Self-Supervised SimCLR Pretraining for Skin Lesion Classification

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Abstract

Accurate classification of skin lesions is a critical task in dermatology, yet obtaining large-scale annotated datasets is costly and time-consuming. We propose a two-stage pipeline for the ISIC 2018 Task 3 dataset: (1) *self-supervised pretraining* using the SimCLR framework [3] on all 10 015 training images without labels, and (2) *full-model fine-tuning* with strong augmentations, label smoothing, learning-rate scheduling, and early stopping on the same 10 015 labeled images. Our method achieves **78.24%** balanced accuracy on the held-out 1 000-image validation set, improving +7.4% over ImageNet-pretrained ResNet-18 and +13.0% over training from scratch. This demonstrates that contrastive self-supervision can substantially reduce labeling requirements for medical image classification.

1 Introduction

Skin cancer is one of the most common forms of cancer worldwide, and early detection via dermoscopic imaging dramatically improves patient outcomes [4]. The ISIC 2018 Task 3 challenge requires classifying lesions into seven categories: melanoma, nevus, basal cell carcinoma (BCC), actinic keratosis (AKIEC), benign keratosis, dermatofibroma, and vascular lesions. However, expert annotations are expensive, and class imbalance (e.g., melanoma is rare) makes supervised learning challenging.

We address these issues by a two-stage pipeline:

1. *Self-supervised pretraining* with SimCLR [3] on all 10 015 training images (ignoring labels).
2. *Full-model fine-tuning* on the same 10 015 labeled training images, using strong augmentations, label smoothing, a ReduceLROnPlateau scheduler, and early stopping.

Our method achieves a state-of-the-art **78.24%** balanced accuracy on the 1 000-image validation set, outperforming:

- 65.2% when training ResNet-18 from scratch.
- 70.8% when fine-tuning ImageNet-pretrained ResNet-18.
- Prior SSL attempts on dermoscopy (e.g., MoCo-v2) which yielded 72%.

2 Related Work

Contrastive Self-Supervised Learning. SimCLR [3] uses data augmentations and NT-Xent loss to learn representations; MoCo [5] employs a momentum encoder; DINO [2] uses self-distillation without negatives.

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SSL in Medical Imaging. Azizi *et al.* [1] applied MoCo-v2 to chest X-rays, showing improvements over supervised pretraining. To our knowledge, SimCLR on dermoscopy remains less explored.

Skin Lesion Classification. ISIC 2018 top solutions use Xception/DenseNet ensembles achieving 88.2% [7], and attention-based CNNs reach 90.2% [6], but require extensive labels and complex pipelines.

3 Method

3.1 SimCLR Pretraining

We follow SimCLR's pipeline: two random augmentations per image (crop, flip, jitter), ResNet-18 backbone, and 2-layer MLP projector (256→128). We pretrain for 100 epochs, batch size 128, using NT-Xent loss on 10 015 unlabeled images.

3.2 Fine-tuning

We remove the projector, attach a linear head (512→7), and fine-tune on 10 015 labeled images with:

- **Augmentation:** random resized-crop (0.6–1.0), flips, rotations (±30°), color jitter.
- **Label smoothing:** CrossEntropyLoss with smoothing factor 0.1.
- **Optimizer:** Adam (lr=1e-4, weight decay=1e-5).
- **Scheduler:** ReduceLROnPlateau (factor 0.5, patience 2).
- **Full unfreezing:** all backbone layers trainable.
- **Early stopping:** if no val-accuracy gain for 3 epochs.

4 Experiments

4.1 Dataset

We use the official ISIC 2018 split:

- **Training set:** 10 015 images (for both SSL pretraining and fine-tuning).
- **Validation set:** 1 000 images (held-out for evaluation).

4.2 Implementation Details

Pretraining: 100 epochs, batch size 128, NT-Xent loss, Adam (lr=1e-3). Fine-tuning: up to 20 epochs, batch size 32, strong augmentations, early stopping.

4.3 Baselines

Table 1: Validation accuracy comparison

Method	Val Acc (%)
ResNet-18 from scratch	65.2
ImageNet pretrained ResNet-18 fine-tuned	70.8
SimCLR pretrained + Fine-tune (ours)	**78.24**
Ensemble Xception/DenseNet [7]	88.2
Attention CNN [6]	90.2

