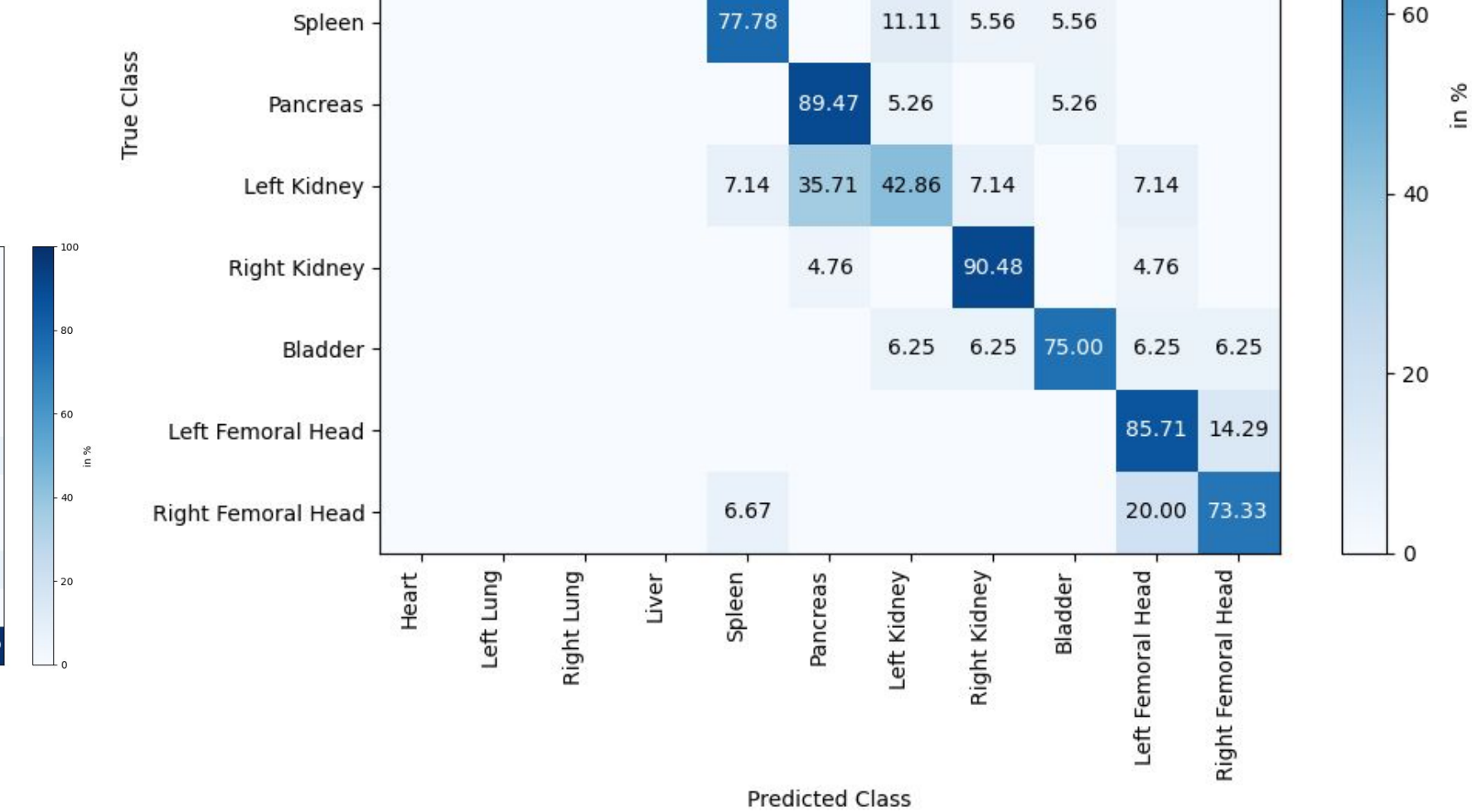


Accuracy: Comparison



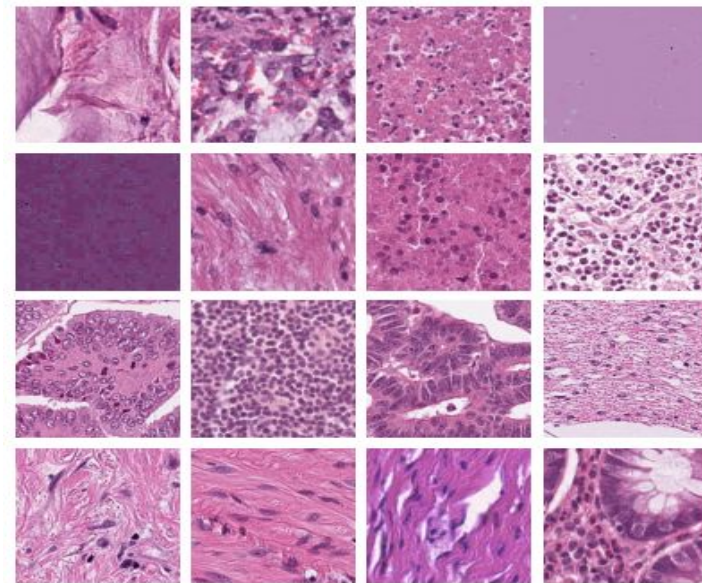
Accuracy: Comparison



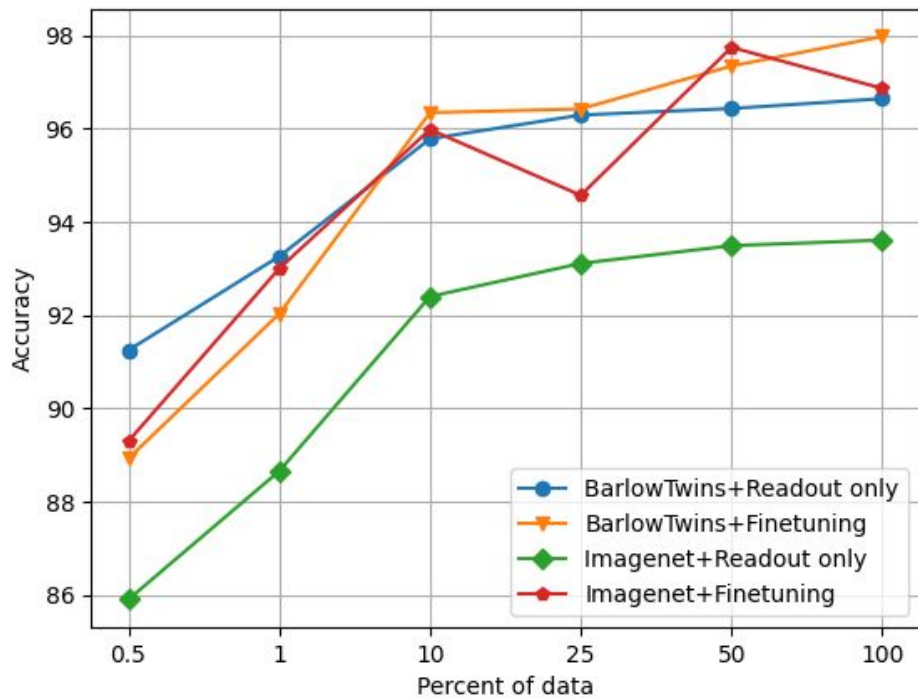


