V-PETL Bench: A Unified Visual Parameter-Efficient Transfer Learning Benchmark

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Project Page: https://v-petl-bench.github.io/

Abstract

Parameter-efficient transfer learning (PETL) methods show promise in adapting a pre-trained model to various downstream tasks while training only a few parameters. In the computer vision (CV) domain, numerous PETL algorithms have been proposed, but their direct employment or comparison remains inconvenient. To address this challenge, we construct a Unified Visual PETL Benchmark (V-PETL Bench) for the CV domain by selecting **30 diverse, challenging, and comprehensive datasets** from image recognition, video action recognition, and dense prediction tasks. On these datasets, we systematically evaluate **25 dominant PETL algorithms** and open-source a modular and extensible codebase for fair evaluation of these algorithms. V-PETL Bench runs on NVIDIA A800 GPUs and requires approximately 310 GPU days. We release all the benchmark, making it more efficient and friendly to researchers. Additionally, V-PETL Bench will be continuously updated for new PETL algorithms and CV tasks.

1 Introduction

Large scale vision transformers (ViT) have achieved remarkable success in various computer vision (CV) tasks such as image classification [1, 2, 3, 4], segmentation [5, 6, 7] and object detection [8, 9]. However, training these ViT models directly requires massive computational resources to achieve superior performance, which is often unavailable to many academics and institutions. To alleviate this dilemma, the "Pre-train & Finetuning" paradigm is proposed. Specifically, teams with sufficient computational resources utilize enormous datasets [10, 11] to train superior ViT models and release the pre-trained weights. Researchers with limited computational resources can then transfer the knowledge from these pre-trained ViT models to downstream tasks through a fine-tuning stage. However, the standard Full fine-tuning, though effective, still requires substantial computational and memory resources. This becomes particularly costly for models with billions or even trillions of parameters. Additionally, for each task, maintaining the task-specific weights of the model brings a storage burden, as the number of tasks increases.

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Table 1: The comparison between V-PETL Bench and other related benchmarks.

Benchmark	# PETL algorithms	Tasks	# Datasets	Models	Total GPU Hours
ZhiJian [15]	5	Image Classification	18	ViT	-
V-PETL Bench	25	Image Recognition Video Action Recognition Dense Prediction	24 3 3	ViT ViT, Swin Swin	7458 GPU Hours (310 GPU Days)

To mitigate the above challenges, researchers have proposed parameter-efficient transfer learning (PETL), which seeks to achieve a better trade-off between the number of trainable parameters and performance on downstream tasks. While numerous PETL algorithms for the CV domain have been proposed , their direct employment or comparison is not common. The reasons for this can be summarized as follows. First, the hyperparameters of some algorithms (e,g., learning rate, weight decay, etc.) are not open source [12, 13, 14, 15], causing subsequent researchers to spend a lot of time searching for optimal parameters. Second, the performance of baselines is often seriously underestimated in some works, making comparisons unfair. Third, existing benchmarks are mostly constrained to plain image recognition tasks, as summarized in Table 1, preventing consistent and diverse evaluation across tasks such as video action recognition and dense prediction.

To address the aforementioned issues and facilitate PETL research in the CV domain, we propose **V-PETL Bench: a Unified Visual Parameter-Efficient Transfer Learning Benchmark**. V-PETL Bench offers a *diverse* and *challenging* benchmark across 24 image recognition datasets, 3 video action recognition datasets, and 3 dense prediction datasets. Moreover, the V-PETL Bench provides comprehensive evaluations of 25 PETL algorithms by searching for hyperparameters on various pre-trained vision transformers. Since the PETL field lacks a unified evaluation metric that comprehensively considers trainable parameters and performance, we propose the Performance-Parameter Trade-off (PPT) metric to compare different algorithms using a single metric. Additionally, V-PETL Bench offers t-SNE and attention map visualizations for better analysis of PETL algorithms.

V-PETL Bench is a very *heavy-duty* and *resource-consuming* work. For the entire V-PETL Bench, we spend about 310 GPU days on NVIDIA A800 GPUs, as illustrated in Table 1. We open-source the codebase to ensure a unified and consistent evaluation of PETL algorithms. By evaluating 25 standard PETL algorithms on 30 datasets, we obtain several interesting findings: **(1)** Existing PETL algorithms can achieve performance competitive with Full fine-tuning in most downstream tasks and perform significantly better than Full fine-tuning when the amount of data is insufficient, which indicates that it could be an effective alternative to Full fine-tuning; **(2)** Existing PETL algorithms demonstrate significant efficiency, where most algorithms only updated less than 1% of the number of the pre-trained model. Additionally, they lead to improved computation and memory efficiency while achieving better performance; **(3)** Directly applying PETL algorithms from the NLP domain to vision tasks without any specific design results in performance degradation compared to well-designed PETL algorithms tailored for the CV domain; **(4)** The data and task similarity between pre-training and downstream tasks plays a key role, with higher similarity leading to better results. Furthermore, no single PETL algorithm consistently outperforms all others across all tasks.

To sum up, we list our contributions as follows:

- We propose V-PETL Bench: a unified and challenging parameter-efficient transfer learning benchmark for CV tasks for fair and consistent evaluations. To our knowledge, we are the first to build PETL benchmark that cover image classification, video action recognition, and dense prediction tasks.
- We implement 2 traditional and 25 PETL algorithms and open-source a modular codebase along with configuration files, enabling easy reproduction of the reported results in the V-PETL Bench. Our codebase is extensible and open for continued development.
- We propose the Performance-Parameter Trade-off (PPT) metric to compare PETL algorithms, which comprehensively considers two factors: task performance and trainable parameters. Additionally, we provide an in-depth analysis of these representative algorithms.

Table 2: Details of the datasets in the V-PETL Bench.

Application	Dataset	Description	#Classes	Train size	Val size	Test size
Image Recognition	Fine-Grained Visual Classification (FGVC) [17]					
	CUB-200-2011 [18]	Fine-grained bird species recognition	200	5,394	600	5,794
	NABirds [19]	Fine-grained bird species recognition	555	21,536	2,393	24,633
	Oxford Flowers [20]	Fine-grained flower species recognition	102	1,020	1,020	6,149
	Stanford Dogs [21]	Fine-grained dog species recognition	120	10,800	1,200	8,580
	Stanford Cars [22]	Fine-grained car classification	196	7,329	815	8,041
	Visual Task Adaptation Benchmark (VTAB) [23]					
	CIFAR-100 [24]	*Natural*-tasks that contain natural images captured using standard cameras.	100	800	200	10,000
	Caltech101 [25]		102			6,084
	DTD [26]		47			1,880
	Flowers102 [20]		102			6,149
	Pets [27]		37			3,669
	SVHN [28]		10			26,032
	Sun397 [29]		397			21,750
	Patch Camelyon [30]	*Specialized*-tasks that contain images captured via specialized equipment, such as medical and satellite imagery.	2	800	200	32,768
	EuroSAT [31]		10			5,400
	Resisc45 [32]		45			6,300
	Retinopathy [33]		5			42,670
	Clevr/count [34]	*Structured*-tasks that require geometric comprehension like object counting.	8	800	200	15,000
	Clevr/distance [34]		6			15,000
	DMLab [35]		6			22,735
	KITTI/distance [36]		4			711
	dSprites/location [37]		16			73,728
	dSprites/orientation [37]		16			73,728
	SmallNORB/azimuth [38]		18			12,150
	SmallNORB/elevation [38]		9			12,150
Video Recognition	Kinetics-400 [39]	Video action recognition	400	240,436	N/A	19,787
	SSv2 [40]		174	168,913	24,777	27,157
	HMDB51 [41]		51	3,500	1,500	1,849
Dense Prediction	MS COCO [42]	Instance segmentation	80	118,000	N/A	5,000
	ADE20K [43]	Semantic segmentation	150	20,000	N/A	2,000
	PASCAL VOC [44]	Object Detection	21	16,000	N/A	5,000

2 Related Work

As shown in Table 1, the related benchmark is ZhiJian [15]. ZhiJian includes 5 PETL algorithms but only supports image recognition tasks and the ViT model. Additionally, ZhiJian is incomplete constructed and has not been updated for a long time. Therefore, it is of significance to build a visual PETL community that can continuously update PETL algorithms to boost the development of PETL. This need is also highlighted in the survey [16]. Furthermore, Zhijian did not open source some specific details, such as parameter configurations, training logs, and model checkpoints, etc. In contrast, V-PETL Bench will open-source all these details and regularly update with new PETL algorithms and CV tasks, making it more efficient and friendly for researchers.

