A PyTorch-like Pseudocode

Algorithm 1: PyTorch-like pseudocode for MYOL loss computation

Input: Input views `v1, v2`

```
p1, p2 = pred(encoder(v1)), pred(encoder(v2)) # online network
z1, z2 = encoder_t(v1), encoder_t(v2) # target network
# input mixup
lam = Beta(alpha, alpha).sample()
randidx = randperm(len(v1))
mixed_v = lam * v1 + (1-lam) * v2[randidx]

# norm_mse: normalized mean squared error
loss_byol = (norm_mse(p1, z2) + norm_mse(p2, z1)) / 2

# projection mixup
mixed_z = lam * z1 + (1-lam) * z2[randidx]
loss_myol = norm_mse(pred(encoder(mixed_v)), mized_z)

loss = loss_byol + loss_myol
```

B Self-Supervised Learning Methods Comparison

In this section, we compare BYOL (Grill *et al.* 2020) with other self-supervised learning methods SimCLR (Chen *et al.* 2020) and MoCo (He *et al.* 2020). SimCLR is a simple contrastive learning method that uses a large batch size to ensure a sufficient number of negative pairs. MoCo, on the other hand, addresses the negative sample challenge by utilizing a memory bank. While both SimCLR and MoCo serve as baseline methods for Un-Mix (Shen *et al.* 2022) and i-Mix (Lee *et al.* 2021), our experiments show that BYOL is a sufficient baseline for achieving efficient and robust self-supervised learning on small images.

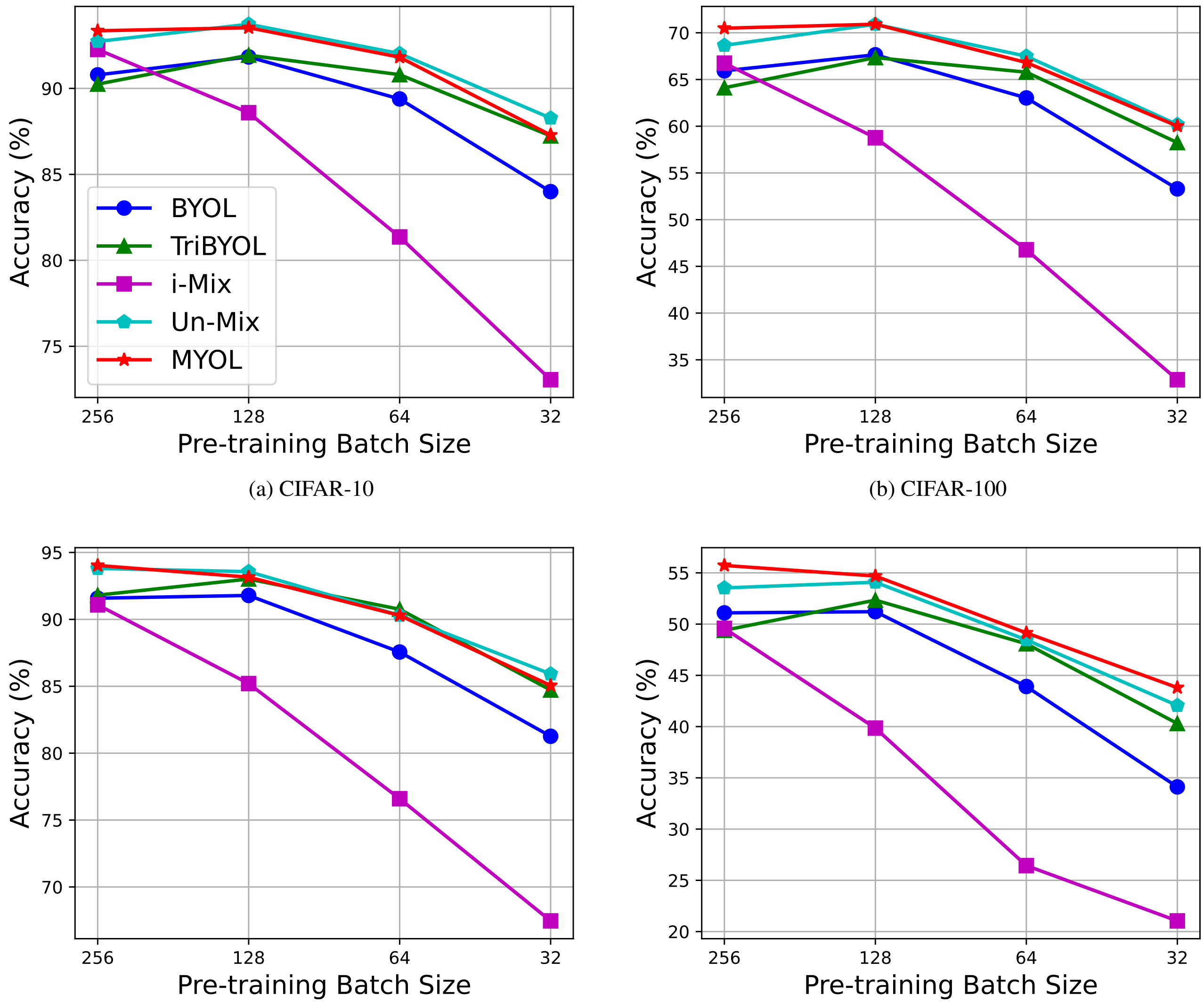
Table 1: Comparison of SimCLR, MoCo, and BYOL in terms of linear evaluation performance with varying pre-training batch sizes in terms of classification accuracy (%).