Colorectal Cancer Histopathology Dataset

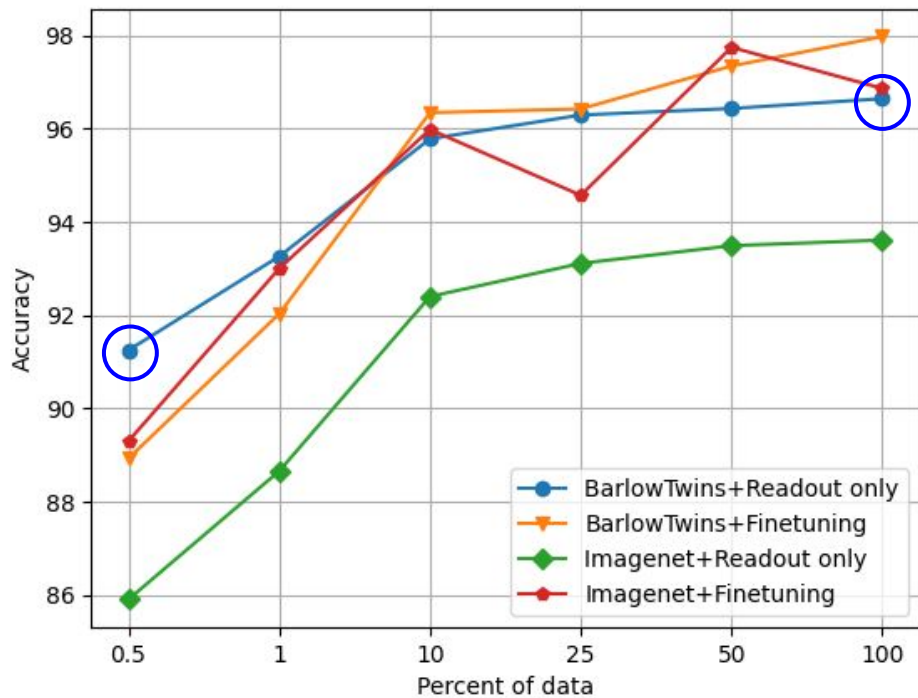
- 107180 Total Images
- Also pretraining using Barlow Twins



