Scanner Variability

SeeGene Project Report

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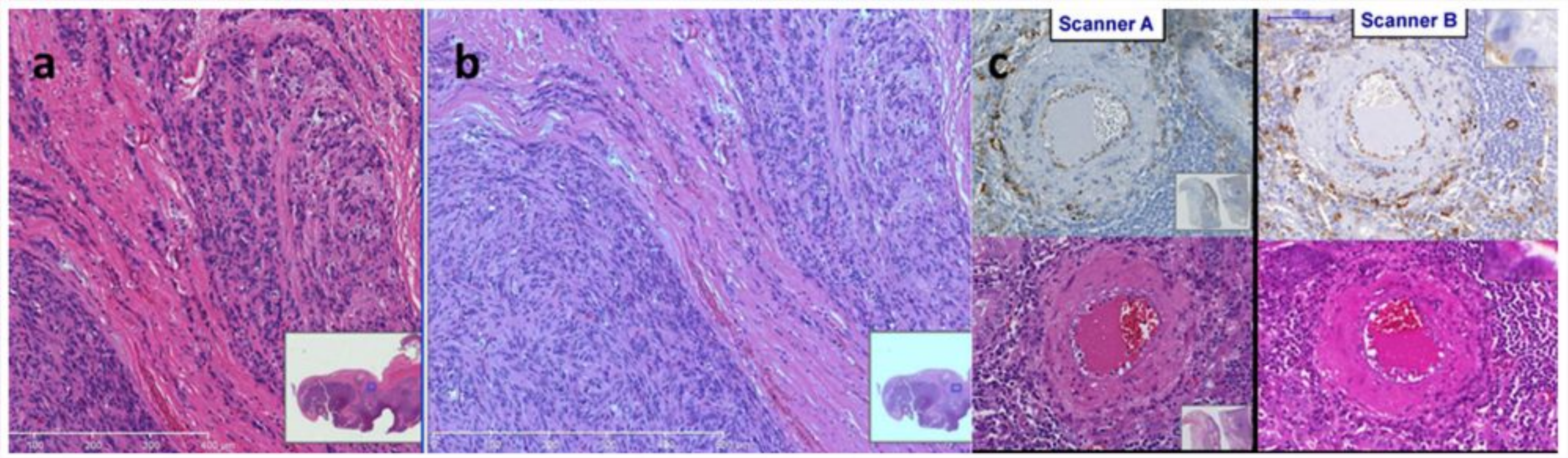
Scanner Variability | **What's the issue?**

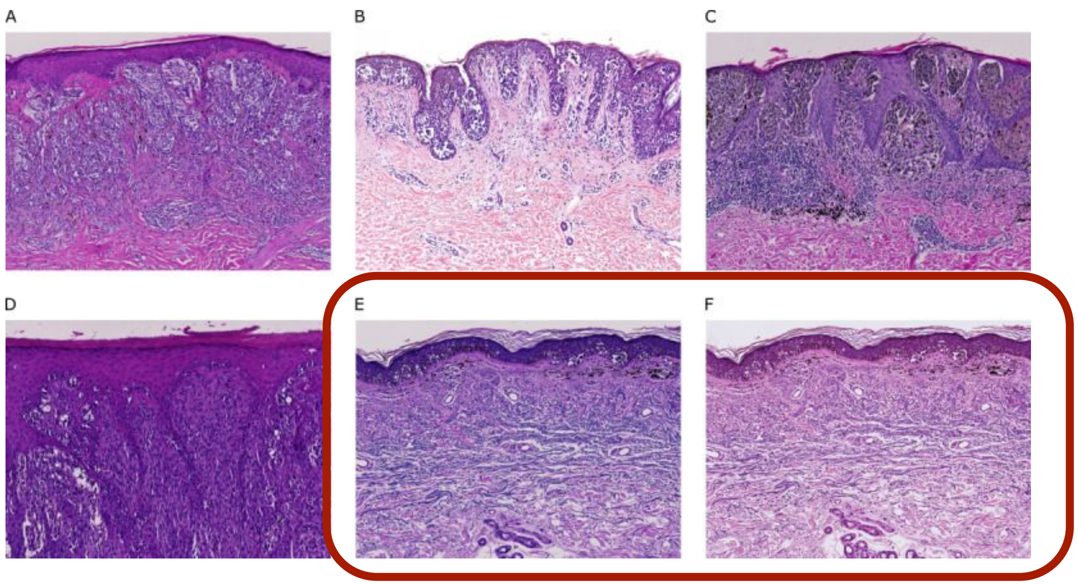
Each time the scanner is changed to digitize tissue images, **the properties of the whole slide image change**. Although for the pathologists these changes are meaningless, **they might have a great effect on the machine learning model**.



