DIET-CP: Lightweight and Data Efficient Self Supervised Continued Pretraining

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Abstract

Continued pretraining offers a promising solution for adapting foundation models to a new target domain. However, in specialized domains, available datasets are often very small, limiting the applicability of SSL methods developed for large-scale pretraining, and making hyperparameter search infeasible. In addition, pretrained models are usually released as backbone-weights only, lacking important information to continue pretraining. We propose to bridge this gap with DIET-CP, a simple continued pretraining strategy, where any strong foundation model can be steered towards the new data distribution of interest. DIET-CP relies on a very simple objective, requires no labels, introduces no more hyperparameters than supervised finetuning. It is stable across data modalities and backbone choices, while providing a significant performance boost for state-of-the-art models such as DINOv3 using only 1000 images.

Keywords: Self Supervised Learning, Continued Pretraining, Domain Adaptation

1. The DIET for Self Supervised Continued Pretraining

Foundation models promise robust features for a variety of tasks and domains, powered by increasingly larger and diverse pretraining datasets. However, despite the all-time-high transfer-learning performance of pretrained models, there still remains a margin to expert models trained within one domain and modality (Koch et al., 2024; Ambsdorf et al., 2025). Continued pretraining on the target domain is a potential solution to this problem (Gupta et al., 2023; Parmar et al., 2024; Guo et al., 2025). However, while state-of-the-art foundation models such as DINOv3 (Siméoni et al., 2025) can–in theory–be further pretrained, researchers and practitioners are often facing three problems that make this approach infeasible: (1.) Models are released as backbone weights only, missing crucial information to continue pretraining, such as teacher weights or optimizer state. (Oquab et al., 2023; Siméoni et al., 2025) (2.) State-of-the-art self-supervised learning methods introduce a multitude of hyperparameters, which are costly and difficult to tune for the target domain,

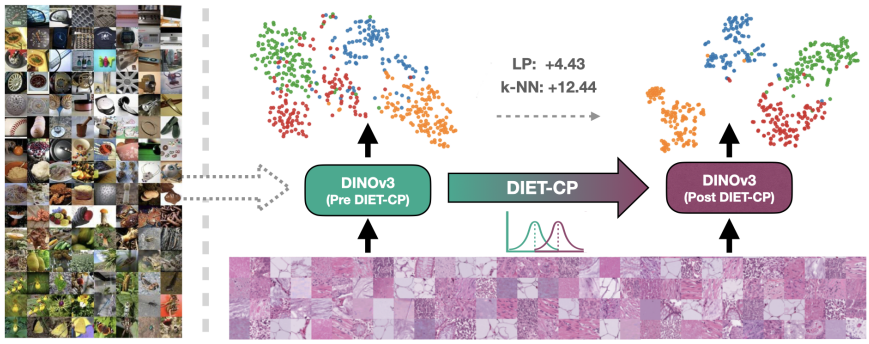

Figure 1: DIET-CP is a label-free and efficient method for steering foundation models towards a data distribution of interest, improving class separability in the embedding space and leading to improved unsupervised and linear probing performance. t-SNE plots are generated from a PathMNIST subset.

or even intractable if only few samples are available. (Ibrahim et al., 2024) (3.) The pretraining methods themselves are optimized for large-scale datasets, while target datasets are significantly smaller (El-Nouby et al., 2021).

Motivated to overcome these practical hurdles, we propose DIET-CP: A label-free and efficient method for steering foundation models towards a new distribution of interest. Our method relies on a very simple objective that requires only the pretrained backbone, that is free of additional hyperparameters, stable over data modality and backbone employed, all while providing significant performance boost. On medical image classification, we improve the F1 classification performance of DINOv3 by 12.44 on k-NN, 4.43 absolute percentage points on linear probing, from only a small amount of target data and no labels.

