Bridging the gap between natural and medical images through deep colorization

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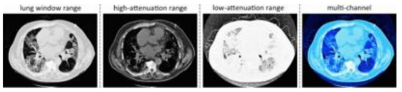
https://gitlab.com/grains2/DeepMedicalColorization

Key contributions

- New flexible and general transfer strategy from natural (RGB) to medical (grayscale) images
- Design of different **lightweight colorization modules**
- **End-to-end training** combines learning from scratch (color module) and fine-tuning (backbone)
- Extensive experiments on CheXPert demonstrate effectiveness in the **small and very small data** regime

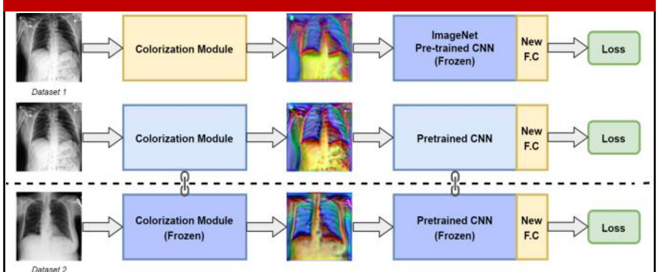
Background

- **Transfer learning from ImageNet** is a standard strategy to tackle the lack of large-scale training sets in the medical domain
- Standard model fine-tuning tackles shape, texture and color discrepancies at once
- Pseudo-colorization was proposed to bring the target medical domain closer to the RGB source domain: however, existing methods rely on **hand-crafted transformations** including intensity windowing [1] or image preprocessing [2]



[1] H.-C. Shin et al. IEEE Transactions on Medical Imaging, 35(5), 2016.
[2] P. Teare et al. Journal of digital imaging, 30(4), 2017.

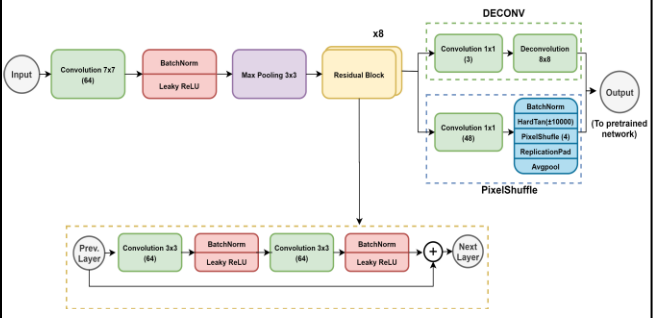
Transfer learning through colorization



Two-step learning procedure:

- Train colorization module T from scratch, while Freezing Backbone E
- Fine-tune both T and E

Colorization architecture inspired by **DE²CO** [3]



[3] F. M. Carlucci, P. Russo, and B. Caputo, ICRA, 2018.

Experiments

- Datasets: CheXPert (224,316 images), multi-label classification (5 labels)
- Baseline: standard fine-tuning from ImageNet
- Performance metric: Area under the ROC curve

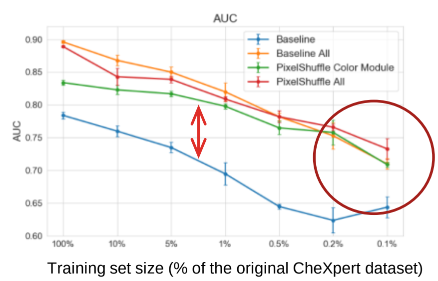
Results

1. Transfer learning through colorization is effective

Results are stable across different colorization architectures, with deep and shallow backbones.

Colorization Module	Learning Strategy	Mean AUC (ResNet18)	Mean AUC (DenseNet121)
Train Last Layer & Colorization module (T) from scratch, Backbone (E) frozen			
-	Baseline	78.4 ± 0.5	78.6 ± 0.2
DECONV	Color Module	84.0 ± 0.3	83.5 ± 0.3
PixelShuffle	Color Module	83.4 ± 0.4	84.3 ± 0.8
ColorU	Color Module	83.9 ± 0.8	83.9 ± 0.5
Fine-tune Colorization Module (T) and Backbone (E)			
-	Baseline All	89.6 ± 0.2	89.8 ± 0.2
DECONV	All	88.9 ± 0.3	89.2 ± 0.2
PixelShuffle	All	88.9 ± 0.1	89.6 ± 0.1
ColorU	All	89.3 ± 0.3	89.7 ± 0.3

2. Transfer learning through colorization is preferable in the small data regime (400-2K images)



For all training sets: colorization increases performance w.r.t. frozen backbone, but fine-tuning (with or without colorization) is needed

3. Colorization module transfers well to similar medical datasets

- Transfering the colorization module from CheXPert to CheXray14 improves performance with frozen backbone (**68.3 vs. 66.9**)
- Transfering through CheXPert achieves higher performance than transfering directly from ImageNet **(77.3 vs. 72.9)**