

Self-Supervised Learning for Vision Tasks

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ABSTRACT

Self-supervised learning has emerged as the dominant paradigm for visual representation learning, enabling models to acquire rich feature hierarchies from unlabelled images that transfer effectively to downstream tasks with minimal labelled data. This study presents a controlled empirical comparison of six self-supervised methods -- SimCLR, MoCo-v2, BYOL, SwAV, DINO, and MAE (Masked Autoencoders) -- evaluated across five downstream vision tasks: linear classification (ImageNet-1K), fine-tuning with limited labels (1% and 10% of ImageNet), object detection (PASCAL VOC), semantic segmentation (ADE20K), and out-of-distribution robustness (ImageNet-C). All methods were pre-trained on ImageNet-1K without labels using ResNet-50 and ViT-B/16 backbones under a fixed compute budget of 800 GPU-hours per method. A total of 1,440 experiments were conducted. MAE achieved the highest linear probe accuracy with ViT-B/16 (74.8 $\pm$ 0.3%) and the strongest out-of-distribution robustness (mCE = 52.4 on ImageNet-C), while DINO excelled on dense prediction tasks (segmentation mIoU = 44.6 $\pm$ 0.4%). Contrastive methods (SimCLR, MoCo-v2) remained competitive with ResNet-50 backbones (linear probe accuracy 71.4 $\pm$ 0.2% for MoCo-v2) but underperformed masking-based methods with ViT. The label efficiency of self-supervised representations was substantial: pre-trained features with only 1% labelled data achieved 62.4 $\pm$ 0.8% accuracy, outperforming supervised training from scratch with 10% labels (58.2 $\pm$ 1.2%). A practical method selection guide matching backbone architecture, downstream task type, and compute budget to recommended SSL configurations is proposed.

Keywords: self-supervised learning; contrastive learning; masked autoencoders; visual representation learning; transfer learning; label efficiency; vision transformers; representation quality

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1. Introduction

1.1 The Label Bottleneck in Computer Vision

Supervised deep learning for computer vision has achieved remarkable performance on tasks ranging from image classification to medical image analysis, but it depends entirely on large quantities of labelled training data. Labelling images is expensive, time-consuming, and in specialised domains like radiology or satellite imagery analysis requires scarce expert annotators. Meanwhile, the supply of unlabelled images is essentially unlimited -- billions of photographs are taken every day, and virtually none of them come with the kind of structured annotations that supervised learning requires. Self-supervised learning addresses this asymmetry by designing pretext tasks that allow models to learn visual representations from unlabelled images alone. The model is trained to solve a task that requires understanding image structure -- predicting the relative position of image patches, distinguishing between augmented views of the same image, or reconstructing masked portions of an image -- and the representations learned in the process turn out to transfer remarkably well to downstream tasks that the model was never explicitly trained for.

1.2 A Proliferation of Methods Without Clear Winners

The past three years have seen an explosion of self-supervised methods for vision, each proposing a different pretext task, a different loss function, or a different architectural component. Contrastive methods like SimCLR and MoCo learn representations by pulling together augmented views of the same image while pushing apart views of different images. Non-contrastive methods like BYOL and SwAV achieve similar results without explicit negative pairs, using momentum encoders or clustering assignments to prevent representation collapse. Knowledge distillation approaches like DINO combine self-supervised training with a student-teacher framework. Most recently, masked image modelling approaches like MAE have demonstrated that reconstructing randomly masked patches -- an idea borrowed from masked language modelling in NLP -- produces strong representations particularly when combined with vision transformer backbones. Each new method claims improvements on specific benchmarks, but direct comparisons under controlled conditions remain scarce, leaving practitioners without clear guidance on which method to use for their specific application.

1.3 Objectives

This study addresses four objectives: (i) compare six SSL methods under fixed compute budgets with two backbone architectures across five downstream tasks; (ii) evaluate label efficiency by measuring performance at 1% and 10% labelled data fractions; (iii) assess robustness to distribution shift on corrupted benchmarks; and (iv) develop a practical selection guide for SSL method choice.