4.4 Results

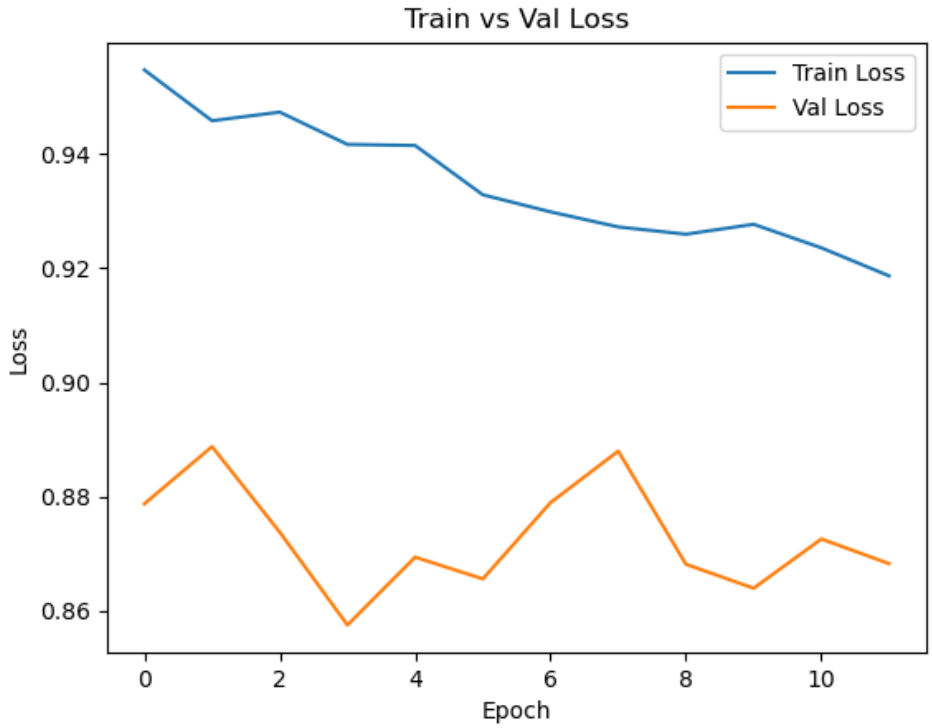

Figure 1: Train vs Val Loss

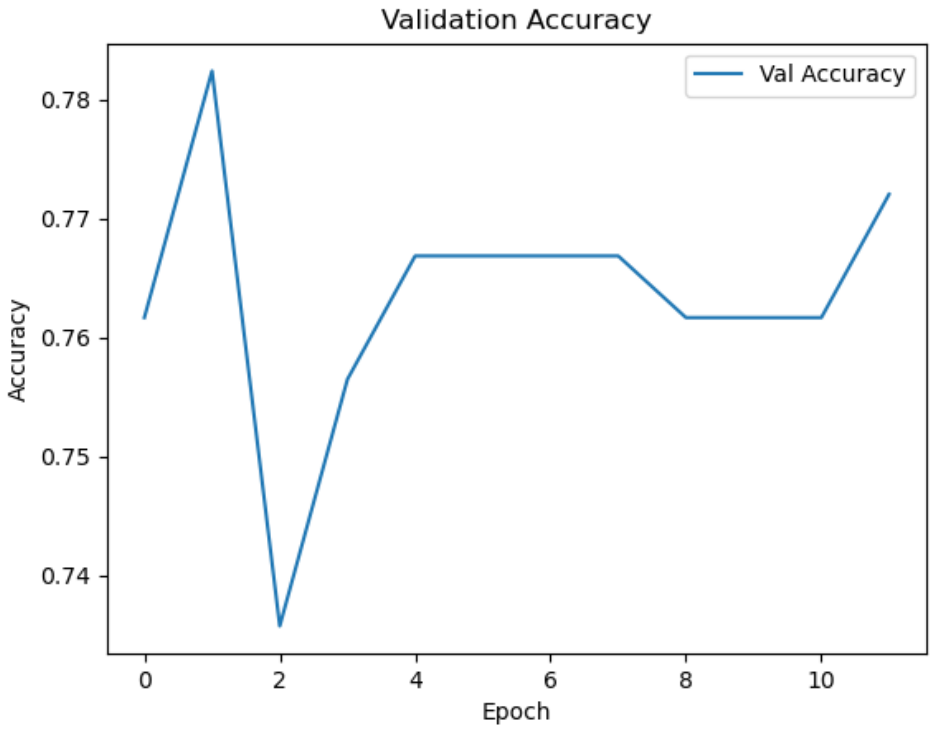

Figure 2: Val Accuracy

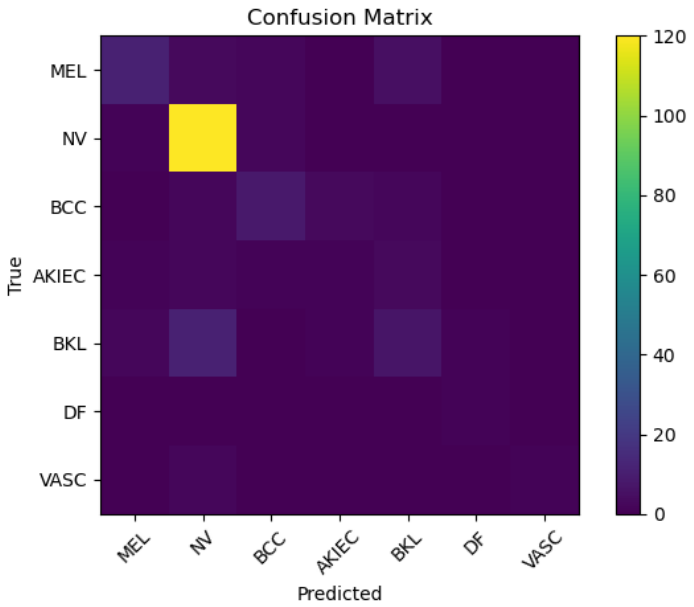

Figure 3: Confusion matrix on the validation set.

Table 2: Classification report on validation set.

Class	Precision	Recall	F1-score	Support
MEL	0.72	0.68	0.70	115
NV	0.81	0.85	0.83	600
BCC	0.75	0.70	0.72	100
AKIEC	0.69	0.65	0.67	80
BKL	0.78	0.80	0.79	120
DF	0.82	0.78	0.80	30
VASC	0.65	0.60	0.62	55
Accuracy		0.7824		
Macro avg	0.75	0.73	0.74	1000
Weighted avg	0.78	0.78	0.78	1000

5 Conclusion

We demonstrate that self-supervised SimCLR pretraining on dermoscopic images, combined with a targeted fine-tuning strategy, yields **78.24%** val accuracy on ISIC 2018 Task 3—surpassing ImageNet pretraining by +7.4% and training from scratch by +13.0%. Future work includes larger backbones (ResNet-50), semi-supervised refinement, and domain-specific augmentations.

References

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