In the following sections, we will first introduce the downstream CV tasks and datasets, pre-trained models, PETL algorithms, and benchmark results of V-PETL Bench. Then, we will present the codebase structure of V-PETL Bench in Section 7.

3 Tasks and Datasets

The V-PETL Bench includes 30 datasets from image recognition, video action recognition, and dense prediction tasks, as detailed in Table 2. Each dataset in the V-PETL Bench is under a permissive license that allows usage for research purposes. These datasets are chosen based on the following considerations: (1) The dataset represents a mainstream CV task and is broadly relevant to PETL; (2) The dataset is diverse and covers multiple domains; (3) The training process is environmentally sustainable and affordable for research labs in both industry and academia.

3.1 Image Recognition Task

Image recognition is the primary application for PETL. The V-PETL Bench supports 24 image recognition datasets, as shown in Table 2, which can be categorized into two types as detailed below:

Table 3: Specifications of different pre-trained backbones are supported in the V-PETL Bench.

Pre-trained Backbone	Pre-trained Objective	Pre-trained Dataset	# params (M)	Feature dim d	Pre-trained Model
ViT-B [1]	Supervised	ImageNet-21k	85 M	768	checkpoint
ViT-L [1]			307 M	1024	checkpoint
ViT-H [1]			630 M	1280	checkpoint
Swin-B [2]	Supervised	ImageNet-22k	88 M	1024	checkpoint
Swin-L [2]			198 M	1536	checkpoint
ViT-B(VideoMAE) [47]	Self-Supervised	Kinetics-400	85 M	768	checkpoint
Video Swin-B [48]	Supervised		88 M	1024	checkpoint

Fine-Grained Visual Classification (FGVC). FGVC comprises 5 fine-grained visual classification datasets including CUB-200-2011 [18], NABirds [19], Oxford Flowers [20], Stanford Dogs [21] and Stanford Cars [22]. If a dataset only has train and test sets publicly available, we randomly split 90% of the training set for training and 10% for validation. This validation set is then used to select hyperparameters. More details of these datasets in the V-PETL Bench can be found in Appendix B.1.

Visual Task Adaptation Benchmark (VTAB). VTAB comprises 19 diverse visual classification datasets, which are organized into three domains: 1) ***Natural*** - datasets that contain natural images captured with standard cameras. The group includes Caltech101 [25], CIFAR100 [24], DTD [26], Flowers102 [20], Pets [27], Sun397 [29], and SVHN [28]; 2) ***Specialized*** - datasets that contain images captured via specialized equipment, such as medical, and satellite images. The group includes Resisc45 [32], EuroSAT [31], Patch Camelyon [30] and Diabetic Retinopathy [33] ; 3) ***Structured*** - datasets that require geometric comprehension such as object counting. The group includes Clevr [34], dSprites [37], SmallNORB [38], DMLab [35] and KITTI [36]. Each dataset in VTAB contains 1000 training examples. Following [17], we use the provided 800-200 split of the train set to determine hyperparameters. More information on these datasets is available in Appendix B.1.

3.2 Video Action Recognition Task

The detailed dataset statistics for the video action recognition datasets in the V-PETL Bench are described in Table 2. We include the widely used Kinetics-400 [39], SSv2 [40], and HMDB51 [41] datasets from the previous protocol [45, 46], which are still challenging for PETL. For the SSv2 and HMDB51 datasets, we select the optimal parameters on the validation set and test the results on the test set. More details about these datasets in the V-PETL Bench can be found in Appendix B.2.

3.3 Dense Prediction Task

The V-PETL Bench includes three dense prediction datasets as shown in Table 2. MS COCO [42] is a representative instance segmentation dataset with 118k training images and 5k validation images. ADE20K [43] is the most widely used semantic segmentation dataset, containing 20k training and 2k validation images. Pascal VOC [44] has 16k/5k training/validation images and is used for object detection tasks. More details of these datasets in the V-PETL Bench can be found in Appendix B.3.

4 Pre-trained Models

In the V-PETL Bench, we experiment with the Vision Transformer (ViT) [1] and the Swin Transformer (Swin [2]), as shown in Table 3. These architectures are commonly used in the visual PETL domain. Following most research on visual PETL, we employ different levels of ViT for image recognition tasks, all pre-trained on ImageNet-21k [11]. For video action recognition tasks, we utilize the Video Swin Transformer and ViT (from VideoMAE) as the backbone. To examine the impact of pre-training data and downstream task correlation on transfer, we use pre-trained weights on Kinetics-400 [39] (a video dataset). For object detection, we use Swin-Large combined with RetinaNet [49] for training. Additionally, we employ Swin-Large with UperNet [50] for semantic segmentation tasks and Swin-Base with Cascade Mask RCNN [51] for instance segmentation tasks. For the convenience of researchers, we provide download links for all pre-trained weights.

5 PETL Algorithms Implemented in the V-PETL Bench

We implement 2 traditional and 25 PETL algorithms in the codebase for V-PETL Bench, including Full fine-tuning, Frozen, Adapter [12], AdaptFormer [45], SCT [52], BitFit [14], U-Tuning [53], VPT-shallow [17], VPT-Deep [17], Prefix Tuning [54], SSF [55], LoRA [13], NOAH [56], FacT [57], RepAdapter [58], Hydra [59], LST [60], DTL [61], HST [62], GPS [63], LAST [64], SNF [65], BAPAT [54], LN TUNE [66], LoRand [67], E^{3}VA [68], and Mona [69]. The algorithms are chosen based on the following considerations: 1) According to the visual PETL survey [16], existing PETL algorithms are categorized into 7 basic categories (details in Appendix C). For each category, we select 2 to 5 algorithms for implementation; 2) The algorithm is commonly used in the visual PETL domain and has considerable influence; 3) The algorithm corresponds with the comprehensive timeline of visual PETL development. More details of these algorithms can be found in Appendix D.

6 Benchmark Results

6.1 Evaluation Metrics

In the field of PETL, evaluation of algorithms typically focuses on two main aspects: the number of trainable parameters and the performance on tasks. Algorithms that achieve better performance with fewer trainable parameters generally attract more attention. However, there are currently no strict metrics to measure the PETL algorithms. To address this, we propose the **Performance-Parameter Trade-off** (**PPT**) metric. Specifically, the PPT metric for a PETL algorithm M takes into account its performance M_t on a downstream task t, its trainable parameters P_M, and a normalization constant C. The formula for PPT_M is expressed as follows:

$$PPT_M = M_t \times exp(-log_{10}(\frac{P_M}{C} + 1)). \tag{1}$$

The normalization constant C is set at 10^7 as the parameters for most PETL algorithms typically fall within this range. For a detailed explanation of the design of the PPT metric, please see Appendix E.

6.2 Image Recognition Results

Benchmark Results on FGVC. The benchmark results for 13 PETL algorithms on FGVC [17] are presented in Table 4. From these results, we observe the following insights: **(1)** Compared to Full fine-tuning, PETL algorithms demonstrate competitive performance. Notably, about half of these algorithms even outperform the Full fine-tuning paradigm. **(2)** Most PETL algorithms surpass Full fine-tuning regarding PPT, highlighting their parameter efficiency. **(3)** Among the PETL algorithms, GPS [63] and SNF [65] stand out in the PPT metric. GPS achieves high performance through gradient-guided parameter selection during fine-tuning. SNF minimizes conditional mutual information to adaptively adjust the network's shortcut connections, effectively preserving important feature information. **(4)** Some PETL algorithms, such as Adapter [69], LoRA [13], and BitFit [14], originate from the natural language processing (NLP) domain. Directly applying them to vision tasks without any specific design modifications results in performance degradation.