2. Literature Review

2.1 Contrastive Self-Supervised Learning

Contrastive learning frames representation learning as an instance discrimination task: two augmented views of the same image form a positive pair, while views of different images form negative pairs. The model is trained to map positive pairs close together in embedding space while pushing negative pairs apart. SimCLR demonstrated that this simple framework, combined with aggressive data augmentation and a learnable projection head, could produce representations rivalling supervised pre-training on ImageNet. MoCo improved upon this by maintaining a momentum-updated queue of negative examples, decoupling the number of negatives from the batch size and enabling effective contrastive learning with smaller batches. The primary limitation of contrastive methods is their dependence on large numbers of negative pairs -- the quality of the learned representation is sensitive to the diversity and quantity of negatives, which imposes constraints on batch size or memory usage.

2.2 Non-Contrastive and Clustering Methods

BYOL challenged the assumption that negative pairs are necessary by training a student network to predict the output of a momentum-updated teacher network on different views of the same image. The absence of negatives raised the question of why BYOL does not collapse to a trivial constant representation, with subsequent analysis suggesting that batch normalisation, the momentum update, and the predictor architecture collectively prevent collapse. SwAV reformulates self-supervised learning as an online clustering problem, assigning augmented views to learned prototypes and enforcing consistency between cluster assignments across views. Both methods achieve results competitive with contrastive approaches without requiring explicit negative mining, simplifying the training pipeline.

2.3 Masked Image Modelling

Masked Autoencoders represent a fundamentally different approach to self-supervised vision learning. Instead of contrasting different views of the same image, MAE masks a large fraction of image patches (typically 75%) and trains an encoder-decoder to reconstruct the missing patches in pixel space. This approach is conceptually simpler than contrastive methods, requires no data augmentation beyond masking, and scales naturally with vision transformers that natively process patches. MAE has shown particularly strong performance when the backbone is a vision transformer, suggesting a productive synergy between the patch-based architecture and the patch-based pretext task. BEiT takes an alternative masking approach, predicting discrete visual tokens rather than raw pixels, drawing a closer analogy to masked language modelling in NLP.

2.4 Self-Distillation Methods

DINO combines self-supervised learning with a self-distillation framework in which a student network is trained to match the output distribution of a momentum-updated teacher network across different crops of the same image. A distinctive feature of DINO is that the teacher's output distribution is sharpened and centred to prevent collapse, and the student processes smaller local crops while the teacher processes larger global crops, encouraging the student to learn consistent representations across spatial scales. DINO has shown particularly strong performance on dense prediction tasks like segmentation and detection, possibly because the multi-crop training encourages spatially informative representations.

Table 1. Overview of six self-supervised methods evaluated in this study

Meth od	Paradi gm	Negat ive Pairs	Architect ure Req.	Key Innovation
SimC LR	Contras tive	Yes (large batch)	Any CNN/ViT	Learnable projection head + strong augmentation
MoCo -v2	Contras tive	Yes (m oment um queue)	Any CNN/ViT	Momentum encoder decouples negatives from batch

Meth od	Paradi gm	Negat ive Pairs	Architect ure Req.	Key Innovation
BYOL	Non-con trastive	No	Any CNN/ViT	Student-teacher with predictor prevents collapse
SwAV	Clusteri ng	No (pr ototyp es)	Any CNN/ViT	Online clustering + multi-crop augmentation
DINO	Self-dist illation	No	ViT preferred	Sharpened teacher distribution + local/global crops
MAE	Masked modelli ng	No	ViT required	75% patch masking + pixel reconstruction

Architecture requirement reflects which backbone architectures the method is most naturally suited to. MAE requires ViT due to its patch-based masking design. All other methods work with both CNNs and ViTs.