Badano, Aldo, et al. "Consistency and Standardization of Color in Medical Imaging: a Consensus Report." Journal of digital imaging. 28. (2014).

Scanner Variability | **What's the issue?**

Schmitt et al. [*] investigated batch effect (spurious signals) caused by hidden variables on digital dermatopathology: patient age, slide preparation date, slide origin, and **scanner type**.



Schmitt, Max et al. "Hidden Variables in Deep Learning Digital Pathology and Their Potential to Cause Batch Effects: Prediction Model Study." Journal of medical Internet research vol. 23,2 e23436 (2021)

Scanner Variability | **What's the issue?**

- Several CNNs (Resnet50) were trained to predict those variables. If the variables are learnable, **they might have the potential to create batch effects in pathology datasets**.
- Among the variables, **scanner type and slide origin were 100% and 97.9% learnable respectively**.
- The authors concluded that it is not unlikely that these hidden variables may interfere with the generation of accurate CNN-based classifiers. However, **the list of artifacts was not exhaustive nor there was conclusive proof that the models were actually learning from the hidden variables.**

Schmitt, Max et al. "Hidden Variables in Deep Learning Digital Pathology and Their Potential to Cause Batch Effects: Prediction Model Study." Journal of medical Internet research vol. 23,2 e23436 (2021)

Scanner Variability | **What's the issue?**

"**Another serious artifact is color variation**. The sources of variation include different lots or manufacturers of staining reagents, thickness of tissue sections, staining conditions and scanner models. **Learning without considering the color variation could worsen the performance of machine learning algorithm**. If sufficient data on every stained tissue acquired by every scanner can be incorporated, the influence of color variation on classification accuracy may become negligible; however, that seems very unlikely at the moment." [*]

* Komura, Daisuke, et al. "Machine Learning Methods for Histopathological Image Analysis." Computational and Structural Biotechnology Journal. (2018).

Scanner Variability | **Literature Review**

- **Conversion to grayscale** ignores the important information regarding the color representation.
- **Color normalization** tries to adjust the color distribution of the source image to that of a reference image. However, this method might be expensive because we need to adjust for every reference data.
- **Color augmentation** is performed by applying random hue, saturation, brightness, and contrast. The advantage of color augmentation lies in the easy implementation regardless of the object being analyzed.

* Komura, Daisuke, et al. "Machine Learning Methods for Histopathological Image Analysis." Computational and Structural Biotechnology Journal. (2018).