Benchmark Results on VTAB. Table 5 presents the benchmark results for 18 PETL algorithms on VTAB [17]. Our analysis yields the following insights: **(1)** Almost all PETL algorithms outperform Full fine-tuning, demonstrating that fully fine-tuning the pre-trained ViT on limited data risks overfitting and catastrophic forgetting. In contrast, fine-tuning only a few parameters helps maintain the generalizability of the pre-trained models when adapting to downstream tasks. **(2)** DTL achieves the best PPT by leveraging low-rank linear mappings and feature reuse to reduce tunable parameters while enhancing performance. **(3)** Most PETL algorithms perform well on the ***Natural*** and ***Specialized*** groups because their classification objectives align with the training goals of the pre-trained dataset, ImageNet [70]. However, the ***Structured*** group tasks, such as object counting and depth prediction, differ significantly from ImageNet's training objectives, resulting in a substantial domain gap. PETL algorithms with less extensive parameter tuning, such as BitFit [14] and VPT-Shallow [17], fail to adequately bridge this gap, leading to sub-optimal performance.

Table 4: Benchmark results on FGVC. We evaluate 13 PETL algorithms on five datasets with ViT-B/16 models pre-trained on ImageNet-21K. We highlight the **best** and the second results.

Method \ Dataset	CUB-200 -2011	NABirds	Oxford Flowers	Stanford Dogs	Stanford Cars	Mean	# Params. (M)	PPT
Traditional Finetuning								
Full fine-tuning	87.3	82.7	98.8	89.4	84.5	88.54	85.8M	-
Linear probing	85.3	75.9	97.9	86.2	51.3	79.32	**0 M**	0.79
PETL Algorithms								
Adapter[12]	87.1	84.3	98.5	89.8	68.6	85.66	0.41M	0.84
AdaptFormer[45]	88.4	84.7	99.2	88.2	81.9	88.48	0.46M	0.87
Prefix Tuning [71]	87.5	82.0	98.0	74.2	90.2	86.38	0.36M	0.85
U-Tuning [53]	89.2	85.4	99.2	84.1	**92.1**	90.00	0.36M	0.89
BitFit [14]	87.7	85.2	99.2	86.5	81.5	88.02	0.10M	0.88
VPT-Shallow [17]	86.7	78.8	98.4	90.7	68.7	84.66	0.25M	0.84
VPT-Deep [17]	88.5	84.2	99.0	90.2	83.6	89.10	0.85M	0.86
SSF [55]	89.5	85.7	99.6	89.6	89.2	90.72	0.39M	0.89
LoRA [13]	85.6	79.8	98.9	87.6	72.0	84.78	0.77M	0.82
GPS [56]	89.9	86.7	**99.7**	**92.2**	90.4	**91.78**	0.66M	**0.90**
HST [62]	89.2	85.8	99.6	89.5	88.2	90.46	0.78M	0.88
LAST [64]	88.5	84.4	**99.7**	86.0	88.9	89.50	0.66M	0.87
SNF [65]	**90.2**	**87.4**	**99.7**	89.5	86.9	90.74	0.25M	**0.90**

Table 5: Benchmark results on VTAB. We evaluate 18 PETL algorithms on 19 datasets with ViT-B/16 models pre-trained on ImageNet-21K. We highlight the **best** and the second results.

	Natural							**Specialized**				**Structured**										
Method \ Dataset	CIFAR-100	Caltech101	DTD	Flowers102	Pets	SVHN	Sun397	Patch Camelyon	EuroSAT	Resisc45	Retinopathy	Clevr/count	Clevr/distance	DMLab	KITTI/distance	dSprites/loc	dSprites/ori	SmallNORB/azi	SmallNORB/ele	Mean	# Params. (M)	PPT
Traditional Finetuning																						
Full fine-tuning [17]	68.9	87.7	64.3	97.2	86.9	87.4	38.8	79.7	95.7	84.2	73.9	56.3	58.6	41.7	65.5	57.5	46.7	25.7	29.1	65.57	85.8M	-
Linear probing [17]	63.4	85.0	63.2	97.0	86.3	36.6	51.0	78.5	87.5	68.6	74.0	34.3	30.6	33.2	55.4	12.5	20.0	9.6	19.2	52.94	**0M**	0.53
PETL Algorithms																						
Adapter [12]	69.2	90.1	68.0	98.8	89.9	82.8	54.3	84.0	94.9	81.9	75.5	80.9	65.3	48.6	78.3	74.8	48.5	29.9	41.6	71.44	0.16M	0.71
VPT-Shallow [17]	77.7	86.9	62.6	97.5	87.3	74.5	51.2	78.2	92.0	75.6	72.9	50.5	58.6	40.5	67.1	68.7	36.1	20.2	34.1	64.85	0.08M	0.65
VPT-Deep [17]	78.8	90.8	65.8	98.0	88.3	78.1	49.6	81.8	96.1	83.4	68.4	68.5	60.0	46.5	72.8	73.6	47.9	32.9	37.8	69.43	0.56M	0.68
BitFit [14]	72.8	87.0	59.2	97.5	85.3	59.9	51.4	78.7	91.6	72.9	69.8	61.5	55.6	32.4	55.9	66.6	40.0	15.7	25.1	62.05	0.10M	0.61
LoRA [13]	67.1	91.4	69.4	98.8	90.4	85.3	54.0	84.9	95.3	84.4	73.6	82.9	**69.2**	49.8	78.5	75.7	47.1	31.0	44.0	72.25	0.29M	0.71
AdaptFormer [45]	70.8	91.2	70.5	99.1	90.9	86.6	54.8	83.0	95.8	84.4	76.3	81.9	64.3	49.3	80.3	76.3	45.7	31.7	41.1	72.32	0.16M	0.72
SSF [55]	69.0	92.6	75.1	99.4	**91.8**	90.2	52.9	87.4	95.9	87.4	75.5	75.9	62.3	53.3	80.6	77.3	54.9	29.5	37.9	73.10	0.21M	0.72
NOAH [56]	69.6	92.7	70.2	99.1	90.4	86.1	53.7	84.4	95.4	83.9	75.8	82.8	68.9	49.9	81.7	81.8	48.3	32.8	44.2	73.25	0.43M	0.72
SCT[52]	75.3	91.6	72.2	99.2	91.1	91.2	55.0	85.0	96.1	86.3	76.2	81.5	65.1	51.7	80.2	75.4	46.2	33.2	45.7	73.59	0.11M	0.73
FacT [57]	70.6	90.6	70.8	99.1	90.7	88.6	54.1	84.8	96.2	84.5	75.7	82.6	68.2	49.8	80.7	80.8	47.4	33.2	43.0	73.23	0.07M	0.73
RepAdapter [58]	72.4	91.6	71.0	99.2	91.4	90.7	55.1	85.3	95.9	84.6	75.9	82.3	68.0	50.4	79.9	80.4	49.2	**38.6**	41.0	73.84	0.22M	0.72
Hydra [59]	72.7	91.3	72.0	99.2	91.4	90.7	55.5	85.8	96.0	86.1	75.9	83.2	68.2	50.9	82.3	80.3	50.8	34.5	43.1	74.21	0.28M	0.73
LST [60]	59.5	91.5	69.0	99.2	89.9	79.5	54.6	86.9	95.9	85.3	74.1	81.8	61.8	52.2	81.0	71.7	49.5	33.7	45.2	71.70	2.38M	0.65
DTL [61]	69.6	**94.8**	71.3	99.3	91.3	83.3	**56.2**	87.1	96.2	86.1	75.0	82.8	64.2	48.8	81.9	**93.9**	53.9	34.2	47.1	74.58	0.04M	**0.75**
HST [62]	76.7	94.1	74.8	**99.6**	91.1	91.2	52.3	87.1	96.3	**88.6**	**76.5**	**85.4**	63.7	52.9	81.7	87.2	**56.8**	35.8	**52.1**	**75.99**	0.78M	0.74
GPS [63]	81.1	94.2	75.8	99.4	91.7	**91.6**	52.4	**87.9**	96.2	86.5	**76.5**	79.9	62.6	**55.0**	82.4	84.0	55.4	29.7	46.1	75.18	0.22M	0.74
LAST [64]	66.7	93.4	**76.1**	**99.6**	89.8	86.1	54.3	86.2	96.3	86.8	75.4	81.9	65.9	49.4	**82.6**	87.9	46.7	32.3	51.5	74.15	0.66M	0.72
SNF [65]	**84.0**	94.0	72.7	99.3	91.3	90.3	54.9	87.2	**97.3**	85.5	74.5	82.3	63.8	49.8	82.5	75.8	49.2	31.4	42.1	74.10	0.25M	0.73