Pre-training Batch Size	Method	CIFAR-10	CIFAR-100	STL-10	Tiny-ImageNet
256	SimCLR	87.14±0.15	62.96±0.34	83.21±0.12	45.92±0.13
	MoCo	88.08±0.28	64.07±0.37	85.17±0.07	48.37±0.16
	BYOL	**90.79±0.12**	**65.93±0.22**	**91.58±0.32**	**51.10±0.08**
128	SimCLR	84.49±0.16	58.99±0.33	80.02±0.22	42.82±0.40
	MoCo	85.61±0.05	61.42±0.42	82.60±0.03	46.43±0.06
	BYOL	**91.83±0.14**	**67.65±0.34**	**91.79±0.03**	**51.21±0.13**
64	SimCLR	80.05±0.43	54.01±0.55	76.15±0.39	38.41±0.25
	MoCo	82.67±0.34	58.35±0.31	79.53±0.16	42.91±0.30
	BYOL	**89.39±0.24**	**63.03±0.19**	**87.56±0.57**	**43.91±0.24**
32	SimCLR	75.60±0.27	46.83±0.50	70.23±0.17	31.19±0.19
	MoCo	79.22±0.01	**54.37±0.03**	75.89±0.42	**39.35±0.34**
	BYOL	**84.00±0.47**	53.30±0.24	**81.26±0.29**	34.12±1.53

C Plots for the Entire Datasets

In this section, we show the plots for the entire datasets that were used in the experiments, as well as the plots for the Tiny-ImageNet dataset.