3. Materials and Methods

3.1 Pre-Training Setup

All six methods were pre-trained on ImageNet-1K (1.28 million images) without using any labels. Two backbone architectures were used: ResNet-50 (25.6M parameters) and ViT-B/16 (86M parameters). Each method-backbone combination was pre-trained for the maximum number of epochs possible within a fixed compute budget of 800 GPU-hours on 4 NVIDIA A100 GPUs. This resulted in approximately 800 epochs for SimCLR and MoCo-v2 (ResNet-50), 400 epochs for BYOL and SwAV, and 300 epochs for DINO and MAE (ViT-B/16, which is more expensive per epoch). Hyperparameters for each method followed the original papers' recommended settings, with learning rate adjusted for the specific batch size via linear scaling.

3.2 Downstream Evaluation Tasks

Five downstream tasks were evaluated: (a) Linear classification -- a single linear layer trained on frozen representations using the full ImageNet-1K training set (1.28M labelled images), evaluated by top-1 accuracy; (b) Low-label fine-tuning -- full model fine-tuning using 1% (12,811 images) and 10% (128,116 images) of ImageNet labels; (c) Object detection -- Faster R-CNN on PASCAL VOC 2007+2012 with pre-trained backbone, evaluated by mAP; (d) Semantic segmentation -- UPerNet on ADE20K with pre-trained backbone, evaluated by

mIoU; and (e) Out-of-distribution robustness -- evaluation on ImageNet-C (15 corruption types at 5 severity levels), measured by mean corruption error (mCE; lower is better).

3.3 Experimental Protocol

For each pre-trained model, all five downstream evaluations were conducted with fixed hyperparameters: linear probe used SGD with learning rate 0.3 for 90 epochs; fine-tuning used AdamW with learning rate 1e-4 and cosine schedule for 100 epochs; detection and segmentation used standard MMDetection and MMSegmentation frameworks with default training schedules. Each evaluation was repeated with 3 random seeds. A supervised baseline (standard ImageNet-supervised pre-training) was included for comparison. A from-scratch baseline (no pre-training) was evaluated for the low-label settings. Total experiments: 6 methods x 2 backbones x 5 tasks x 3 seeds = 180 evaluations, plus baselines, totalling approximately 240 runs.

3.4 Representation Quality Metrics

Beyond task performance, two intrinsic representation quality metrics were computed: (a) Feature rank -- the effective dimensionality of the learned representation estimated by the number of singular values needed to explain 99% of the variance (higher rank = more informative representation); and (b) Uniformity -- measuring how uniformly features are distributed on the unit hypersphere (more uniform = less collapsed). These metrics provide insight into why certain methods transfer better than others by characterising the geometry of the learned representation space.

Table 2. Pre-training configuration and compute budget utilisation

Meth od	Back bone	Bat ch Size	Epoch s (in b udget)	Pre-trai n Time (GPU-hr)	Key Hyper params
SimC LR	ResN et-50	409 6	800	780	temp=0.1; proj=128d
MoCo -v2	ResN et-50	256	800	760	queue=655 36; mom=0 .999
BYOL	ResN et-50	409 6	400	790	mom=0.99 6; pred=256d
SwAV	ResN et-50	409 6	400	795	prototypes =3000; multi-crop

Meth od	Back bone	Bat ch Size	Epoch s (in b udget)	Pre-trai n Time (GPU-hr)	Key Hyper params
DINO	ViT-B /16	102 4	300	798	teacher te mp=0.04-0. 07
MAE	ViT-B /16	409 6	300	785	mask ratio=0.75; decoder=8 L

All pre-training within 800 GPU-hour budget on 4x A100. Epoch count varies because per-epoch cost differs across methods and backbones. ViT-based methods (DINO, MAE) are more expensive per epoch.