Method. We propose refining the representations of a foundation model in a self-supervised setting using cross entropy on the Datum IndEx as Target for Continual Pretraining (DIET-CP) (Ibrahim et al., 2024). The formulation of the continued pretraining loss for a backbone f_θ is as follows:

$$\mathcal{L}_{\text{DIET}}(\boldsymbol{x}_n) = \text{XEnt}\big(W\, f_\theta(\boldsymbol{x}_n),\, n\big), \qquad \boldsymbol{x}_n \in \mathbb{R}^D. \tag{1}$$

where n is the one-hot encoded *index* of each datum. W represents a linear classification head for the DIET loss. This simple objective is an effective pretraining strategy for small datasets. Recent theoretical insights show that DIET's instance discrimination objective recovers ground truth factors of the underlying data generation process under certain assumptions, provably yielding linearly decodable representations (Reizinger et al., 2025). For continual pretraining, DIET-CP offers the following benefits: (1.) no teacher checkpoints or other auxiliary parameters are needed to continue pretraining, as the DIET loss requires no projector network or self-distillation. (2.) DIET-CP is effective with only a small number of training samples, and as little as 500-1000 samples can be sufficient for

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a considerable performance increase, as demonstrated in the experiments below. (3.) Compared to supervised finetuning, no additional hyperparameters are introduced. DIET-CP can be performed with the same parameters as any supervised finetuning strategy. This is especially crucial for the low-data regime we are investigating here, where few samples and even fewer labels are available and cross-validation of SSL hyperparameters may become intractable.

1.1. Experiments

The effect of using DIET continued pretraining is evaluated on a series of classification datasets that are both *in-domain* (natural images), and *out-of-domain* (medical images, optical astronomical images) for three pretrained vision foundation models. We run Equation (1) as continued pretraining on the fine-tuning dataset to align the foundation model to the target distribution. For each task, DIET continued pretraining is used on a random subset of the training data ($N = 1000$) and we record k-NN and linear probing metrics on the validation set before and after training on the subset. Due to class imbalance on most datasets, we report the F1 score and refer to the Appendix for additional results and training specifications.

Pretrained Backbones. We evaluate the method on three popular pretrained vision encoders. DINOv2 (Oquab et al., 2023) is a family of models trained via teacher–student self-distillation using a refined iBOT method (Zhou et al., 2022). DINOv3 (Siméoni et al., 2025) represents the latest version of this method, using a larger dataset and a further refined pretraining strategy to yield more robust and high-resolution features. Lastly, we use the popular masked-autoencoder (MAE) by He et al. (He et al., 2022) trained on ImageNet22k (Deng et al., 2009). All models are ViT-B architectures (Dosovitskiy et al., 2020) and initialized from publicly released checkpoints.

Datasets. As a highly relevant *out-of-domain* application, we cover a diverse set of medical imaging datasets, using a subset of MedMNISTv2 (Yang et al., 2021, 2023). The datasets vary in size and class imbalance and span various medical modalities: BreastMNIST (ultrasound, benign vs. malignant) (Al-Dhabyani et al., 2020), DermaMNIST (7-class dermoscopy) (Tschandl et al., 2018; Codella et al., 2019), OCTMNIST and RetinaMNIST (retinal OCT and diabetic retinopathy grading) (Kermany et al., 2018), OrganAMNIST/CMNIST/SMNIST (11-class organ recognition from CT in axial/coronal/sagittal views) (Bilic et al., 2019; Xu et al., 2019), PathMNIST (9-class colorectal histology) (Kather et al., 2019), and PneumoniaMNIST (binary pediatric chest X-ray) (Wang et al., 2017). Further, we evaluate DIET-CP on Galaxy10 DECaLS, a 10-class optical telescope imaging dataset of galaxy morphologies (astroNN, 2019; Walmsley et al., 2022). Lastly, we include two natural image datsets that are *in-domain* for the pretrained backbones, but require fine-grained visual categorization into around 100 classes (FGVC-Aircraft (Maji et al., 2013) and Food-101 (Bossard et al., 2014)).

DIET-CP Improves out-of-domain performance on medical images and galaxy morphology classification. Table 1 presents pre- and post DIET-CP performance on MedicalMNIST datasets. On average across all tasks, DINOv2 and DINOv3 improve linear probing (LP) performance by 4.81 and 4.43 absolute percentage on F1 respectively, and

Table 1: F1 classification performance on medical datasets before and after DIET continual pretraining using k-NN and linear probing, averaged over three runs.

