Classification of cellular states for high-speed image based microfluidic cell sorting

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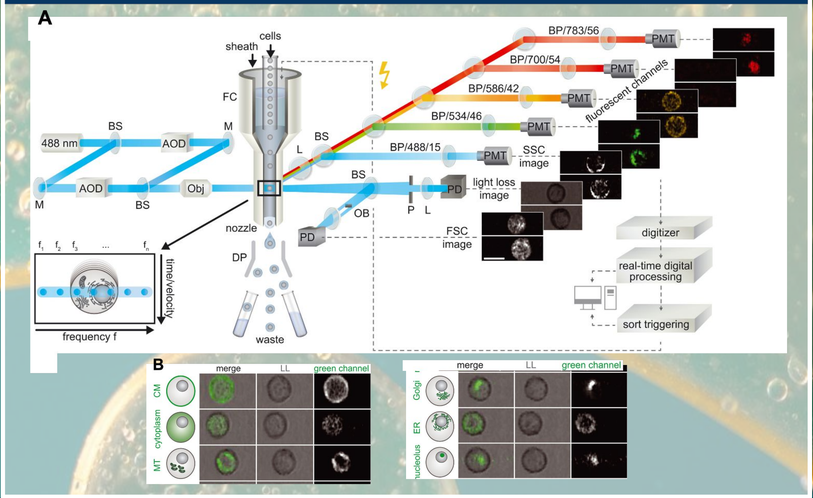
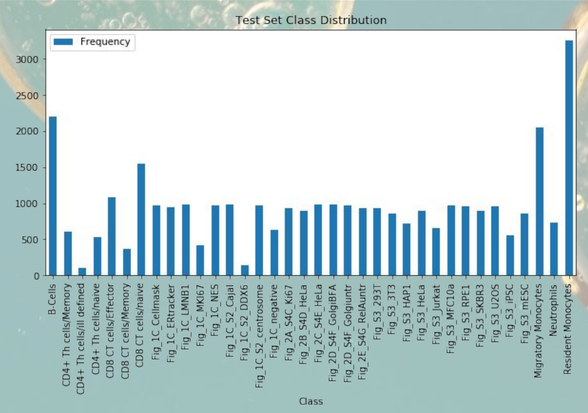
Introduction



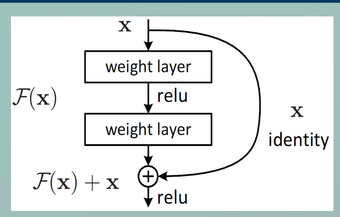
Dataset and Problem Statement

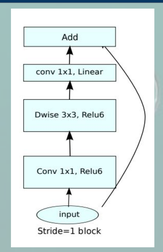


Can we classify 36 cellular image classes with ICS image inputs?

- Many classes are subtle biology variations within the same cell type

Methods

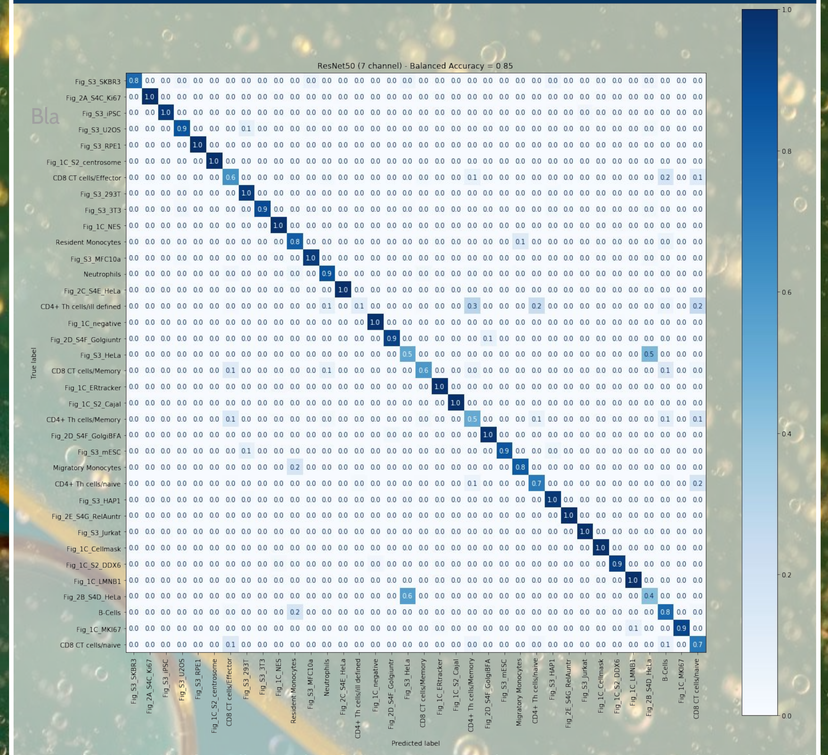




(Right: ResNet intuition, Left: MobileNet illustration)