C.1 Pre-training Batch Sizes Comparison

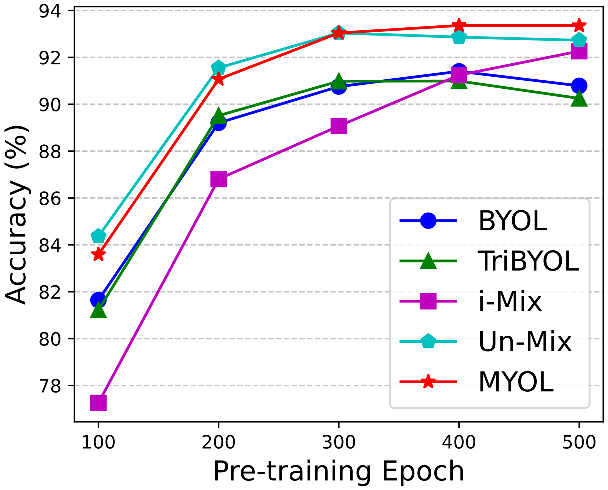


(a) CIFAR-10 (b) CIFAR-100

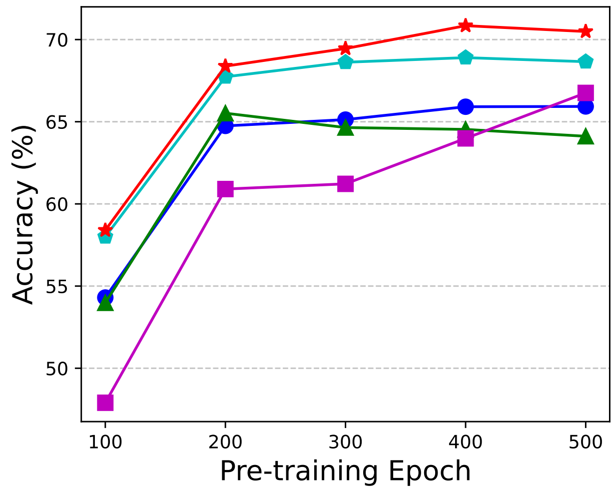
(c) STL-10 (d) Tiny-ImageNet

Figure 1: Comparison of linear evaluation performance according to the pre-training batch sizes in terms of classification accuracy (%).