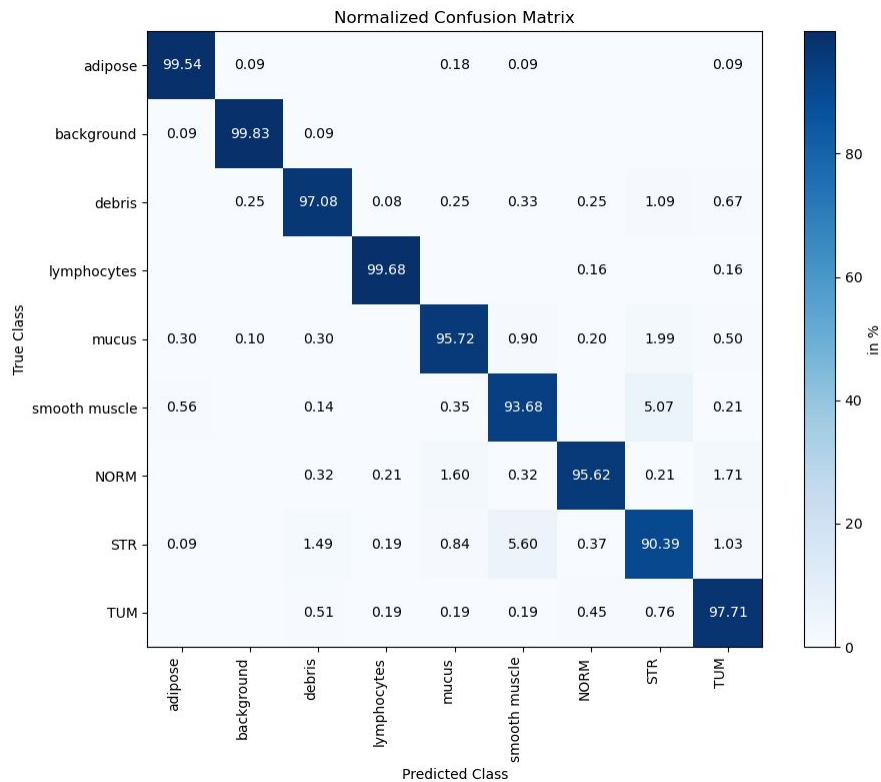
Accuracies



Accuracies

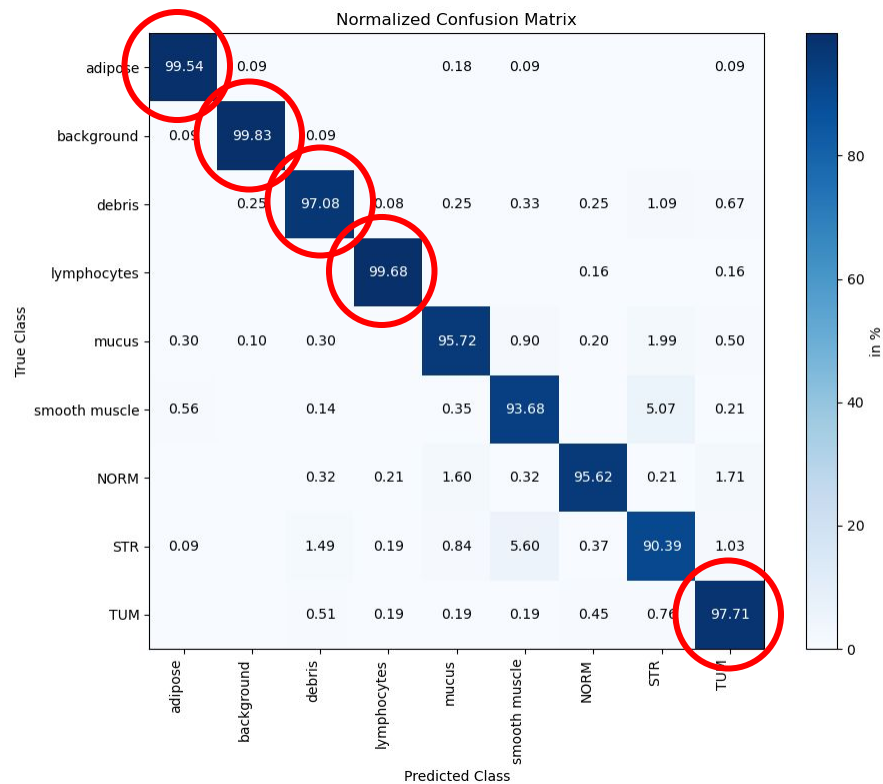


Barlow-Twins + only Linear Read-out-head, 100% Data