- Architectures: ResNet and MobileNet
- ADAM optimizer, trained over 50 epochs, 80-10-10 train/ validation/ test splits
- Image prerocessing to standard shape, channel normalization

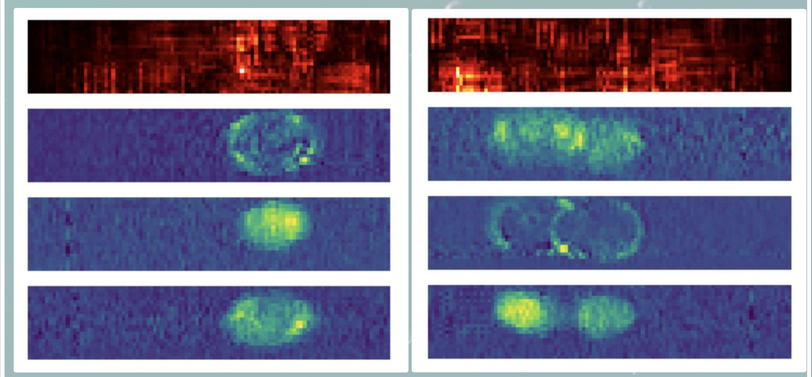
Experiments and Analysis



Confusion Matrix for cell type classification across 36 classes for ResNet 50 7-channel model. The model struggles most with the CD4+ bone marrow cell lineage, which is difficult to separate by other biological methods as well

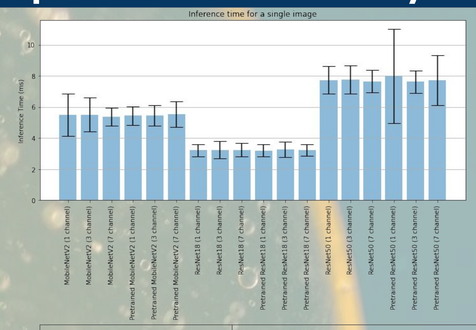
Model	7 channel		3 channel		1 channel	
	Randomly Initialized	Pretrained on ImageNet	Randomly Initialized	Pretrained on ImageNet	Randomly Initialized	Pretrained on ImageNet
ResNet18	0.84	0.84	0.68	0.77	0.53	0.62
ResNet50	0.85	0.84	0.73	0.78	0.35	0.13
MobileNetV2	0.78		0.78		0.68	

Table of model balanced accuracies, varying pretraining on imagenet and 7, 3, and 1 channel inputs



Saliency maps of 2 cells. Left: **Cd4+ Th Cell/Naive** correctly classified. Right: **CD4+ Th Cell/ill defined** classified as **Cd4+ Th Cell/Naive cell**,

Experiments and Analysis



Model Architecture	Average Inference Time per image (ms)
MobileNetV2	5.47
ResNet18	3.23
ResNet50	7.74

Conclusion and Future Work

The study demonstrated the validity of using deep convolutional models to classify multiple cell types and cell states from a new high-throughput cellular imaging modality called Image Cell Sorting. We trained multiple ResNet and MobileNetV2 architectures to predict 36 cell types and states spanning 13 human cell lines and mouse bone marrow cell types.

ResNet50 had an impressive performance even without fluorescence channel information. **ResNet18** had a performance comparable to that of ResNet50 when using information from all 7 channels, but less than half its inference time. **MobileNetV2** had a marginally lower performance, but was able to do so with a fraction of the number of parameters used by ResNet18, which makes it an attractive choice for low-storage environments. However, it did not improve on the inference time, the main criterion of interest beyond model performance.

In the future, we can explore other interpretation methods like integrated gradients, DeepLift, and ablation experiments, which could be more promising alternatives to understand these images. We can also use other efficient models combined with additional acceleration using TPUs that would be capable of sorting 10000+ images/sec in real time, taking full advantage of deep learning on the ICS system.

References

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