		Pre DIET-CP (F1)		**Post DIET-CP** (F1)	
Backbone	**Dataset**	**k-NN**	**LP**	**k-NN**	**LP**
DINOv2	BreastMNIST	64.89	82.21	88.54 (+23.66)	88.90 (+6.69)
	DermaMNIST	21.13	40.45	41.85 (+20.72)	53.21 (+12.76)
	OCTMNIST	41.57	71.05	74.89 (+33.32)	85.41 (+14.37)
	OrganAMNIST	57.17	78.51	72.37 (+15.20)	80.30 (+1.79)
	OrganCMNIST	58.30	76.49	72.40 (+14.10)	79.02 (+2.53)
	OrganSMNIST	46.74	62.47	57.46 (+10.72)	62.21 (-0.26)
	PathMNIST	84.15	93.17	94.53 (+10.38)	95.94 (+2.77)
	PneumoniaMNIST	63.67	89.29	93.43 (+29.75)	95.93 (+6.64)
	RetinaMNIST	39.91	50.05	41.95 (+2.04)	46.06 (-3.99)
	Average	53.06	71.52	70.82 (+17.77)	76.33 (+4.81)
DINOv3	BreastMNIST	72.40	81.92	87.80 (+15.40)	91.78 (+9.86)
	DermaMNIST	22.50	47.26	33.92 (+11.42)	50.52 (+3.26)
	OCTMNIST	47.77	75.44	73.58 (+25.82)	85.02 (+9.58)
	OrganAMNIST	71.53	87.00	80.74 (+9.20)	88.33 (+1.33)
	OrganCMNIST	70.48	78.06	77.61 (+7.14)	84.57 (+6.50)
	OrganSMNIST	60.21	64.15	67.44 (+7.23)	71.95 (+7.81)
	PathMNIST	86.34	93.88	93.35 (+7.01)	95.30 (+1.41)
	PneumoniaMNIST	73.38	91.72	92.68 (+19.31)	96.08 (+4.36)
	RetinaMNIST	38.85	53.52	48.27 (+9.41)	49.25 (-4.27)
	Average	60.38	74.77	72.82 (+12.44)	79.20 (+4.43)
MAE	BreastMNIST	59.33	77.11	75.76 (+16.43)	78.46 (+1.35)
	DermaMNIST	22.90	33.23	30.43 (+7.52)	39.87 (+6.64)
	OCTMNIST	31.79	46.49	48.81 (+17.02)	66.92 (+20.44)
	OrganAMNIST	52.98	69.37	72.31 (+19.33)	78.69 (+9.32)
	OrganCMNIST	45.58	64.88	64.05 (+18.47)	71.17 (+6.28)
	OrganSMNIST	38.37	48.94	51.95 (+13.58)	60.98 (+12.04)
	PathMNIST	73.01	85.24	87.51 (+14.50)	91.76 (+6.52)
	PneumoniaMNIST	83.93	88.92	92.85 (+8.92)	93.34 (+4.42)
	RetinaMNIST	25.06	31.22	34.66 (+9.61)	39.63 (+8.41)
	Average	48.10	60.60	62.04 (+13.93)	68.98 (+8.38)

Table 2: Linear probing and k-NN classification performance (F1) before and after DIET-CP for non-medical datasets. FGVC-Aircraft and Food-101 are *in-domain* fine-grained visual categorization tasks, while Galaxy10-DECaLS is an *out-of-domain* optical telescope imaging dataset.

		FGVC-Aircraft		**Food-101**		**Galaxy10-DECaLS**	
Backbone	**Eval (F1)**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
DINOv2	k-NN	19.59	30.91 (+11.31)	58.64	60.33 (+1.69)	30.53	58.30 (+27.77)
	LP	43.47	38.47 (-5.00)	73.54	65.29 (-8.25)	49.30	64.31 (+15.01)
DINOv3	k-NN	38.91	31.83 (-7.08)	63.37	58.03 (-5.34)	42.45	52.09 (+9.64)
	LP	61.00	48.56 (-12.44)	77.58	68.98 (-8.60)	57.43	62.98 (+5.54)
MAE	k-NN	3.74	6.83 (+3.09)	3.73	11.92 (+8.19)	20.44	33.93 (+13.49)
	LP	6.77	11.54 (+4.77)	10.41	21.10 (+10.69)	26.98	38.94 (+11.96)