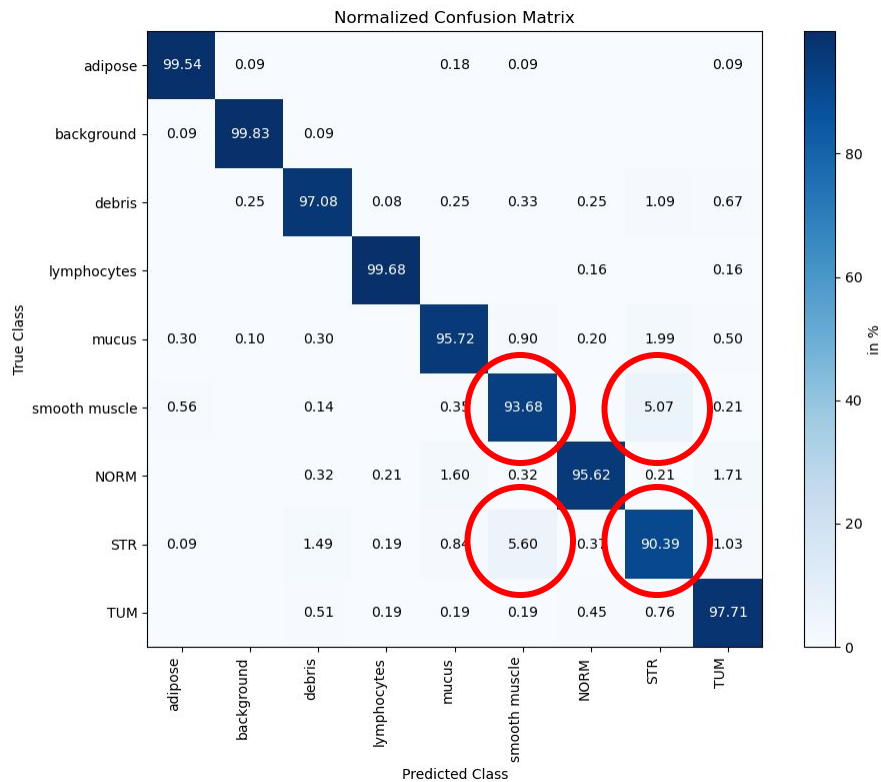
(96.64% accuracy)

Barlow-Twins + only Linear Read-out head, 100% Data



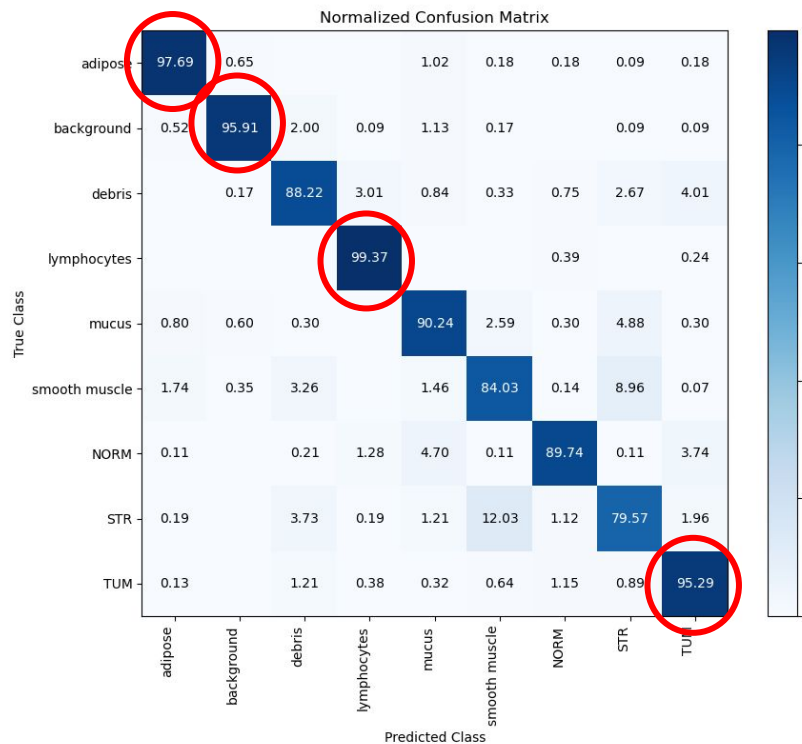
(96.64% accuracy)