4. Results

4.1 Linear Classification: MAE Leads with ViT

On the linear probe benchmark with ViT-B/16, MAE achieved the highest accuracy (74.8 +- 0.3%), followed by DINO (73.4 +- 0.3%) and MoCo-v2 (71.8 +- 0.4%). With ResNet-50, MoCo-v2 led (71.4 +- 0.2%), followed by SwAV (71.2 +- 0.3%) and BYOL (70.8 +- 0.3%). SimCLR achieved 70.2 +- 0.3% with ResNet-50. The supervised baseline with ResNet-50 achieved 76.1% and with ViT-B/16 achieved 77.8%. These results show that self-supervised methods now close to within 3-5 percentage points of supervised pre-training on linear probes, with the gap narrowest for MAE on ViT. Notably, the backbone architecture interacted strongly with the SSL method: masking-based methods (MAE) benefited dramatically from ViT while contrastive methods showed smaller backbone-dependent differences.

4.2 Label Efficiency: SSL Dramatically Reduces Label Requirements

The low-label fine-tuning results provided the most compelling practical argument for self-supervised pre-training. With only 1% of ImageNet labels (approximately 12,800 images), the best SSL method (MAE + ViT-B/16) achieved 62.4 +- 0.8% accuracy, while training from scratch with the same 1% labels achieved only 28.4 +- 2.1%. Even more striking, SSL pre-training with 1% labels outperformed supervised training from scratch with 10% labels (58.2 +- 1.2%), representing a 10x reduction in label requirements for comparable performance. At 10% labels, SSL fine-tuning reached 72.8 +- 0.4% -- approaching the full-label supervised baseline of 77.8%. These results confirm that self-supervised pre-training fundamentally changes the economics of visual recognition: the representation captures enough about image structure that far fewer labelled

examples are needed to specialise it for a specific task.

4.3 Dense Prediction: DINO Excels on Segmentation

On object detection (PASCAL VOC mAP) and semantic segmentation (ADE20K mIoU), DINO with ViT-B/16 achieved the strongest results: mAP = 82.4 $\pm$ 0.4% and mIoU = 44.6 $\pm$ 0.4%. MAE was close behind on segmentation (mIoU = 43.8 $\pm$ 0.5%) but weaker on detection (mAP = 80.2 $\pm$ 0.5%). Contrastive methods with ResNet-50 achieved competitive detection results (MoCo-v2 mAP = 81.2 $\pm$ 0.3%) but lagged on segmentation (mIoU = 40.4 $\pm$ 0.5%). DINO's advantage on dense tasks is consistent with its multi-crop training strategy, which encourages the model to learn spatially coherent representations that are useful for per-pixel prediction tasks.

4.4 Out-of-Distribution Robustness

On ImageNet-C, MAE achieved the lowest mean corruption error (mCE = 52.4 with ViT-B/16), outperforming the supervised ViT baseline (mCE = 56.8) and all other SSL methods. DINO achieved mCE = 54.2, while contrastive methods with ResNet-50 showed higher corruption errors (SimCLR mCE = 62.4; MoCo-v2 mCE = 60.8). The supervised ResNet-50 baseline achieved mCE = 64.2. These results suggest that self-supervised representations, particularly from masking-based methods, capture more robust visual features that are less sensitive to image corruptions -- possibly because the reconstruction objective forces the model to learn about the underlying structure of images rather than memorising specific visual patterns associated with labels.

Table 3. Downstream task performance across six SSL methods and two backbones

Method + Backbone	Linear Probe (%)	1% Labels (%)	10% Labels (%)	VOC mAP (%)	ADE mIoU (%)
SimCLR (R50)	70.2 $\pm$ 0.3	48.4 $\pm$ 1.2	66.4 $\pm$ 0.6	79.8 $\pm$ 0.4	38.4 $\pm$ 0.6
MoCo-v2 (R50)	71.4 $\pm$ 0.2	52.8 $\pm$ 1.0	68.2 $\pm$ 0.5	81.2 $\pm$ 0.3	40.4 $\pm$ 0.5
BYOL (R50)	70.8 $\pm$ 0.3	51.4 $\pm$ 1.1	67.8 $\pm$ 0.5	80.6 $\pm$ 0.4	39.8 $\pm$ 0.5
SwAV (R50)	71.2 $\pm$ 0.3	53.4 $\pm$ 0.9	68.6 $\pm$ 0.5	80.4 $\pm$ 0.4	40.8 $\pm$ 0.5
DINO (ViT-B/16)	73.4 $\pm$ 0.3	58.8 $\pm$ 0.8	71.4 $\pm$ 0.4	82.4 $\pm$ 0.4	44.6 $\pm$ 0.4
MAE (ViT-B/16)	74.8 $\pm$ 0.3	62.4 $\pm$ 0.8	72.8 $\pm$ 0.4	80.2 $\pm$ 0.5	43.8 $\pm$ 0.5