dramatically on k-NN by 17.77 and 12.44, demonstrating the effectiveness of DIET-CP for unsupervised clustering in particular. MAE is a weaker baseline, in particular on linear and k-NN evaluation, but benefits considerably from CP. RetinaMNIST is the only dataset where LP performance degrades for both DINO models and represents an interesting outlier case as the only ordinal regression task, while k-NN performance reliably improves for all models. Results on non-medical datasets are shown in Table 2. Here, we consider FGVC-Aircraft and Food-101 as fine-grained *in-domain* tasks for the vision models, which are trained exclusively, or with a significant bias, on natural images, while the astronomical

images of Galaxy10-DECaLS are considered *out-of-domain*. DIET-CP does not improve fine-grained in-domain performance for the strong DINO models (DINOv2 improves only on k-NN). MAE performance is increased by DIET-CP but remains low. Representing a non-medical *out-of-domain* task, DIET-CP improves Galaxy10-DECaLS performance strongly across all models for both LP and k-NN evaluation.

2. Conclusions and Future Work

DIET-CP is a simple and sample efficient method for steering foundation models towards a distribution of interest via continual pretraining on a small dataset, leading to measurable improvements on downstream tasks that are out-of-domain for the original backbone. A number of limitations remain as avenues for future work, such as the need for label-free prediction metrics on when DIET-CP helps performance, or deteriorates, as observed in some cases for in-domain fine-grained categorization tasks, which could potentially be coupled to determining how many layers of the backbone should be trained.

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Appendix A. Details on DIET-CP Setup

All experiments are performed using the same recipe. We use AdamW over a total of 150 epochs with a 10% warmup to a learning rate of $1e-4$ and cosine annealing. To initialize W without adversely affecting the backbone, DIET-CP can be started with a frozen backbone for the first few steps, which we do for the first 5% of the epochs. Afterwards, we unfreeze the last two transformer blocks and train them jointly with W. Further, DIET benefits from label smoothing on the cross-entropy loss (Ibrahim et al., 2024), but contrary to training from scratch, we found that DIET-CP performs best with lower label smoothing values in our setup(~ 0.3). We use a batch size of 32 and a 0.05 weight decay. For each task, DIET continued pretraining is used on a random subset of the training data ($N = 1000$) and we record k-NN and linear probing metrics on the validation set before and after training on the subset. Due to this simple setup, DIET-CP is very fast on a single GPU (less than 10 minutes for ViT-B on an H100).

All input images are size 224x224 and are converted to RGB. We use positional embedding interpolation to adapt the ViTs to the input resolution. The following augmentation pipeline is employed across all datasets:

```
v2.RGB
RandomResizedCrop(224, antialias=True),
RandomHorizontalFlip(),
RandomApply([transforms.ColorJitter(0.4, 0.4, 0.4, 0.2)], p=0.3)
RandomGrayscale(p=0.2),
RandomApply([transforms.GaussianBlur((3, 3), (1.0, 2.0))], p=0.2)
```