Barlow-Twins + only Linear Read-out head, 100% Data

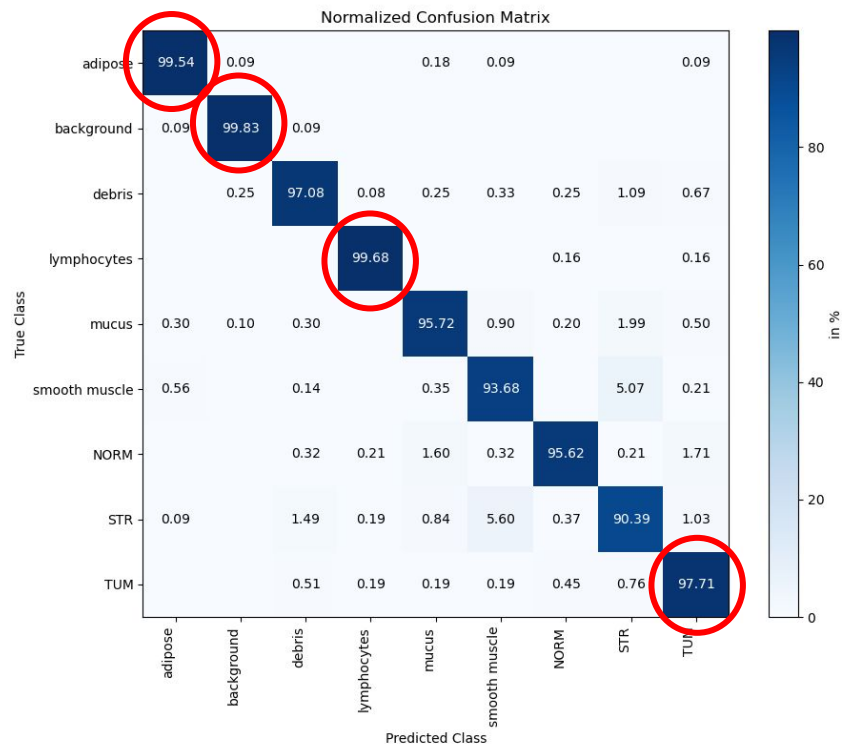


(96.64% accuracy)