Scanner Variability | **Literature Review**

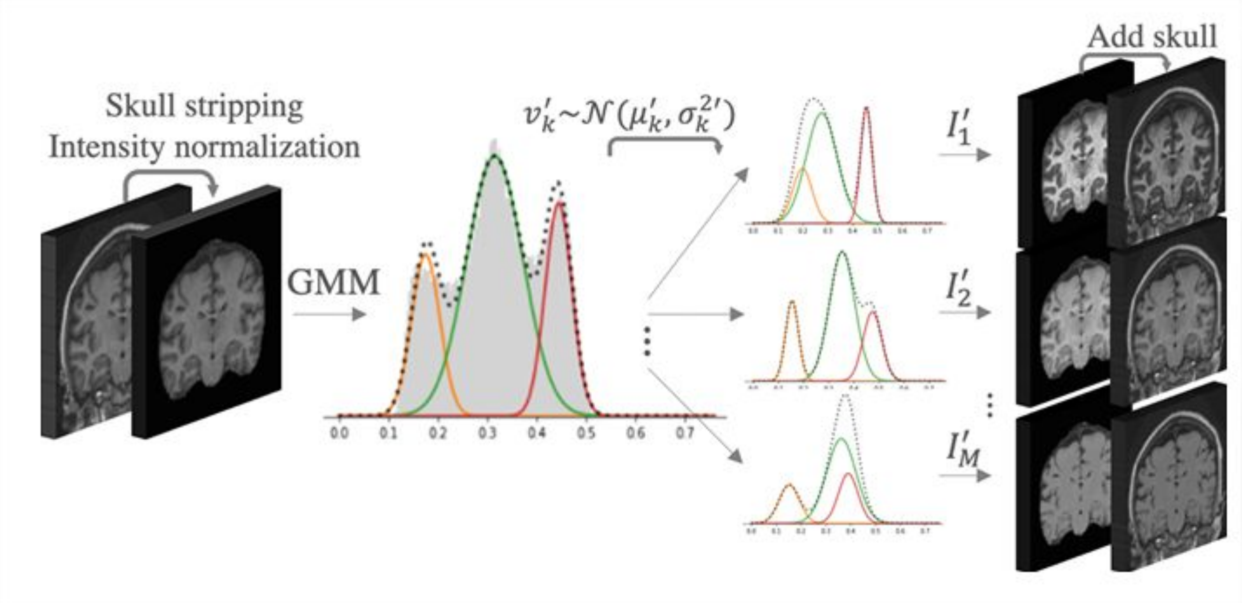
Lafarge et al. deals with dataset variabilities caused by differences in pathology labs (e.g., scanners).

1. Color Augmentation
2. Staining Normalization (Macenko)
3. Domain-Adversarial Neural Network

CA		■			■	■		■
SN			■		■		■	■
DANN				■		■	■	■
ITS	$.61 \pm .02$	$.61 \pm .01$	$.57 \pm .06$	$.61 \pm .02$	$.55 \pm .01$	$\mathbf{.62 \pm .02}$	$.61 \pm .01$	$.57 \pm .01$
ETS	$.33 \pm .08$	$.58 \pm .03$	$.46 \pm .02$	$.55 \pm .05$	$.48 \pm .08$	$\mathbf{.62 \pm .00}$	$.51 \pm .02$	$.53 \pm .03$

Maxime W. Lafarge et al. “Domain-Adversarial Neural Networks to Address the Appearance Variability of Histopathology Images.” Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support. DLMIA (2017)

Meyer et al. [*] proposed to resolved the scanner variability problem for brain MRI datasets by implementing data augmentation: **increasing the intensity and contrast variability of a single-scanner dataset**.