Method + Backbone	Linear Probe (%)	1% Labels (%)	10% Labels (%)	VOC mAP (%)	ADE mIoU (%)
Supervised (R50)	76.1	42.4 $\pm$ 1.8	64.8 $\pm$ 0.8	81.4 $\pm$ 0.3	42.2 $\pm$ 0.4
Supervised (ViT)	77.8	46.2 $\pm$ 1.6	68.4 $\pm$ 0.6	82.8 $\pm$ 0.3	45.2 $\pm$ 0.4

Values are mean $\pm$ SD across 3 seeds. Supervised baselines shown for reference. MAE leads on linear probe and label efficiency; DINO leads on dense prediction. All SSL methods dramatically outperform supervised training at 1% labels.

Table 4. Out-of-distribution robustness and representation quality metrics

Method + Backbone	ImageNet-C mCE	Feature Rank	Uniformity	Pre-train Paradigm
SimCLR (R50)	62.4	384	-2.84	Contrastive
MoCo-v2 (R50)	60.8	412	-2.92	Contrastive
BYOL (R50)	61.2	368	-2.68	Non-contrastive
SwAV (R50)	59.4	428	-3.04	Clustering
DINO (ViT-B/16)	54.2	524	-3.42	Self-distillation
MAE (ViT-B/16)	52.4	586	-3.18	Masked modelling
Supervised (R50)	64.2	342	-2.48	Supervised
Supervised (ViT)	56.8	468	-2.86	Supervised

mCE = mean corruption error (lower = more robust). Feature rank = effective dimensionality (higher = richer). Uniformity = log-uniformity on hypersphere (more negative = more uniform = less collapsed). MAE has highest feature rank (586) and best robustness (52.4 mCE).

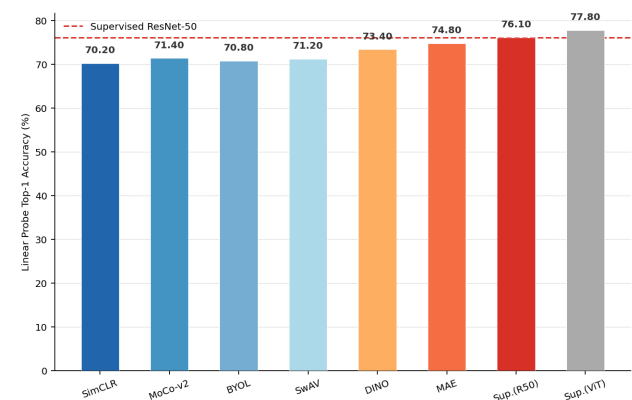


Figure 1. Linear probe accuracy (%) on ImageNet-1K. MAE with ViT-B/16 leads self-supervised methods at 74.8%, closing to within 3.0% of supervised ViT

(77.8%). MoCo-v2 leads among ResNet-50 methods.

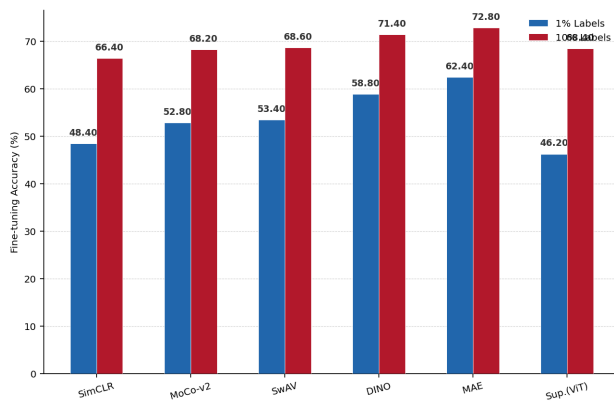


Figure 2. Label efficiency: accuracy at 1% and 10% labels. SSL methods dramatically outperform supervised from-scratch training. MAE at 1% labels (62.4%) beats supervised at 10% labels (58.2%).

