Raw image space improves single-cell classification in Acute Myeloid Leukemia

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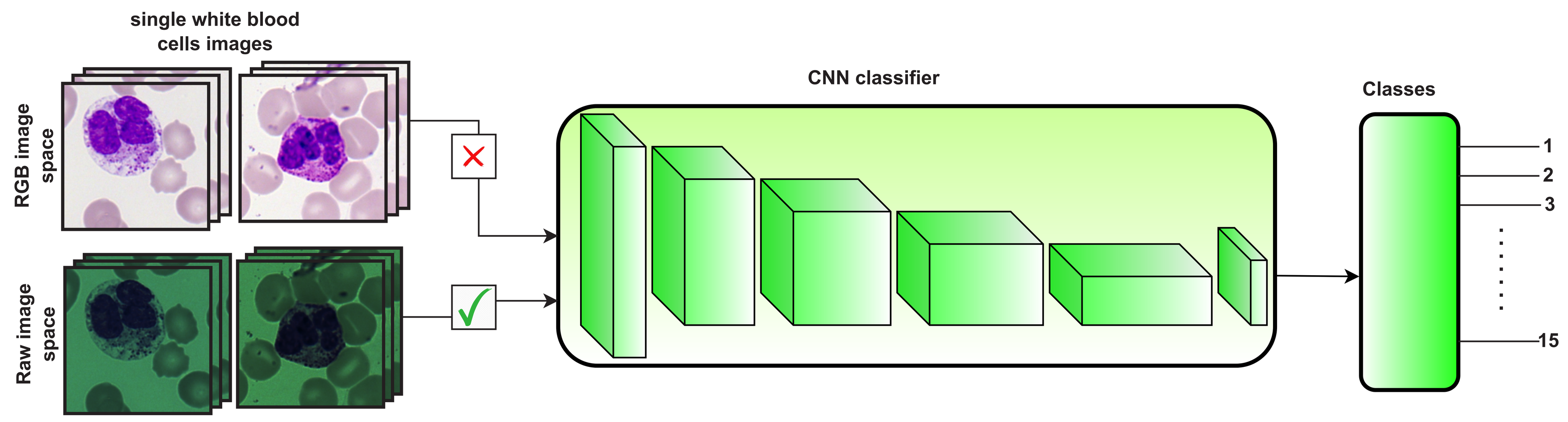
Rao Muhammad Umer, Christian Metak, and Carsten Marr

Institute of AI for Health (AIH), Helmholtz Munich, Germany.

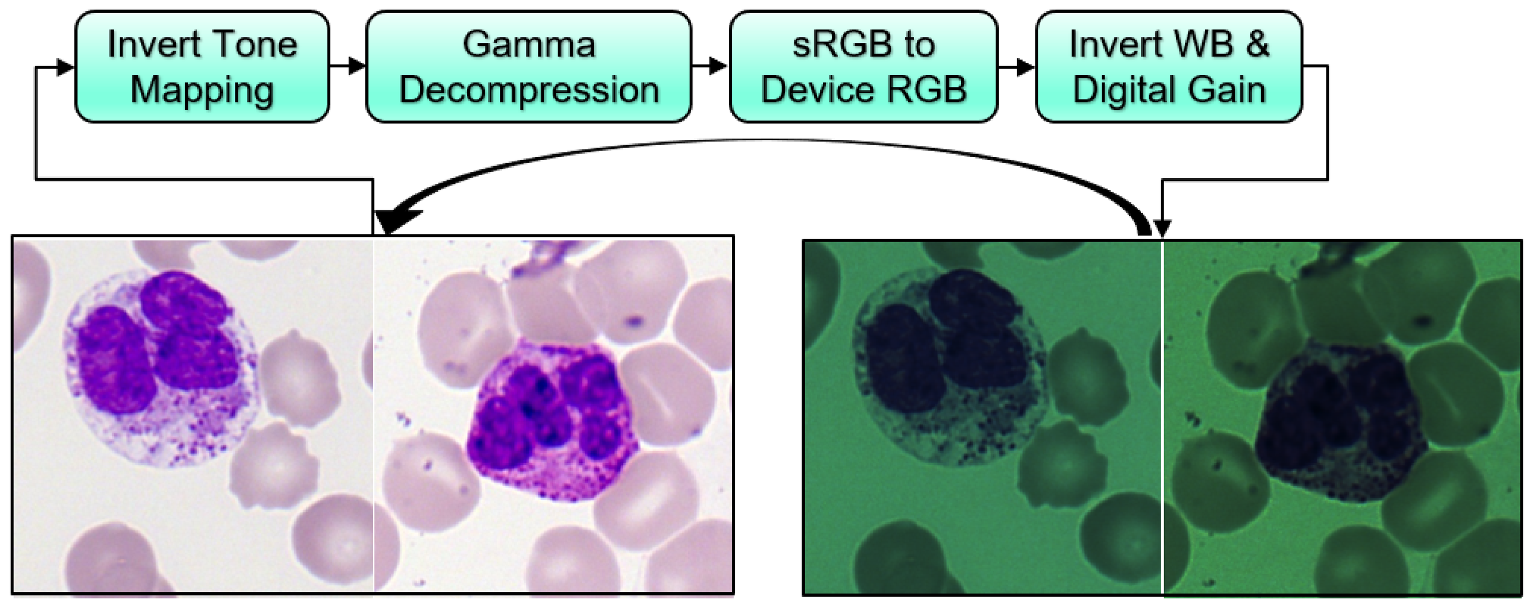
Contact: raoumer.github.io

Problem Definition and Motivation

Goal: Can the single white blood cell (WBC) classification be improved for other image space?