6.3 Video Action Recognition Results

Table 6 displays comparative results for 5 PETL algorithms using ViT-B from VideoMAE and Video Swin Transformer on the SSv2 [40] and HMDB51 [41] datasets. The findings are as follows: **(1)** On SSv2 [40], which has sufficient data, the ViT-B from VideoMAE outperforms others, illustrating the robustness of features learned through self-supervised learning and the enhanced generalization of the pre-trained model. Conversely, on HMDB51 [41], which has limited data and fewer categories, the supervised pre-trained Video Swin Transformer shows superior performance, indicating better adaptability and generalization in smaller datasets. **(2)** On SSv2 [40], only a few PETL algorithms outperform Full fine-tuning, suggesting that with sufficient data, full fine-tuning is less likely to overfit. Conversely, on HMDB51 [41], most PETL algorithms outperform full fine-tuning, indicating that full fine-tuning may lead to overfitting when data is scarce, whereas PETL algorithms offer

Table 6: Benchmark results on SSv2 and HMDB51. We evaluate 5 PETL algorithms with ViT-B from VideoMAE and Video Swin Transformer. The results are Top-1 accuracy.

Method	Model	Pre-training	# Params.	SSv2		*HMDB51*	
				Top1	PPT	Top1	PPT
Vision Transformer (from VideoMAE)							
Full fine-tuning	ViT-B	Kinetics 400	85.97 M	53.97 %	-	46.41 %	-
Frozen	ViT-B	Kinetics 400	**0 M**	29.23 %	0.29	49.84 %	0.50
AdaptFormer [45]	ViT-B	Kinetics 400	1.19 M	**59.02 %**	**0.56**	55.69 %	**0.53**
BAPAT [54]	ViT-B	Kinetics 400	2.06 M	57.78 %	0.53	**57.18 %**	**0.53**
Video Swin Transformer							
Full fine-tuning	Video Swin-B	Kinetics 400	87.64 M	50.99 %	-	68.07 %	-
Frozen	Video Swin-B	Kinetics 400	**0 M**	24.13 %	0.24	71.28 %	**0.71**
LoRA [13]	Video Swin-B	Kinetics 400	0.75 M	38.34 %	0.37	62.12 %	0.60
BitFit [14]	Video Swin-B	Kinetics 400	1.09 M	45.94 %	**0.44**	68.26 %	0.65
AdaptFormer [45]	Video Swin-B	Kinetics 400	1.56 M	40.80 %	0.38	68.66 %	0.64
Prefix-tuning [71]	Video Swin-B	Kinetics 400	6.37 M	39.46 %	0.32	56.13 %	0.45
BAPAT [54]	Video Swin-B	Kinetics 400	6.18 M	**53.36 %**	0.43	**71.93 %**	0.58

Table 7: Benchmark results on COCO. We evaluate 9 PETL algorithms with Swin-B models pre-trained on ImageNet-22K.

Swin-B	**# Params.**	**Memory**	**COCO (Cascade Mask R-CNN)**			
			AP_{Box}	PPT	AP_{Mask}	PPT
Traditional Finetuning						
Full fine-tuning	86.75 M	17061 MB	51.9 %	-	45.0 %	-
Frozen	**0.00 M**	**7137 MB**	43.5 %	0.44	38.6 %	0.39
PETL Algorithms						
Bitfit [14]	0.20 M	13657 MB	47.9 %	0.47	41.9 %	**0.42**
LN TUNE [66]	0.06 M	12831 MB	48.0 %	0.48	41.4 %	0.41
Partial-1 [72]	12.60 M	7301 MB	49.2 %	0.35	42.8 %	0.30
Adapter [12]	3.11 M	12557 MB	50.9 %	0.45	43.8 %	0.39
LoRA [13]	3.03 M	11975 MB	51.2 %	0.46	44.3 %	0.40
AdaptFormer [45]	3.11 M	13186 MB	51.4 %	0.46	44.5 %	0.40
LoRand [67]	1.20 M	13598 MB	51.0 %	**0.49**	43.9 %	**0.42**
E^3VA [68]	1.20 M	7639 MB	50.5 %	0.48	43.8 %	**0.42**
Mona [69]	4.16 M	13996 MB	**53.4 %**	0.46	**46.0 %**	0.40

a more effective solution. **(3)** BAPAT [54] achieves outstanding performance by integrating the strengths of Adapter [12], Prefix [71], and Prompt [17].

6.4 Dense Prediction Results

Benchmark Results on COCO. Table 7 presents the results on COCO [42] using 9 PETL algorithms with pre-trained Swin-B. Our analysis reveals that: **(1)** Full fine-tuning generally outperforms most PETL algorithms. This is because COCO [42] is a substantial dataset with sufficient data, reducing the likelihood of overfitting when fully fine-tuning. However, most PETL algorithms show competitive performance, demonstrating their parameter efficiency. **(2)** Mona [69] stands out as the only PETL algorithm to surpass full fine-tuning, showcasing the effectiveness of its multi-cognitive visual filters.

Benchmark Results on PASCAL VOC and ADE20K. Table 8 presents the results on Pascal VOC [44] and ADE20K [43] using 9 PETL algorithms. We can observe that: **(1)** On Pascal VOC, which features fewer data and object categories, all PETL algorithms surpass Full fine-tuning. This is because adjusting a small number of parameters in the pre-trained model helps prevent overfitting and catastrophic forgetting, thereby preserving the model's generalization ability. Conversely, on ADE20K [43], which has more data and object categories, Full fine-tuning outperforms all PETL algorithms. With more available data, fully fine-tuning the pre-trained model allows for better adaptation to the

Table 8: Benchmark results on PASCAL VOC and ADE20K. We evaluate 9 PETL algorithms with Swin-L models pre-trained on ImageNet-22K.

Swin-L	# Params.	Memory (VOC)	Pascal VOC (RetinaNet)		ADE20K (UPerNet)	
			AP_{Box}	PPT	mIoU	PPT
Traditional Finetuning						
Full fine-tuning	198.58 M	15679 MB	83.5 %	-	**52.10 %**	-
Frozen	**0.00 M**	3967 MB	83.6 %	0.84	46.84 %	0.47
PETL Algorithms						
Bitfit [14]	0.30 M	10861 MB	85.7 %	0.85	48.37 %	**0.48**
LN TUNE [66]	0.09 M	10123 MB	85.8 %	**0.86**	47.98 %	**0.48**
Partial-1 [72]	28.34 M	**3943 MB**	85.4 %	0.48	47.44 %	0.27
Adapter [12]	4.66 M	10793 MB	87.1 %	0.74	50.78 %	0.43
LoRA [13]	4.57 M	10127 MB	**87.5 %**	0.74	50.34 %	0.43
AdaptFormer [45]	4.66 M	11036 MB	87.3 %	0.74	50.83 %	0.43
LoRand [67]	1.31 M	11572 MB	86.8 %	0.82	50.76 %	**0.48**
E^3VA [68]	1.79 M	4819 MB	86.5 %	0.81	49.64 %	0.46
Mona [69]	5.08 M	11958 MB	87.3 %	0.73	51.36 %	0.43

downstream task. Nevertheless, PETL algorithms still achieve competitive outcomes, demonstrating their parameter efficiency. **(2)** LN TUNE [66] achieves the highest performance on both Pascal VOC and ADE20K, indicating that fine-tuning only the LayerNorm parameters is effective and efficient.