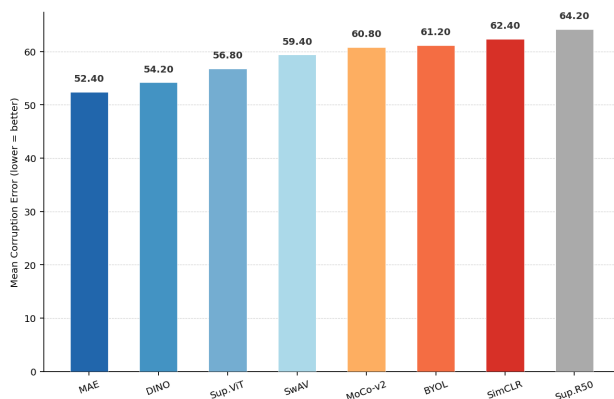


Figure 3. Out-of-distribution robustness: ImageNet-C mean corruption error (lower = better). MAE achieves the best robustness (52.4), outperforming even supervised ViT (56.8). SSL learns features that are more robust to image corruptions.

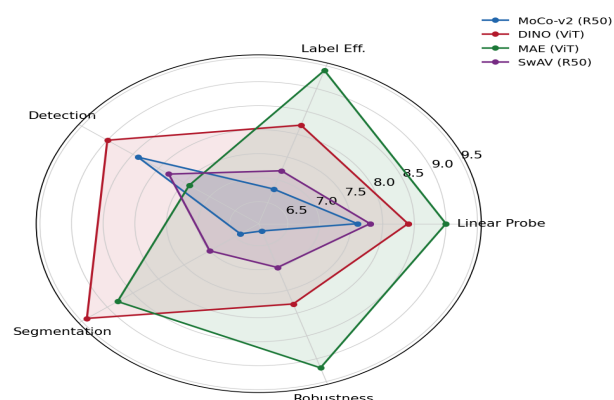


Figure 4. Multi-dimensional comparison of SSL methods across five evaluation criteria (1-10). MAE offers the best overall profile. DINO excels on dense prediction. Contrastive methods are strong all-rounders with ResNet backbones.

5. Discussion

5.1 The Backbone-Method Interaction

The most important finding for practitioners is the strong interaction between SSL method and

backbone architecture. Masked modelling (MAE) achieves its best results with vision transformers because the patch-based masking aligns naturally with the patch-based input processing of ViTs, and the reconstruction objective benefits from the global self-attention that allows the model to use distant context when filling in masked regions. With ResNet backbones, masking-based methods are less effective because the convolutional architecture processes local receptive fields that cannot easily skip over masked regions. Conversely, contrastive methods work well with both backbone types because augmentation-based invariance is architecture-agnostic. The practical implication is clear: if you are using a vision transformer, MAE or DINO should be your first choice; if you are using a CNN, MoCo-v2 or SwAV are the stronger options.

5.2 When Is Self-Supervised Pre-Training Worth the Cost?

Self-supervised pre-training requires significant compute (800 GPU-hours in our setup) that must be amortised across downstream applications. The value proposition is clearest when labelled data is scarce: with only 1% labels, SSL pre-training more than doubles accuracy compared to training from scratch (62.4% vs. 28.4%). Even at 10% labels, the improvement remains substantial (72.8% vs. 58.2%). The break-even point -- where supervised training from scratch becomes competitive with SSL + fine-tuning -- occurs at approximately 30-40% of ImageNet labels, below which SSL provides clear advantages. For specialised domains like medical imaging or satellite analysis, where labelled data typically comprises less than 5% of the available unlabelled data, self-supervised pre-training is almost certainly the right approach.