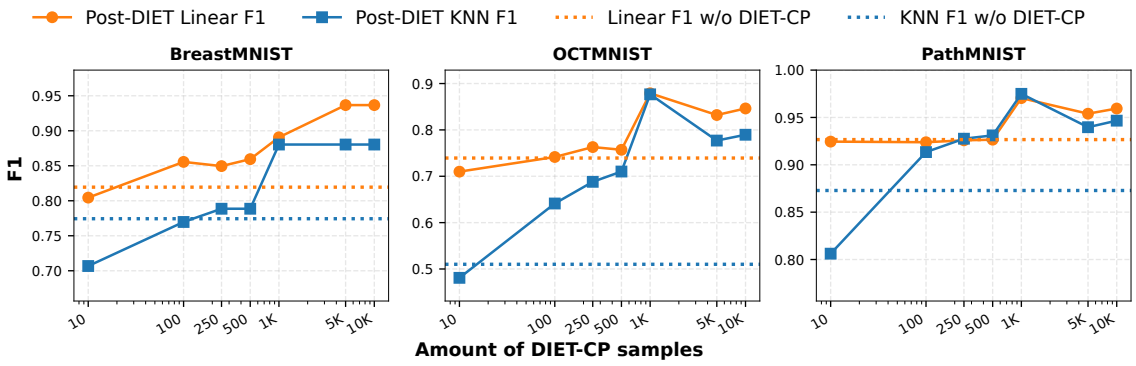


Figure 2: Ablation study over the number of samples used for DIET-CP of a DINOv2 ViT-S. For training the k-NN and LP classifiers, a constant set of 1000 labels is used.

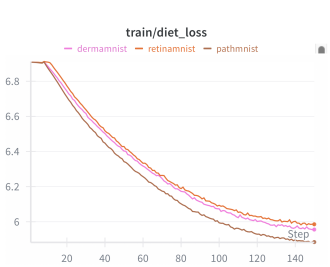
Appendix B. Additional results

B.1. Number of DIET samples

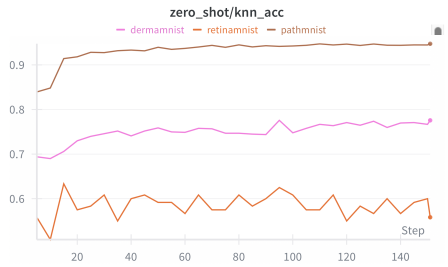
An ablation over the number of training samples for DIET-CP is presented in Figure 2. By training a DINOv2 ViT-S, we observe that 1000 samples are sufficient for a clear performance gain on linear probing, while k-NN metrics improve earlier. Some datasets do not improve beyond 1000 training samples, while other (such as BreastMNIST) appear to benefit slightly from more samples.

B.2. DIET loss during continued pretraining

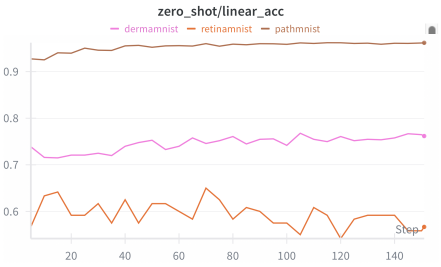
Figure 3 shows plotted loss curves of DINOv2 ViT-S models during continued pretraining over three different MedMNIST tasks. The loss is monotonically decreasing, even as linear probing and k-NN performance plateaus. Similarly, Figure 4 different backbones exhibit distinctive behaviour in DIET convergence, with no direct correlation to downstream performance levels when observed on the same task, highlighting the need for metrics predicting pretraining success.



(a) DIET Loss

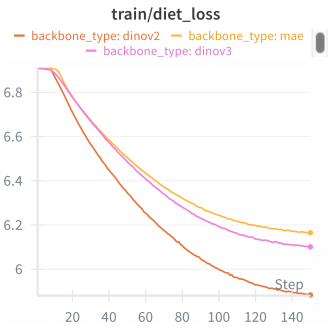


(b) k-NN Accuracy

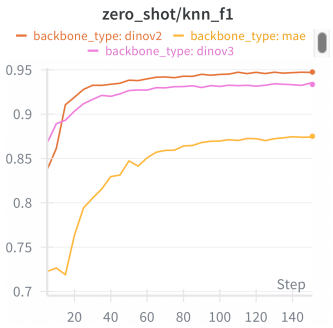


(c) LP Accuracy

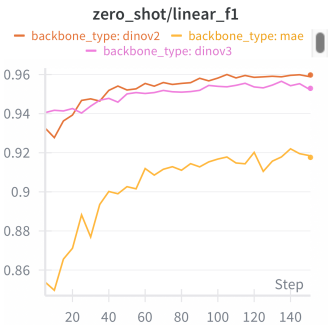
Figure 3: DIET loss curves for DINOv2 ViT-S and corresponding k-NN and linear probing accuracy on three MedMNIST datasets during training over 150 epochs.