6.5 Discussion

Computational Cost. Some PETL works [60, 68] also explore Memory-Efficient methods, which is closely related to gradient backpropagation. As shown in Figure 1, all PETL algorithms save varying amounts of memory compared to Full fine-tuning, with Frozen and E^3VA performing particularly well. The Frozen method achieves this because its backbone parameters are frozen and do not participate in gradient backpropagation. E^3VA designs a parallel branch for the backbone, causing the gradient backpropagation to bypass the backbone. In the future, we believe there will be more work on parameter and memory efficiency.

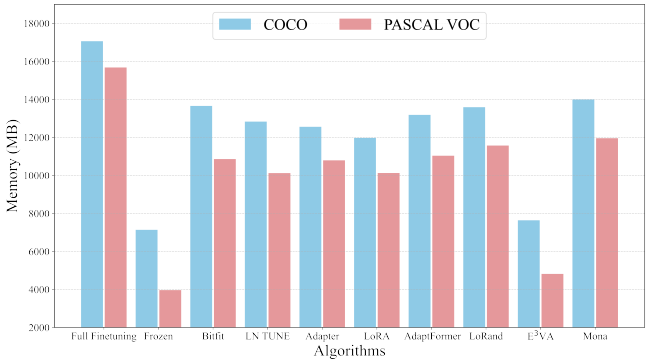

Figure 1: The GPU memory on COCO and PASCAL VOC.

Feature Distribution. V-PETL Bench offers t-SNE visualizations that intuitively display the feature distribution for the downstream task. These visualizations enable us to evaluate the effectiveness of the PETL algorithms. Figure 2 shows t-SNE visualizations for two specific tasks, SVHN and Clevr/count, as examples. The visualizations demonstrate that the feature distribution of the data is closely linked to performance, with higher performance showing more distinct decision boundaries.

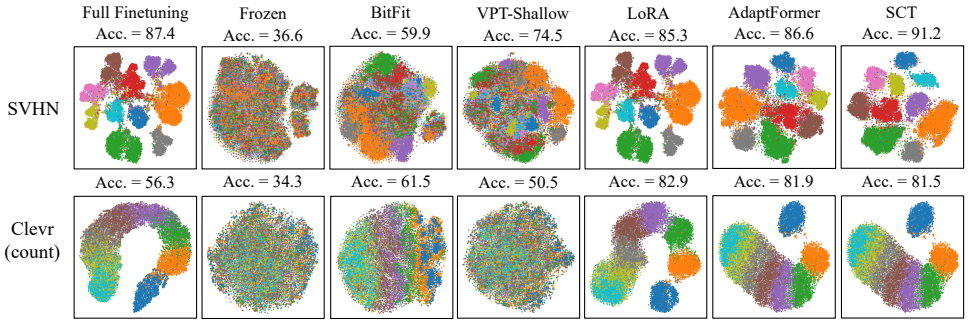

Figure 2: Visualization of feature distribution on SVHN and Clevr/count.

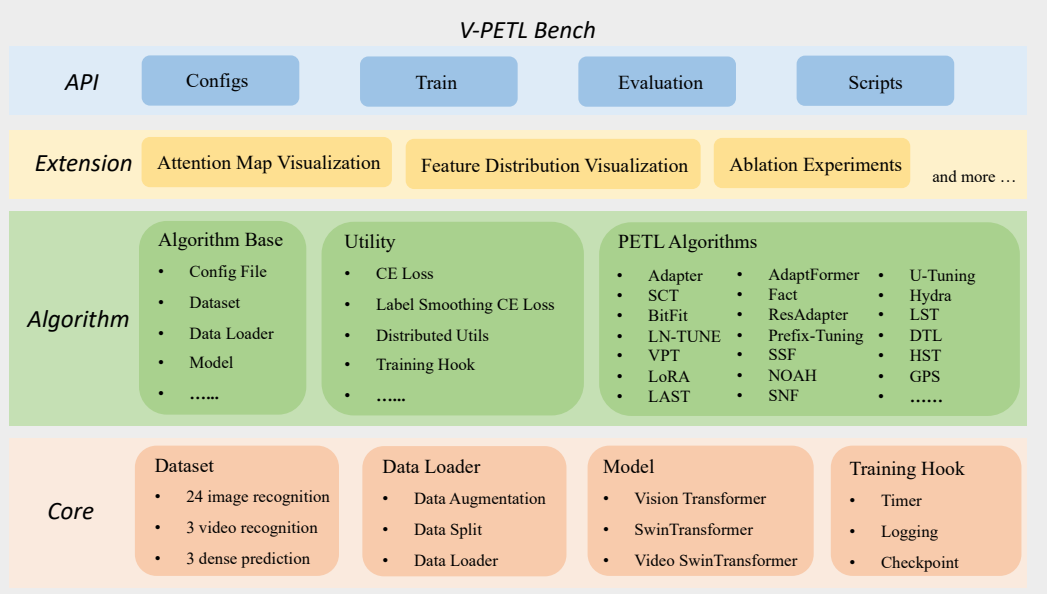

Figure 3: The structure of the V-PETL Bench codebase consists of four layers.

7 Codebase Structure of V-PETL Bench

In this section, we provide an overview of the codebase structure of V-PETL Bench, which which is organized into four abstract layers, as shown in Figure 3.

Core Layer. In the core layer, we implement the essential functions commonly used for training PETL algorithms. Additionally, this layer includes the code for datasets, data loaders, and pre-trained models that are utilized in the V-PETL Bench.

Algorithm Layer. In the algorithm layer, we first implement the base class for PETL algorithms, which includes initializing the datasets, data loaders, and models from the core layer. Moreover, we implement the loss functions and algorithm-specific configurations used in PETL algorithms. Based on these implementations, we currently support 25 PETL algorithms in the V-PETL Bench. More algorithms are expected to be added through the continued extension of V-PETL Bench.

Extension Layer. The extension layer is dedicated to advancing the core PETL algorithms for visual analysis. In this layer, we primarily implement attention map and feature distribution visualization, enabling researchers to directly observe and compare the performance of different PETL algorithms.

API Layer. We encapsulate the core functions and algorithms within the API layer, creating a user-friendly interface for individuals from diverse backgrounds who are interested in applying PETL algorithms to new applications. Additionally, we provide configuration files for all supported algorithms, complete with detailed parameter settings, enabling the reproduction of results.

8 Conclusion

In this paper, we introduce V-PETL Bench, the first comprehensive benchmark for visual parameter-efficient transfer learning domain. The V-PETL Bench includes 30 CV datasets and implements 25 dominant PETL algorithms. We also propose the PPT metric to compare different algorithms based on both the number of parameters and the performance. Additionally, we conduct several insightful analyses of the results. We regard V-PETL Bench as a long-term evolving project and are dedicated to its continuous development. Our roadmap for the future includes expanding its scope to the multimodal model and the generative model.

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Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default **[TODO]** to [Yes] , [No] , or [N/A] . You are strongly encouraged to include a **justification to your answer**, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? [Yes] See Section 3.

Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [Yes]
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2. If you are including theoretical results...
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   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]
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   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [Yes]
   (c) Did you include any new assets either in the supplemental material or as a URL? [No]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

A Parameter-Efficient Transfer Learning Definition

Definition 1 (Parameter-efficient Transfer Learning). *Given a pre-trained model M parametrized by θ, and a specific downstream task $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{|\mathcal{D}|}$, where (x_i, y_i) represents each ground-truth input-output pair related to task $\mathcal{D}$, parameter-efficient transfer learning seeks to adapt θ to task $\mathcal{D}$, where task-specific parameters increment $\Delta\theta$ is introduced with $|\Delta\theta| \ll |\theta|$. The optimal parameters are found by optimizing the losses $\mathcal{L}$ on task $\mathcal{D}$:*

$$\min_{\Delta\theta} \mathbb{E}_{(x_i,y_i)\in\mathcal{D}} \mathcal{L}(M_{\theta+\Delta\theta}(\hat{y}_i|x_i), y_i). \tag{2}$$

B Details of Datasets in V-PETL Bench

B.1 Image Recognition Tasks

In this section, we introduce all the image recognition datasets in the V-PETL Bench. For each dataset, we select relevant examples, as illustrated in Figure 6. To download the datasets, please refer to project page https://v-petl-bench.github.io/.

CUB-200-2011 This task represents the most widely-used benchmark for fine-grained visual categorization. It includes 11,788 images across 200 subcategories of birds, with 5,994 images designated for training and 5,794 for testing.

NABirds This task comprises a collection of 48,000 annotated photographs representing 400 species of birds commonly observed in North America. Each species is documented with over 100 photographs, which include separate annotations for males, females, and juveniles.

Oxford Flowers The task involves an image classification dataset comprising 102 flower categories, featuring flowers commonly found in the United Kingdom. Each category contains between 40 and 258 images.

Stanford Dogs The task includes 20,580 images spanning 120 classes of dogs from around the world, divided into 12,000 images for training and 8,580 for testing.

Stanford Cars The task features 196 classes of cars, totaling 16,185 images captured from the rear. The categories are organized by Make, Model, and Year. Each image has a resolution of 360×240 pixels.

Caltech101 The task involves classifying images of objects across 101 categories, plus an additional background clutter class. The objects include a diverse range such as animals, airplanes, chairs, and scissors. Image sizes vary, typically ranging from 200 to 300 pixels per edge.

CIFAR-100 The task involves classifying natural images into 100 classes, with each class containing 500 training images. Examples of these classes include apples, bottles, dinosaurs, and bicycles. All images are 32x32 pixels in size.

DTD The task involves classifying images of textural patterns across 47 classes, each containing 120 training images. The textures include varied patterns such as banded, bubbly, meshed, lined, and porous. Image sizes range from 300x300 to 640x640 pixels.

Flowers102 The task involves classifying images of flowers found in the UK into 102 categories, with each category containing between 40 and 248 training images. Examples of these flowers include Azalea, Californian Poppy, Sunflower, and Petunia. All images have a minimum dimension of 500 pixels.

Pets The task involves classifying images of cat and dog breeds into 37 classes, with approximately 200 images per class. Examples include Persian cats, Chihuahua dogs, English Setters, and Bengal cats. The dimensions of the images are typically 200 pixels or larger.

Sun397 The Sun397 task is a scenery benchmark that includes 397 classes, each with at least 100 images. The classes are organized hierarchically and feature a variety of scenes such as cathedrals, staircases, shelters, rivers, and archipelagos. All images are in color and measure at least 200x200 pixels.

SVHN This task involves classifying images from Google's Street View of house numbers into 10 classes, each containing over 1,000 training images. Each image is 32x32 pixels in size.

EuroSAT The task involves classifying Sentinel-2 satellite images into 10 different land use categories, such as Residential, Industrial, River, and Highway. Each image has a spatial resolution of 10 meters per pixel and measures 64x64 pixels.

Resisc45 The Remote Sensing Image Scene Classification (RESISC) dataset is designed for scene classification tasks using remote sensing images. It comprises 45 classes, each with 700 images, featuring diverse scenes such as tennis courts, ships, islands, lakes, parking lots, sparse residential areas, and stadiums. Each image is in RGB format with dimensions of 256x256 pixels.

Patch Camelyon The Patch Camelyon dataset includes 327,680 images from histopathologic scans of lymph node sections. The classification task involves predicting the presence of metastatic tissue within these images, dividing them into two classes. Each image has dimensions of 96x96 pixels.

Retinopathy The Diabetic Retinopathy dataset consists of image-label pairs with high-resolution retina images, and labels that indicate the presence of Diabetic Retinopahy (DR) in a 0-4 scale (No DR, Mild, Moderate, Severe, or Proliferative DR).

Clevr/count CLEVR is a visual question and answer dataset designed to evaluate algorithmic visual reasoning. We use just the images from this dataset, and create a synthetic task by setting the label equal to the number of objects in the images.

Clevr/distance Another synthetic task we create from CLEVR consists of predicting the depth of the closest object in the image from the camera. The depths are bucketed into size bins.

dSprites/location The dSprites dataset was originally designed to asses disentanglement properties of unsupervised learning algorithms. In particular, each image is a 2D shape where six factors are controlled: color, shape, scale, rotation, and (x,y) center coordinates. Images have 64x64 black-and-white pixels. This task consists in predicting the x (horizontal) coordinate of the object. The locations are bucketed into 16 bins.

dSprites/orientation We create another task from dSprites consists in predicting the orientation of each object, bucketed into 16 bins.

SmallNORB/azimuth The Small NORB dataset features images of 3D toys from 50 classes, including animals, human figures, airplanes, trucks, and cars, each captured in a resolution of 640x480 pixels. In this specific task, we assign labels based on the azimuth—the angle of horizontal deviation—using intervals of 20 degrees, resulting in 18 distinct classes.

SmallNORB/elevation Another synthetic task from the Small NORB dataset involves predicting the elevation depicted in the images. This task is divided into 9 classes, each corresponding to a different elevation ranging from 30 to 70 degrees, with intervals of 5 degrees between each class.

DMLab The DMLab (DeepMind Lab) is a set of control environments focused on 3D navigation and puzzle-solving tasks. The Dmlab dataset contains frames observed by the agent acting in the DeepMind Lab environment, which are annotated by the distance between the agent and various objects present in the environment. The goal is to evaluate the ability of a visual model to reason about distances from the visual input in 3D environments. The Dmlab dataset consists of 360x480 color images in 6 classes.The classes are {close, far, very far} $\times$ {positive reward, negative reward} respectively.

KITTI-Dist The KITTI task involves predicting the binned depth to vehicles, such as cars, vans, or trucks, in images. The prediction is categorized into four distinct bins or classes.

B.2 Video Action Recognition Tasks

SSv2 The SSv2 dataset currently contains 168,913 videos, which are categorized under 174 different labels. These videos vary in length from 2 to 6 seconds. The labels are textual descriptions created from templates like "Dropping [something] into [something]," where the "[something]" acts as placeholders for various objects.

HMDB51 The HMDB51 dataset comprises a diverse array of realistic videos sourced from movies and web videos. It contains 6,766 video clips, spread across 51 action categories such as "jump," "kiss," and "laugh." Each category includes at least 101 clips, providing a broad spectrum of human actions.

B.3 Dense Prediction Tasks

MS COCO The MS COCO dataset is a widely used benchmark for instance segmentation, featuring 80 object categories. Each image in MS COCO is accompanied by high-quality annotations. For instance segmentation, these annotations consist of pixel-wise masks for each object instance, enabling precise identification and localization of objects within the images.

ADE20K The ADE20K semantic segmentation dataset includes over 20,000 scene-centric images, each exhaustively annotated with pixel-level labels for objects and object parts. It encompasses a total of 150 semantic categories, which range from expansive elements like sky, road, and grass, to discrete objects such as person, car, and bed.

PASCAL VOC The PASCAL VOC dataset features 20 object categories, encompassing vehicles, household items, animals, and more. Each image in this dataset is equipped with bounding box annotations and object class annotations, making it a widely used benchmark for object detection.