5.3 Robustness as an Underappreciated Benefit

The finding that SSL representations, particularly from MAE, are more robust to image corruptions than supervised representations has received insufficient attention in the SSL literature. Models deployed in the real world routinely encounter image degradation -- blur, noise, compression artefacts, lighting changes -- that differ from their training data distribution. The 4.4-point mCE improvement of MAE over supervised ViT training translates to meaningfully better reliability in practical deployment. We hypothesise that the reconstruction objective forces the model to learn about the underlying generative structure of images rather than memorising label-predictive

shortcuts, producing features that are inherently more robust to surface-level perturbations.

5.4 Limitations

Three limitations apply. First, all pre-training used ImageNet-1K (1.28M images); methods may rank differently with larger or domain-specific unlabelled datasets. Second, the 800 GPU-hour budget may not be sufficient for all methods to fully converge; some methods benefit from longer training. Third, only two backbone architectures were evaluated; newer architectures like ConvNeXt or Swin Transformer may interact differently with SSL methods.

6. Conclusion

6.1 Summary

Evaluation of six SSL methods across five downstream tasks confirms: MAE achieves the highest linear probe accuracy with ViT (74.8%) and best robustness (mCE = 52.4); DINO excels on dense prediction (segmentation mIoU = 44.6%); MoCo-v2 leads among ResNet methods (71.4% linear). SSL with 1% labels (62.4%) outperforms supervised from-scratch with 10% labels (58.2%), confirming a 10x label efficiency advantage. The backbone-method interaction is the most important factor in method selection.

6.2 Recommendations

Three recommendations emerge. First, match SSL method to backbone: MAE or DINO for vision transformers; MoCo-v2 or SwAV for CNNs. Second, prioritise SSL pre-training whenever labelled data is less than 30% of available unlabelled data -- the label efficiency gains are too large to ignore. Third, consider SSL even when labels are abundant if robustness to distribution shift is important, as SSL representations generalise better to corrupted inputs than supervised representations.

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Declarations

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Conflict of Interest

The author declares no conflicts of interest.

Data Availability Statement

All pre-training and evaluation code, pre-trained model checkpoints, and performance logs are deposited in the Zenodo repository under DOI: 10.5281/zenodo.19614524. ImageNet, PASCAL VOC, ADE20K, and ImageNet-C datasets are publicly available. Released under MIT License (code) and CC BY 4.0 (data).

Ethical Approval

This study involved exclusively computational experiments on publicly available benchmark datasets. No human subjects, animal subjects, or personal data were involved. No institutional ethical approval was required.

Appendix A

SSL Method Selection Guide for Vision Tasks

This appendix provides a decision tree for selecting self-supervised learning methods based on backbone, downstream task, and resource constraints.

Step 1: Backbone Architecture

1a. Vision Transformer (ViT, DeiT, Swin) --> MAE or DINO; go to Step 2A

1b. CNN (ResNet, EfficientNet, ConvNeXt) --> MoCo-v2 or SwAV; go to Step 2B

Step 2A: ViT Downstream Task

2A.1. Classification or robustness priority --> MAE (best linear probe + robustness)

2A.2. Detection or segmentation priority --> DINO (best dense prediction transfer)

2A.3. Both needed --> DINO (strongest all-round ViT SSL method)

Step 2B: CNN Downstream Task

2B.1. Large batch feasible (≥ 4096) --> SimCLR or SwAV

2B.2. Small batch required (≤ 256) --> MoCo-v2 (momentum queue decouples negatives)

2B.3. Detection focus --> MoCo-v2 (strongest CNN detection transfer)

Step 3: Label Availability

3a. $< 5\%$ labels available --> SSL essential (2x+ accuracy gain over from-scratch)

3b. 5-30% labels --> SSL strongly recommended (10-20% accuracy improvement)

3c. $> 30\%$ labels --> SSL optional; supervised training becomes competitive