(a) DIET Loss



(b) k-NN Accuracy



(c) LP Accuracy

Figure 4: DIET loss curves, k-NN and linear probing accuracy for ViT-B DINOv2, DINOv3, and MAE on PathMNIST. Backbones reach different loss levels, but they are not strongly correlated to downstream performance.

Table 3: Full results table for medical datasets with F1 and accuracy and standard deviation on k-NN and linear probe evaluation pre and post DIET-CP continued pretraining.

Backbone	Dataset	Pre DIET-CP				Post DIET-CP			
		KNN Acc.	KNN F1	Linear Acc.	Linear F1	KNN Acc.	KNN F1	Linear Acc.	Linear F1
DINOv2	breastmnist	79.91±0.74	64.89±1.68	86.75±6.06	82.21±8.50	91.45±0.74	88.54±0.88	91.03±2.56	88.90±2.87
	dermamnist	68.99±0.42	21.13±2.79	71.98±0.28	40.45±1.73	77.87±0.42	41.85±1.63	76.02±0.35	53.21±0.80
	octmnist	73.73±0.79	41.57±0.56	84.67±0.10	71.05±1.44	87.99±0.22	74.89±0.12	92.08±0.13	85.41±0.67
	organamnist	63.74±3.30	57.17±2.07	80.91±2.00	78.51±2.19	77.93±1.95	72.37±3.55	81.03±1.62	80.30±1.52
	organcmnist	63.04±3.96	58.30±0.31	80.31±2.60	76.49±1.67	78.70±0.33	72.40±1.54	82.88±0.09	79.02±0.43
	organsmnist	54.16±3.29	46.74±4.18	67.90±1.79	62.47±1.38	63.03±0.84	57.46±2.24	66.25±1.59	62.21±1.22
	pathmnist	84.10±0.70	84.15±0.71	93.19±0.40	93.17±0.44	94.41±0.48	94.53±0.46	95.88±0.45	95.94±0.44
	pneumoniamnist	64.31±3.24	63.67±2.93	91.13±1.48	89.29±1.58	94.75±0.40	93.43±0.46	96.85±0.67	95.93±0.90
	retinamnist	58.75±6.48	39.91±1.44	61.67±3.54	50.05±3.90	57.08±1.77	41.95±6.35	57.92±2.95	46.06±3.46
	Average	67.86±2.55	53.06±1.85	79.83±2.03	71.52±2.54	80.36±0.79	70.82±1.91	82.22±1.16	76.33±1.37
DINOv3	breastmnist	82.48±1.48	72.40±5.42	87.18±1.28	81.92±1.93	90.60±2.67	87.80±3.44	93.59±1.28	91.78±1.75
	dermamnist	70.56±0.42	22.50±1.24	73.65±1.36	47.26±2.33	74.78±1.04	33.92±1.69	77.40±0.72	50.52±1.90
	octmnist	76.36±0.11	47.77±0.54	85.78±2.38	75.44±3.25	87.47±0.67	73.58±2.85	91.66±0.42	85.02±0.05
	organamnist	75.49±3.21	71.53±4.35	87.13±1.04	87.00±1.46	84.83±1.76	80.74±2.56	89.30±1.41	88.33±1.11
	organcmnist	77.01±1.96	70.48±1.59	81.37±2.06	78.06±2.27	83.25±0.32	77.61±1.35	87.47±1.68	84.57±3.06
	organsmnist	65.31±0.32	60.21±0.46	68.27±1.44	64.15±0.30	72.72±0.35	67.44±0.39	76.24±0.09	71.95±0.63
	pathmnist	90.52±7.24	86.34±1.11	93.93±0.35	93.88±0.28	93.29±0.39	93.35±0.37	95.31±0.36	95.30±0.34
	pneumoniamnist	74.87±5.56	73.38±5.09	93.32±0.50	91.72±0.60	94.15±0.58	92.68±0.65	96.95±0.19	96.08±0.22
	retinamnist	57.78±2.93	38.85±4.35	63.61±2.10	53.52±1.78	60.28±1.73	48.27±1.30	58.61±1.27	49.25±2.56
	Average	74.49±2.58	60.38±2.68	81.58±1.39	74.77±1.58	82.37±1.06	72.82±1.62	85.17±0.82	79.20±1.29
MAE	breastmnist	76.07±0.74	59.33±0.75	84.62±1.28	77.11±1.53	82.48±1.96	75.76±2.99	83.76±0.74	78.46±1.18
	dermamnist	69.92±0.55	22.90±1.32	72.08±1.41	33.23±4.00	73.45±0.21	30.43±2.06	74.01±1.12	39.87±3.31
	octmnist	60.42±1.98	31.79±1.79	73.22±0.59	46.49±2.66	77.89±0.79	48.81±1.40	82.19±0.99	66.92±1.01
	organamnist	62.97±4.22	52.98±2.18	73.32±0.45	69.37±1.38	76.56±0.82	72.31±1.19	80.56±2.79	78.69±2.34
	organcmnist	54.29±2.61	45.58±3.11	69.72±3.09	64.88±4.19	70.74±2.29	64.05±1.82	77.01±1.17	71.17±0.98
	organsmnist	47.94±3.32	38.37±5.18	56.00±4.90	48.94±7.13	58.14±2.05	51.95±1.94	67.17±0.23	60.98±0.08
	pathmnist	73.96±1.72	73.01±1.20	85.41±0.49	85.24±0.75	87.53±0.64	87.51±0.62	91.78±0.23	91.76±0.31
	pneumoniamnist	86.07±1.08	83.93±1.24	90.94±0.40	88.92±0.60	94.37±0.13	92.85±0.14	94.75±0.13	93.34±0.18
	retinamnist	47.92±0.59	25.06±2.87	50.42±0.59	31.22±1.22	53.33±0.00	34.66±0.60	55.00±0.00	39.63±1.96
	Average	64.39±1.87	48.10±2.18	72.86±1.47	60.60±2.61	74.94±0.99	62.04±1.42	78.47±0.82	68.98±1.26