Comparison - Barlow-Twins + only Linear Read-out head

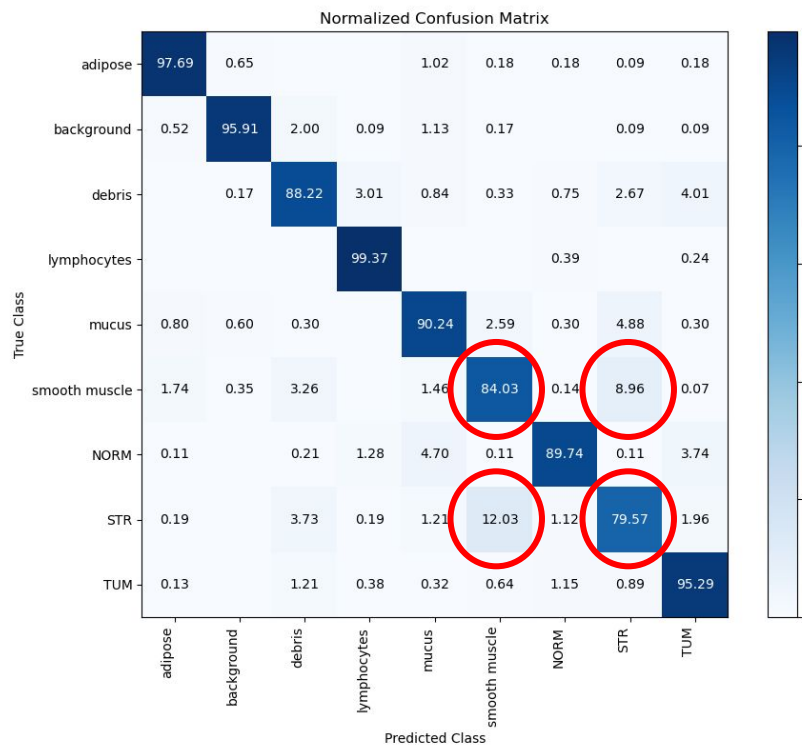


0.5% Training data

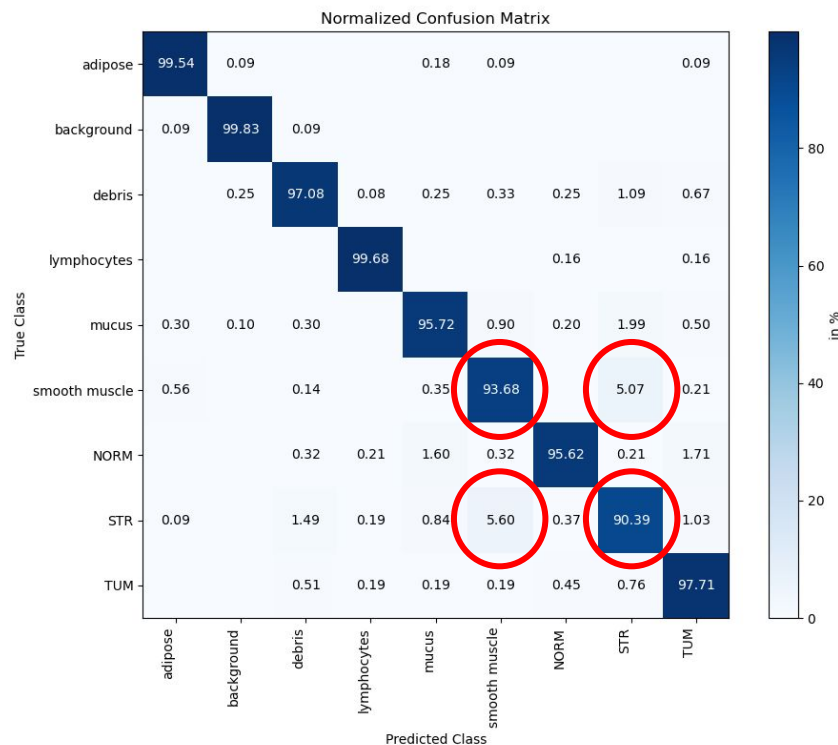