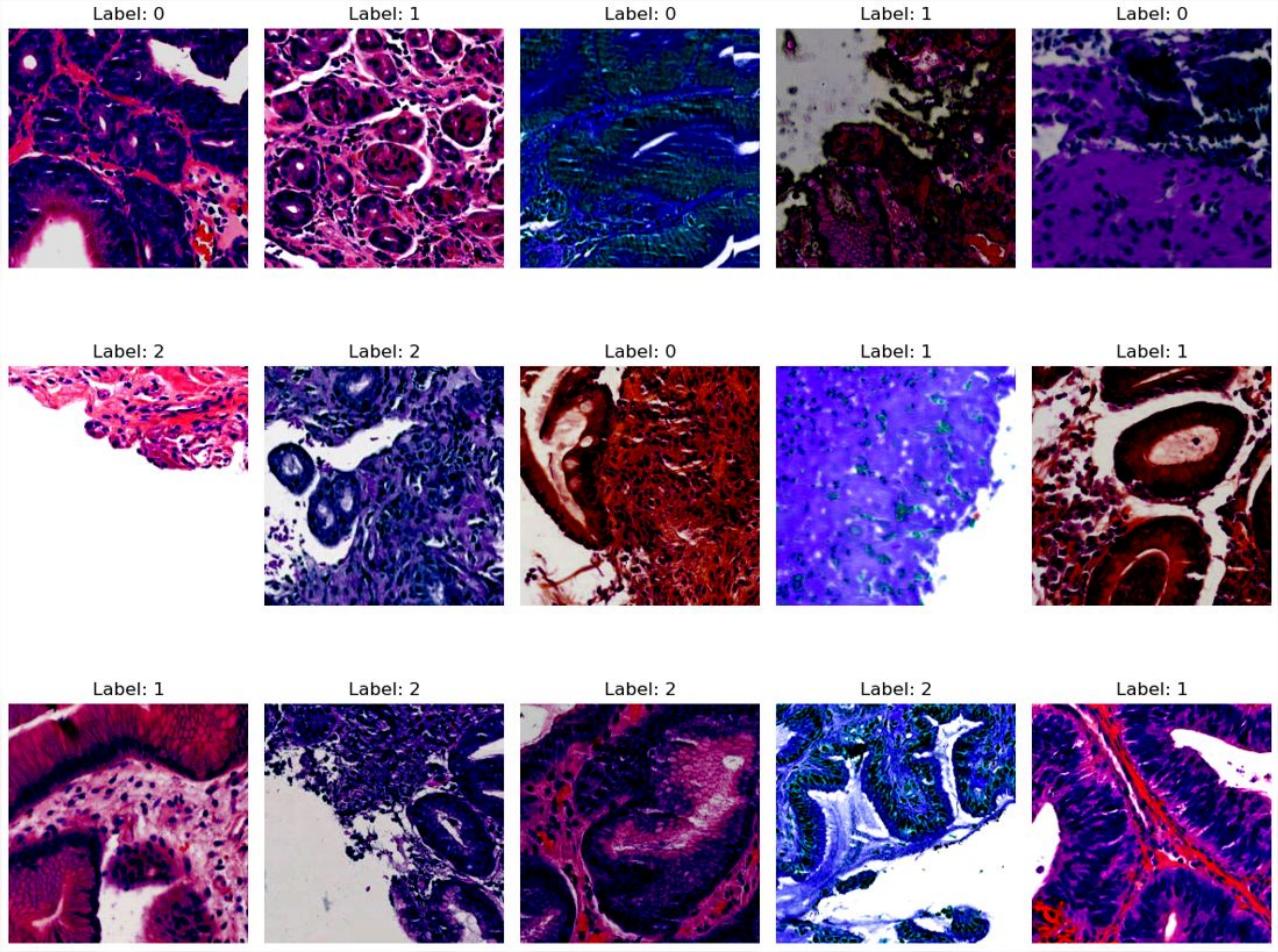
Meyer, Maria et al. An augmentation strategy to mimic multi-scanner variability in MRI. (2021)

Scanner Variability | **First Approach**

There are some approaches to deal with this kind of variability, which include **adversarial training** and **color augmentation**. Color Augmentation has been shown useful and effective in some domain (according to the literature review), hence:

- Split the dataset (WSI) into:
  - Train → Scanner A
  - Test → Scanner B and Scanner C
- **Implement color augmentation during the training process**
- If the model performs well on **scanner B** and **scanner C**, having been trained with **Scanner A**, then we can have more confidence that the model can be robust to scanner variability.

Scanner Variability | **First Approach**



Scanner Variability | **First Approach**

Backbone: ResNet50

Adam Optimizer - lr: 0.001 | Exponential Decay - lrd: 0.85

Epochs: 20 | Early Stopping - Patience: 3 epochs

	Same Scanner	**Scanner B**	**Scanner C**
Baseline	**0.768**	?	?
Color Augmented	0.750	?	?

Currently preparing the data for the new scanners 👷

~ THANK YOU ~