Table 4: Accuracy comparison before and after DIET-CP for non-medical datasets. Improvements (in parentheses) are green for positive, red for negative, and gray if $|\Delta| < 1.0$.

Backbone	Dataset	Pre DIET-CP (Acc.)		Post DIET-CP (Acc.)	
		k-NN	LP	k-NN	LP
dinov2	fgvc_aircraft	21.81	44.74	32.52 (+10.71)	39.48 (-5.26)
	food101	61.59	74.02	61.79 (+0.20)	65.82 (-8.21)
	galaxy10_decals	37.16	54.07	64.57 (+27.40)	67.64 (+13.57)
dinov3	fgvc_aircraft	42.85	62.18	34.42 (-8.43)	49.47 (-12.70)
	food101	65.91	77.89	60.25 (-5.65)	69.38 (-8.51)
	galaxy10_decals	49.65	62.05	59.60 (+9.95)	66.67 (+4.62)
mae	fgvc_aircraft	4.60	7.41	7.87 (+3.27)	11.92 (+4.51)
	food101	4.20	11.00	13.20 (+9.00)	21.46 (+10.45)
	galaxy10_decals	24.52	33.12	40.46 (+15.95)	43.27 (+10.15)

Appendix C. Dataset info

Table 5: Information on the number of samples and classes in the datasets used for experiments. All datasets, except for Food-101 and FGVC-Aircraft are unbalanced. If no official validation split is defined, we sample a random 50% split from the training set.

Dataset	Classes	Train	Val	Test	Class balance
FGVC-Aircraft	102	3400	3400	3400	balanced
Food-101	101	75750	-	25250	balanced
Galaxy10-DECaLS	10	1600	-	1736	skewed
BreastMNIST	2	546	78	156	skewed
DermaMNIST	7	7007	1003	2005	skewed
OCTMNIST	4	97477	10832	1000	skewed
RetinaMNIST	5	1080	120	400	skewed
OrganAMNIST (axial)	11	34561	6491	17778	skewed
OrganCMNIST (coronal)	11	12975	2392	8216	skewed
OrganSMNIST (sagittal)	11	13932	2452	8827	skewed
PathMNIST	9	89996	10004	7180	skewed
PneumoniaMNIST	2	4708	524	624	skewed