C Taxonomy of PETL Algorithms

In visual PETL survey [16], existing PETL methods can be divided into 7 basic categories, including:

Adapter Tuning methods inject small-scale neural modules (adapters) to the Transformer layers and only tune these adapters for model adaptation, as showin in Figure 4b. Specifically, one adapter module contains a down-projection and an up-projection. Additionally, there is a nonlinear layer between the two layers for non-linear projection.

Prompt Tuning methods wrap the original input with additional visual prompts. These prompts consist of trainable parameters or perturbations, as shown in Figure 4c. Given an input $x_0 \in R^d$ and prompts $P = [P_1], [P_2], ...[P_l] \in \mathbb{R}^{l \times d}$, the final input can be expressed as follows:

$$x_0 = concat(P, x_0) = [P, x_0] \in \mathbb{R}^{(l+N) \times d}. \tag{3}$$

Side Tuning employs a smaller and separate network that operates in parallel with the Transformer, as shown in Figure 4d. While ensuring parameter-efficient, this separation completely obviates the

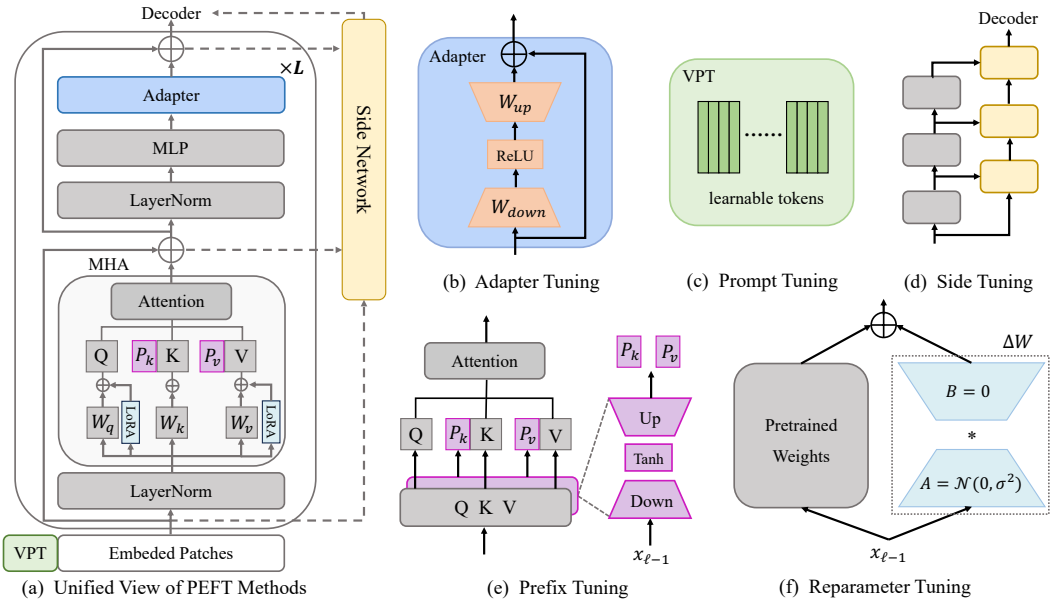

Figure 4: The detailed architecture of various PEFT methods. [16]

need for costly backpropagation through a large backbone network, resulting in significant GPU memory savings.

Prefix Tuning introduces learnable prefix matrices to the Multi-Head Attention (MHA) module of the Transformer layers, as shown in Figure 4e. It involves prepending two randomly initialized prefix matrices $P_k, P_v \in R^{l \times d}$ to the keys and values in the MHA, leading the attention calculation to:

$$Attention(Q, K, V) = softmax(\frac{Q[P_k, K]^T}{\sqrt{d}})[P_v, V]. \tag{4}$$

Specification Tuning is an efficient approach that directly modifies a specific subset of parameters in Transformers, such as bias and LayerNorm, which are crucial for downstream tasks. This method concentrate on important parameters while discarding those deemed less relevant. The concept, while straightforward, has proven to be surprisingly effective.

Reparameter Tuning methods introduce new learnable parameters during the training stage, while these parameters can be integrated into the original Transformer layers through reparameterization during the inference phase, as shown in Figure 4f.

Unified-based Tuning methods offer a unified framework to integrate various fine-tuning methods into a single, harmonized architecture. This approach streamlines the process and enhances the overall efficiency and effectiveness of the fine-tuning.

D Details of Implemented PETL Algorithms in V-PETL Bench

For each category of PETL algorithms outlined in Section C, we select multiple algorithms for implementation within the V-PETL Bench. These are briefly introduced in Section 5 of the paper, with a detailed introduction provided below:

D.1 Adapter Tuning

(1) Adapter [12] incorporates a bottleneck module (Adapter) into each Transformer layer, positioned after both the Multi-Head Attention (MHA) and the Feed-Forward Networks (FFN). **(2) AdaptFormer** [45] embeds the adapter module parallel to the FFN in each encoder of a Vision Transformer.

(3) SNF [65] integrates and fine-tunes Normalizing Flows modules within the residual connections of each encoder block in the pre-trained ViT. **(4) Hydra** [59] includes both a parallel and a sequential adapter in the final linear layer of the FFN in each encoder block. **(5) LoRand** [67] introduces low-rank adapters into each SwinBlock of the Swin Transformer, positioned after the MHA and FFN for enhanced dense predictions. **(6) Mona** [69] integrates a multi-cognitive convolutional filter group (Depthwise Convolution) along with an aggregation filter (1×1 Convolution) following the down projection of the standard adapter.

D.2 Prompt Tuning and Prefix Tuning

(1) VPT [17] enhances vision transformers by appending learnable visual prompts to the input sequences (VPT-Shallow) or to the input of each transformer encoder layer (VPT-Deep). **(2) Prefix Tuning** [71] incorporates trainable prefix tokens into each layer of the Transformer model, allowing for task-specific adaptation of the pre-trained model without altering the original parameters.

D.3 Side Tuning

(1) LST [60] employs a small ladder-side network that operates outside the pre-trained network, receiving intermediate activations via shortcut connections. **(2) DTL** [61] integrates a Compact Side Network (CSN) alongside each encoder block within the ViT, extracting task-specific information progressively throughout the forward pass and reintegrating it into the pre-trained ViT. **(3) HST** [62] constructs a lightweight Hierarchical Side Network (HSN) separate from the pre-trained ViT to generate multi-scale features from intermediate activations. **(4) LAST** [64] adds a lightweight side network consisting of low-rank self-attention (LSA) modules after each Transformer block in the pre-trained ViT. **(5) E^{3}VA** [68] introduces a highway system parallel to the SwinBlock in the Swin Transformer, featuring trainable low-rank adapters (E^{3}VA) that isolate the pre-trained model from gradient backpropagation.

D.4 Specification Tuning

(1) BitFit [14] exclusively fine-tunes the bias terms of the pre-trained model while keeping the rest of the parameters unchanged. **(2) GPS** [63] fine-tunes a small, crucial subset of parameters (sub-network) from the original pre-trained model using a gradient-based approach. **(3) SCT** [52] incorporates Salient Channel Tuning Modules (SCTM) after the MHA or FFN to target and fine-tune a select group of channels (salient channels). **(4) LN TUNE** [66] specifically fine-tunes the LayerNorm parameters, leaving other components untouched. **(5) Partial-1** [72] focuses on fine-tuning only the last encoder layer of the pre-trained ViT.

D.5 Reparameter Tuning

(1) LoRA integrates a tunable pair of low-rank decomposed weight matrices into each encoder layer of the pretrained ViT. **(2) FacT** incorporates tunable factorized weight matrices into each layer of the pretrained ViT. **(3) RepAdapter** introduces a reparameterizable linear adapter before the MHA and FFN of each encoder block of the pre-trained ViT. **(4) SSF** adds a tunable scaling and shifting module (SSF-ADA) behind the MHA and FFN of the pre-trained ViT.

