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]

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]

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
- Transfer learning through colorization is effective

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
- Transferring the colorization module from CheXpert to CheXray14 improves performance with frozen backbone (68.3 vs. 66.9)
- Transferring through CheXpert achieves higher performance than transferring directly from ImageNet (77.3 vs. 72.9)

References