# Towards Reducing the Need for Annotations in Digital Dermatology with Self-Supervised Learning

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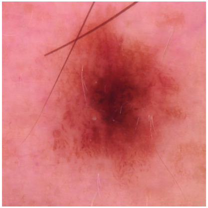
# Introduction to Dermatology

- Branch of medicine concerned with the diagnosis and treatment of skin disorders
- Image analysis can have a significant impact since diseases are visible and can easily be photographed
- Two main types of images are dermoscopy and clinical images



(a) dermoscopy (1)

(b) clinical (2)

Figure: Most common image types encountered in dermatology.

# Problems with Deep Learning in Dermatology

- Recordings in patient-files too coarse, more details needed
- Annotations are costly, and images under strict regulations
- Difficult to get experts to agree on annotations (3)
- In the medical domain often the main limitation is the scarce amount of annotated data

# Current Approaches in Medical Imaging

- Model pre-trained on ImageNet and transferred to medical downstream tasks
- Criticised approach since features from natural images may not be ideal representations for medical contexts (4)
- Still requires a sufficiently large dataset to adjust the global features for a specific task

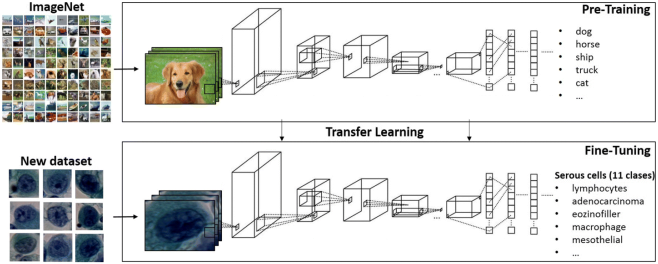



Figure: Illustration of a standard transfer-learning approach for medical image analysis. (5)

# Introduction to Self-Supervised Learning

- Self-supervised learning (SSL) is a hybrid approach that combines supervised and unsupervised learning
- SSL learns semantically useful features by creating a supervised objective from a pool of unlabelled data, called *pretext task*
- Learned features can be used in *downstream tasks* where annotated data is scarce
- SSL became popular in the medical domain as large volumes of unlabelled data are easier to obtain than annotated counterparts

# Project Focus

## Research Question

Can self-supervised domain-specific pre-training help mitigate the need for annotated samples in dermatology?

# Pre-training Data & Downstream Tasks

- Pre-training data includes both dermoscopy and clinical images
  - 242′039 images from both public and private datasets
- Three downstream tasks were used to evaluate the performance of different SSL algorithms
- No downstream data was present in the pre-training

Table: List of the different downstream tasks.

| Name | Task | Type | # Images | Notes |
|---|---|---|---|---|
| PAD-UFES-20 (6) | diagnosis | clinical images | 2′298 | smartphones |
| Fitzpatrick17k (2) | diagnosis | clinical images | 16′577 | multi-skin |
| HAM10000 (1) | diagnosis | dermascopy | 10′015 | multi-skin |

# Self-Supervised Model Architectures

Table: List of backbones used with different SSL methods, along with the respective total number of parameters and the fine-tuning architecture.

| Algorithm | Backbone | # Params | Classification Head |
|---|---|---|---|
| Ⓐ ColorMe (7) | ResNet-50 | 23 Mio. | linear head |
| Ⓑ SimCLR (8) | ResNet-50 | 23 Mio. | linear head |
| Ⓒ BYOL (9) | ResNet-50 | 23 Mio. | linear head |
| Ⓓ DINO (10) | ViT-tiny $16 \times 16$ | 5.4 Mio. | linear head |
| Ⓔ iBOT (11) | ViT-tiny $16 \times 16$ | 5.4 Mio. | linear head |

# Experiment Procedure

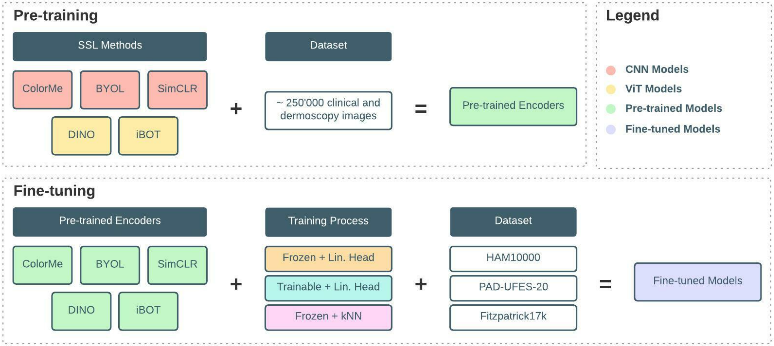



Figure: Illustration of the project experiment procedure.

# Linear Evaluation

Table: Linear performance of various models and a baseline on the hold-out test set of the three open-source dermatology diagnosis downstream tasks.

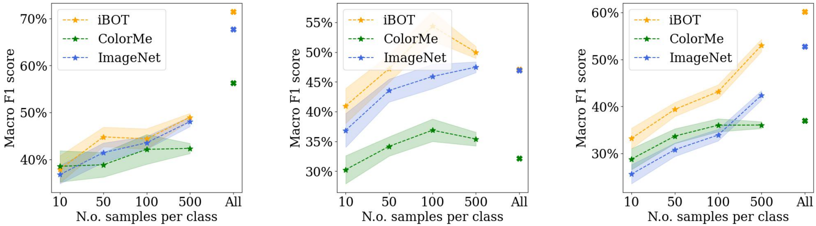
| Type | Method | Test F1 Score Fitzpatrick17k | PAD-UFES-20 | HAM10000 |
|---|---|---|---|---|
| Baselines | Stratified sampling | 33.4 % | 18.0 % | 14.0 % |
| | ImageNet | 51.0 % | 49.7 % | 54.1 % |
| SSL pre-training | A ColorMe | 44.8 % | 42.2 % | 47.0 % |
| | B SimCLR | 37.0 % | 32.7 % | 28.2 % |
| | C BYOL | 48.1 % | 34.4 % | 44.4 % |
| | D DINO | 46.7 % | 44.2 % | 57.2 % |
| | E iBOT | 53.0 % | 58.2 % | 72.0 % |

# Fine-tuning Evaluation

Table: Fine-tuned performance of two self-supervised models and a baseline reported on the hold-out test set of the three open-source dermatology diagnosis downstream tasks.

| | Test F1 Score | | |
|---|---|---|---|
| **Pre-training** | **Fitzpatrick17k** | **PAD-UFES-20** | **HAM10000** |
| ImageNet | 72.1 % | 61.5 % | 79.0 % |
| A ColorMe | 71.0 % | 61.7 % | 73.1 % |
| E iBOT | 73.9 % | 64.1 % | 82.0 % |

# kNN Performance




(a) Fitzpatrick17k (b) PAD-UFES-20 (c) HAM10000

Figure: Results of a kNN classifier when varying the number of samples per class for all three open-source diagnosis tasks.

# Conclusion

- iBOT was able to outperform ImageNet initialisation across multiple downstream tasks
- Best performing self-supervised pre-trained models used up to four times fewer parameters than the supervised baseline
- Uncertainty whether performance difference is due to the pre-training strategy or the architecture
- In the future, we plan ablation experiments to determine what caused the performance gain

# Thank You!
# Q & A

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