Motivation:



RGB image space

Raw image space

- Classification of single WBC is an essential step for the diagnosis of haematologic malignancies such as Acute Myeloid Leukaemia (AML).
- Recently, **deep CNNs** have successfully applied for WBC classification by training in the commonly used **RGB color image space**.
- Due to the **illumination** and **coloring effects** inherited by camera ISP (image signal processing) for the RGB images, the CNNs trained with the RGB images have effect the classification performance.
- We rethink the *CNN training* in **Raw image space**, *diminish* the *illumination* and *coloring* effects due to translate into the **raw linear color space**, and thus *improve* the classification performance.
- We also compare **computational cost** of *CNN-based* classifiers with *attention-based* classifiers.

Network Architectures and Training

We use the following models with pretrained weights:

- **ResNet50** [2]: Pretrained on ImageNet dataset.
- **KimiaNet** [3]: **DenseNet121**, pretrained on TCGA (pathology) data repository [3].
- **ViT** [4]: **Vision Transformer**, pretrained on ImageNet-21k dataset.

Loss function for the network training: We use the standard **cross-entropy** loss given by:

$$\mathcal{L}_{ce} = \frac{1}{N}\sum_{i=1}^{N}\mathcal{H}\left(y_i, p_i\right) \qquad (1)$$

Where, N is the *mini-batch size*, y_i is the ground-truth *one-hot label* for image i, p_i is the *predicted probability* distribution for image i, and $\mathcal{H}(x,y) = -\sum x \log y$ is the cross-entropy between two probability distributions.

Experimental Results

Dataset: We evaluate our approach on the **Matek_19 AML** [1] dataset, contains $18,365$ labeled single-cell RGB images (patch size : $400 \times 400 \times 3$) with 15 cell types, and taken from peripheral blood smears of 100 patients diagnosed with AML.

Quantitative Results:

- **Classification Results on testset (1836 RGB images, 10% of total dataset):**

Methods	#Params↓ [M]	Accuracy↑ [%]	Precision↑	Sensitivity↑	F1-score↑	Weighted ↑ ROC AUC
		Fine-tune the model last layer (Linear fully connected layer)				
ResNet50 [2]	23.54	85.89	0.86	0.86	0.86	0.95
KimiaNet [3]	**7.00**	86.77	0.86	0.87	0.87	0.97
VIT_B_16 [4]	86.58	**90.14**	**0.89**	**0.90**	**0.90**	**0.98**
		Fine-tune the whole model layers				
ResNet50 [2]	23.54	96.57	**0.97**	**0.97**	**0.97**	**1.00**
KimiaNet [3]	**7.00**	**96.73**	**0.97**	**0.97**	**0.97**	**1.00**
VIT_B_16 [4]	86.58	96.57	**0.97**	**0.97**	**0.97**	**1.00**
VIT_B_32 [4]	88.24	95.10	0.95	0.95	0.95	**1.00**
VIT_L_16 [4]	304.34	96.19	0.96	0.96	0.96	**1.00**
VIT_L_32 [4]	306.55	96.08	0.96	0.96	0.96	**1.00**

- **Classification results with five-fold cross-validation:**

No. of Classes	ResNet50 [2]	CNN_Matek_19 [1]
	Precision / Sensitivity / f1-score	
15	**0.992 / 0.989 / 0.990**	0.952 / 0.939 / -

- **RGB vs. RAW Classification results comparison on testset (1836 RGB images, 10% of total dataset):**

Methods	Datasets	Accuracy↑ [%]	Precision↑	Sensitivity↑	F1-score↑	Weighted ↑ ROC AUC
ResNet50	RGB space	96.57	**0.97**	**0.97**	**0.97**	**1.00**
ResNet50	RGB space + Augmentation	96.02	0.96	0.96	0.96	**1.00**
ResNet50	Raw space	**96.84**	**0.97**	**0.97**	**0.97**	**1.00**

- **Computational Cost comparison on testset (1836 RGB images, 10% of total dataset):**

Methods	Ave. Time↓ [ms]	#Params↓ [M]	FLOPs↓ [G]	#Acts↓ [M]	GPU Mem.↓ [M]	#Conv2d↓
ResNet50 [2]	**6.81**	23.54	4.12	11.11	184.03	53
KimiaNet [3]	16.44	**7.00**	**2.88**	**6.90**	**155.15**	120
VIT_B_16 [4]	7.78	86.58	17.6	-	466.86	**38**

Conclusions

- We demonstrate the effectiveness of raw image space for WBC classification in the quantitative results.
- We conclude that CNN-based classifiers are still better choice than attention-based for limited resource constrains.

References

[1] C. Matek, S. Schwarz, K. Spiekermann, and C. Marr, "Human-level recognition of blast cells in acute myeloid leukaemia with convolutional neural networks," *Nature Machine Intelligence*, 2019.

[2] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *CVPR*, 2016.

[3] A. Riasatian *et al.*, "Fine-tuning and training of densenet for histopathology image representation using tcga diagnostic slides," *Medical Image Analysis*, 2021.

[4] A. Dosovitskiy *et al.*, "An image is worth 16x16 words: Transformers for image recognition at scale," in *ICLR*, 2020.