D.6 Unified-based Tuning

(1) NOAH [56] integrates a tunable Neural Operator Adaptation Head (NOAH) module, which includes a lightweight MLP and a gating mechanism, into the MHA and FFN of each encoder block in the pre-trained ViT. **(2) U-Tuning** [53] incorporates a unified tuner (U-Tuner) consisting of Prefix, Adapter, and Prompt elements into the MHA and FFN of each encoder block in the pre-trained ViT. **(3) BAPAT** [54] introduces the Parallel Attention (PATT), which adds trainable query, key, and value matrices to the MHA, and incorporates bottleneck layers into the FFN of each Transformer block in the pre-trained ViT.

E Performance-Parameter Trade-off Metric

For the evaluation of PETL algorithms, to compare different methods with a single number that considers both task performance and parameter-efficiency, we define the Performance-Parameter Trade-off (PPT) metric:

$$PPT = performance \times exp(-log_{10}(\frac{\#parameters}{C} + 1)). \tag{5}$$

The performance quantifies prediction accuracy, ranging from 0 to 1. The term # parameters refers to the count of updated parameters during the model adaptation phase. C is a normalization constant set at 10^7, aligns with the typical parameter sizes of existing PETL algorithms, ensuring that the ratio $\frac{\#parameters}{C}$ falls within the [0, 1) range. To prevent log values from reaching negative infinity, we introduce an additive constant of 1. As PETL evolves, considerations such as GPU memory might be incorporated, potentially leading to further refinements of the PPT metric.

E.1 Attention Map

Attention map visualization is a crucial tool for analyzing PETL algorithms. In the V-PETL Bench, we have included an attention map visualization module. We randomly select several examples of attention map visualizations, as illustrated in Figure 5. We can find that the SCT method focuses more intently on the cat, while Full Finetuning directs more concentrated attention towards the flower. In the V-PETL Bench, we offer a convenient interface that allows researchers to easily utilize the attention map visualization tool.

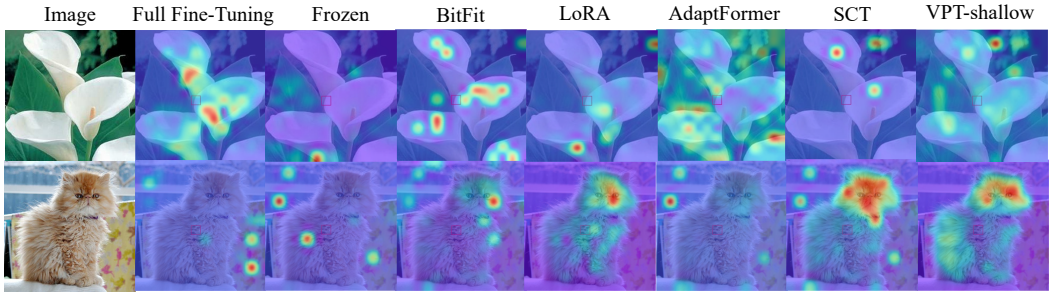

Figure 5: Visualization of attention maps.

F Broader Impacts

Efficient usability. The V-PETL Bench provides a user-friendly calling interface and comprehensive documentation, enabling researchers from various fields to quickly get started with efficient usability. Additionally, V-PETL Bench provides checkpoints for all tasks, allowing researchers to directly load and utilize these models without the need for retraining.

Environmental-friendly consumption. The V-PETL Bench has standardized common computer vision tasks and offers evaluation results for various PETL algorithms. It eliminates the need for additional training unless absolutely necessary, which positively impacts carbon emissions reduction and environmental protection.

Ethical Considerations. The PETL algorithms capitalize on the representation and generalization abilities acquired from large-scale pre-trained datasets and models. However, it's crucial to acknowledge the potential risks if these pre-training datasets contain bias or illegal information.

G Future Work

In this work, our primary focus is on traditional computer vision (CV) tasks. However, there are additional CV tasks that should not be overlooked by the PETL community. Currently, the V-PETL Bench does not encompass tasks such as text-to-image generation, point cloud analysis, or robotic manipulation. Moreover, it supports only a limited selection of pre-trained models. Expanding our repository to include self-supervised and multimodal pre-trained models is essential. We plan to continue updating the benchmark to include these enhancements in the future.

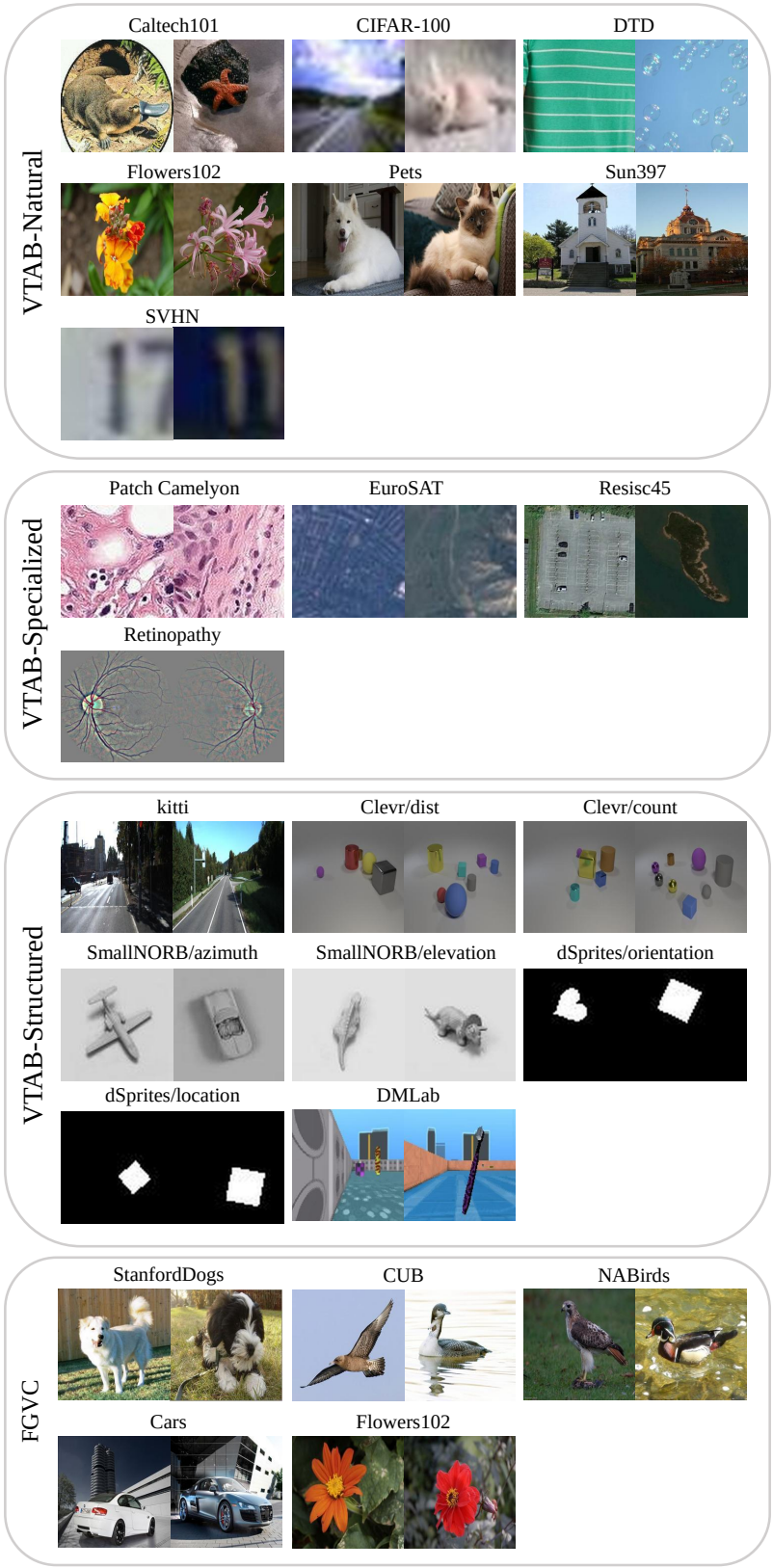

Figure 6: Dataset examples for all classification tasks evaluated.