100% Training data

Comparison - Barlow-Twins + only Linear Read-out head

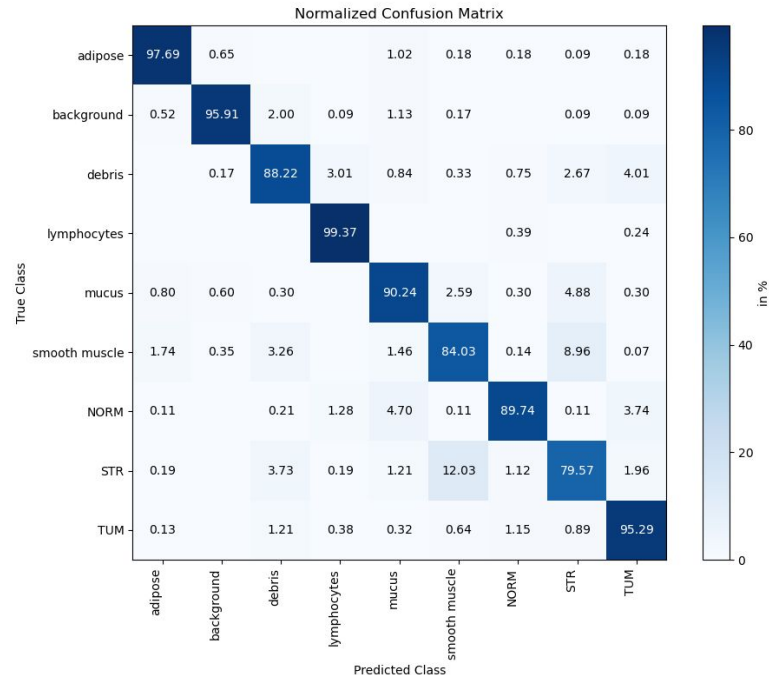
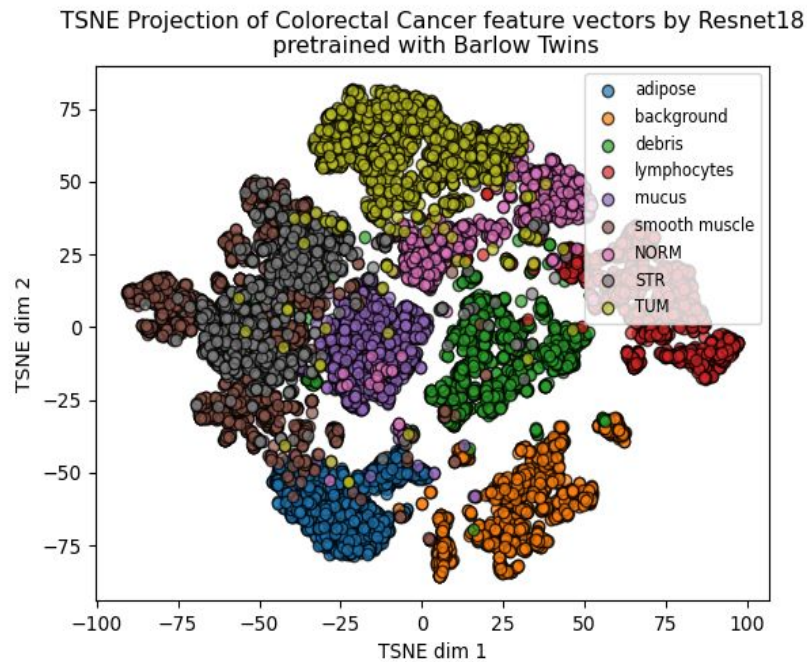