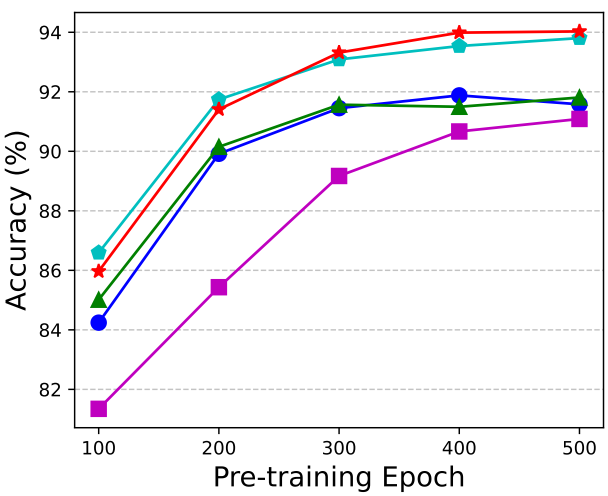
C.2 Pre-training Epochs Comparison



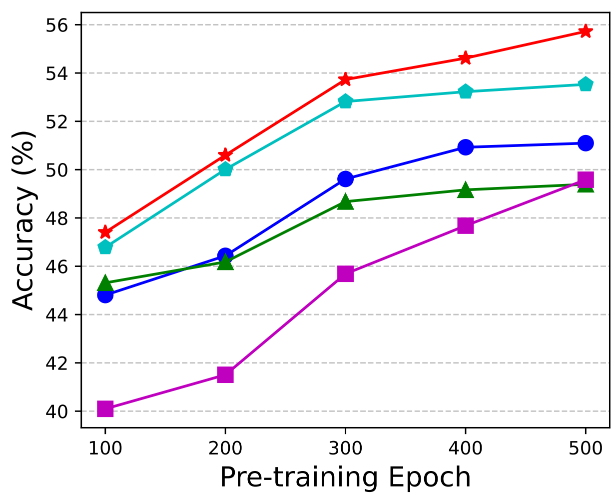
(a) CIFAR-10



(b) CIFAR-100



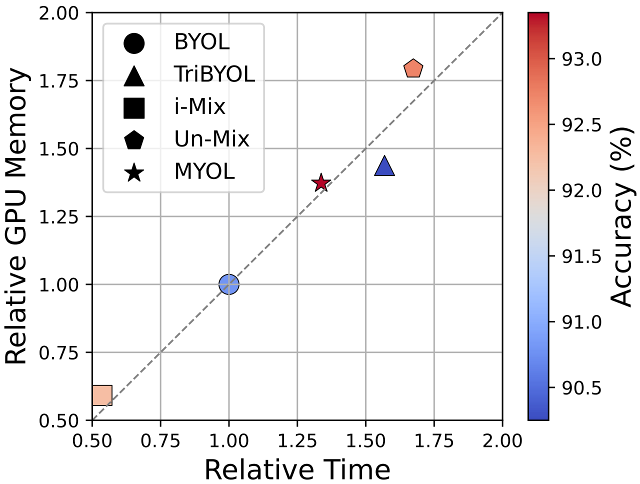
(c) STL-10



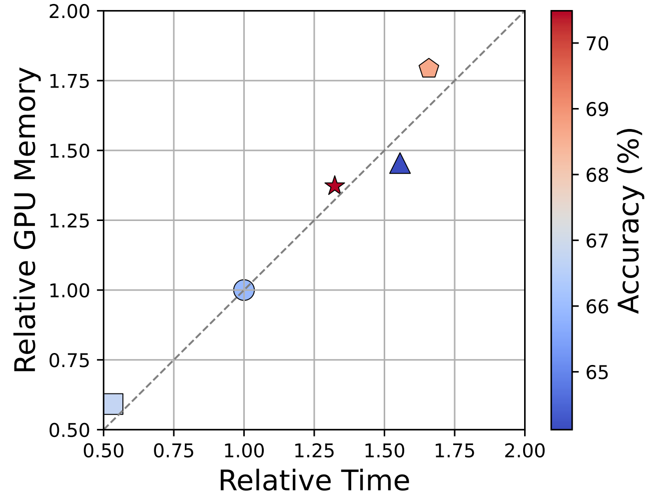
(d) Tiny-ImageNet

Figure 2: Comparison of linear evaluation performance according to the number of pre-training epochs in terms of classification accuracy (%).

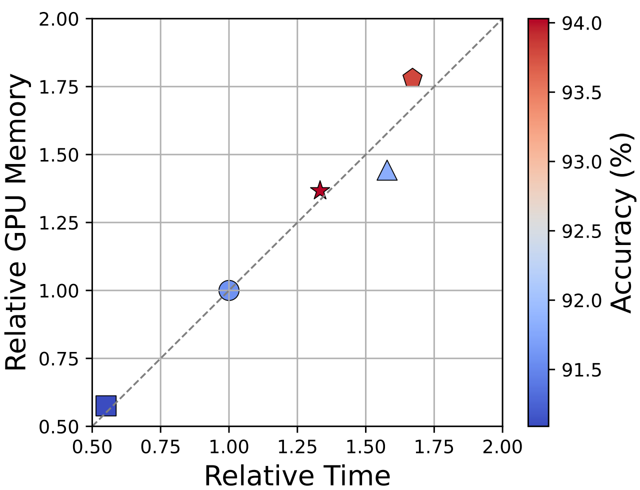
C.3 Time and GPU Memory Comparison



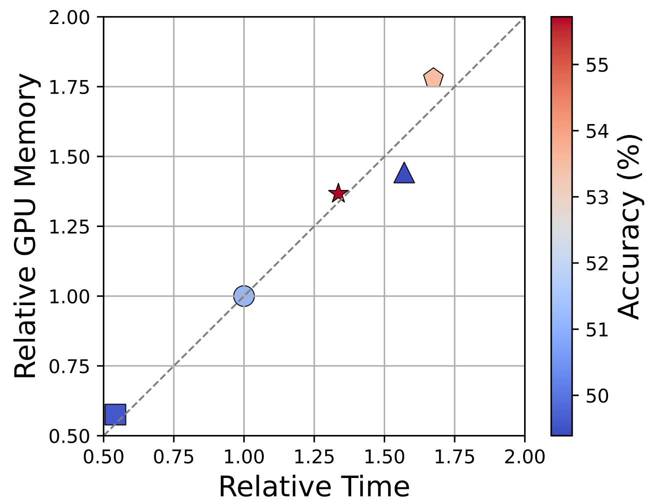
(a) CIFAR-10



(b) CIFAR-100



(c) STL-10



(d) Tiny-ImageNet

Figure 3: Comparison of time and GPU memory required for pre-training on a relative scale, with marker color indicating classification accuracy.

References

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