0.5% Training data



100% Training data

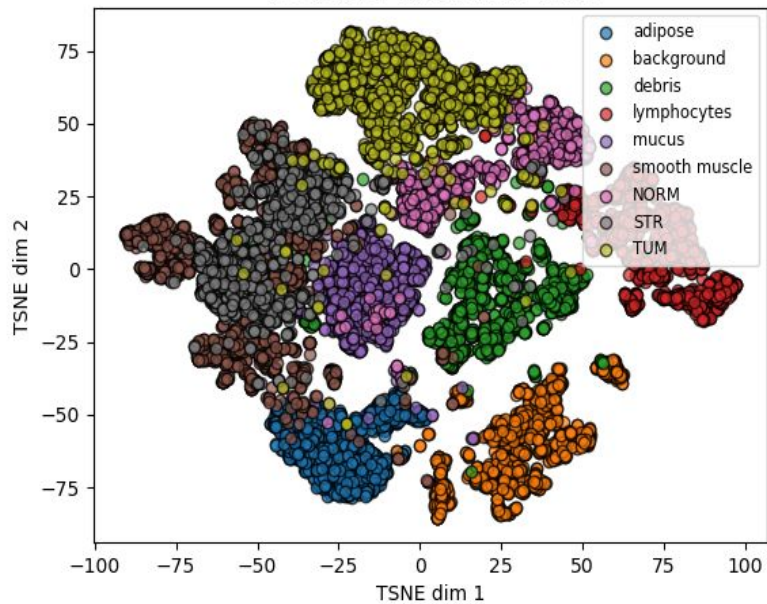
Feature analysis with t-SNE



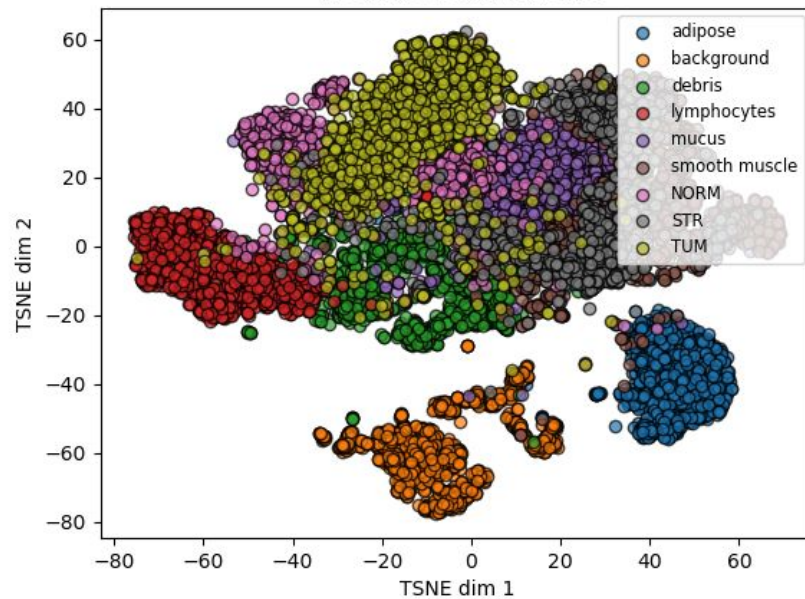
0.5% Training data

Feature analysis with t-SNE

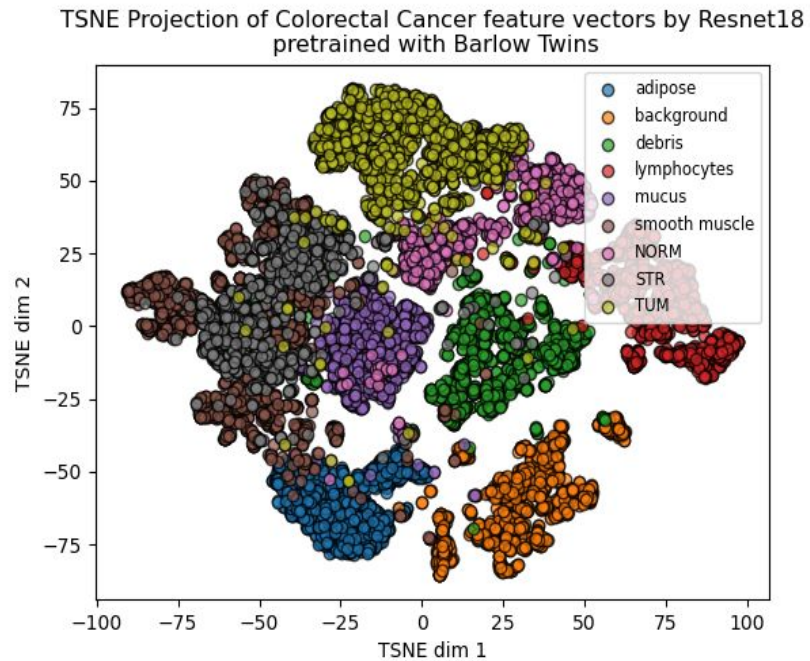
TSNE Projection of Colorectal Cancer feature vectors by Resnet18
pretrained with Barlow Twins



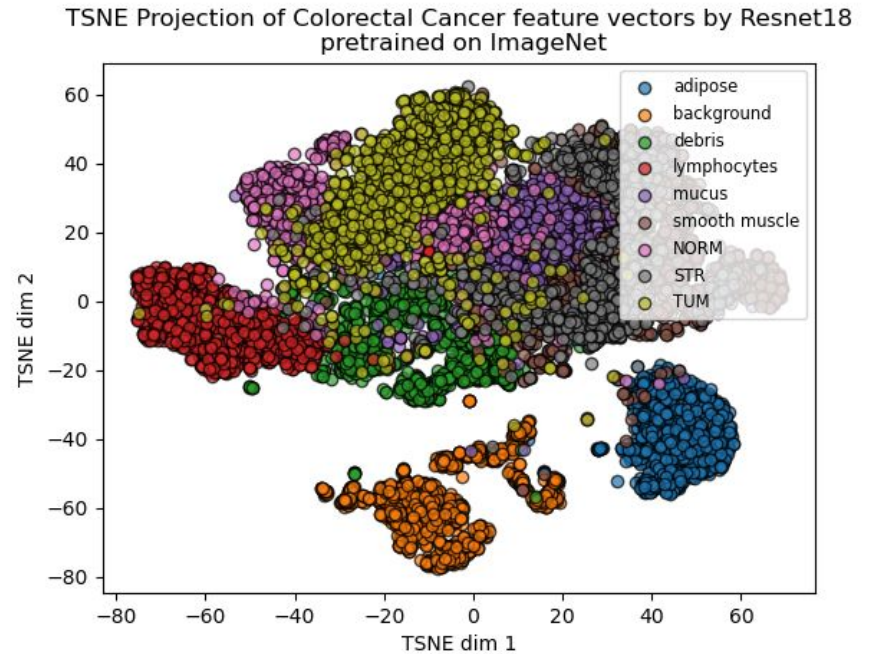
TSNE Projection of Colorectal Cancer feature vectors by Resnet18
pretrained on ImageNet



Feature analysis with t-SNE



Feature analysis with t-SNE



Barlow-Twins Conclusion

- On large dataset:
 - Marginal improvements observed
- On small dataset:
 - Pretrained features exhibit superior generalization
 - Limited fine-tuning necessary
 - Overfitting was observed during fine-tuning of the whole model
- Pre-training facilitates effective natural clustering