
Scalable Informatics Tools for Investigating Intra-Tumor Heterogeneity in Breast Cancer

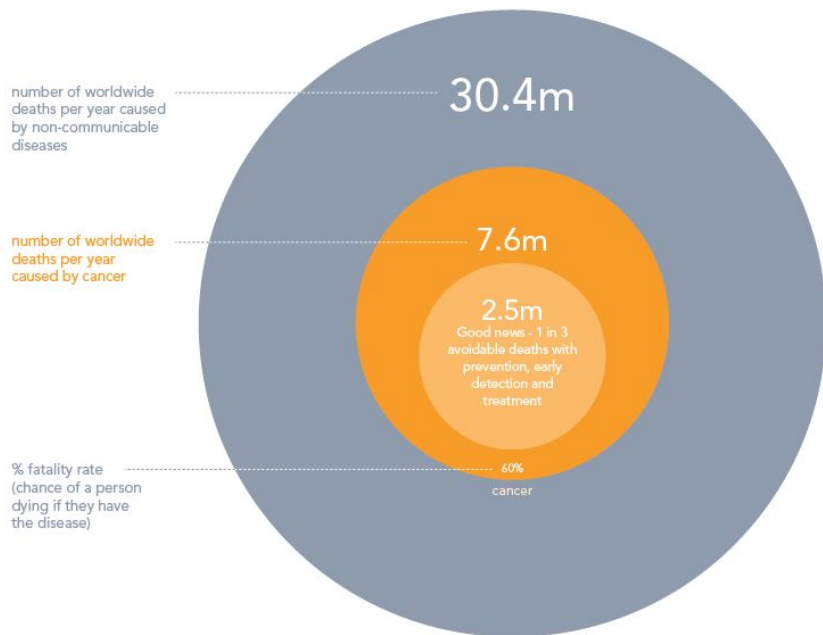
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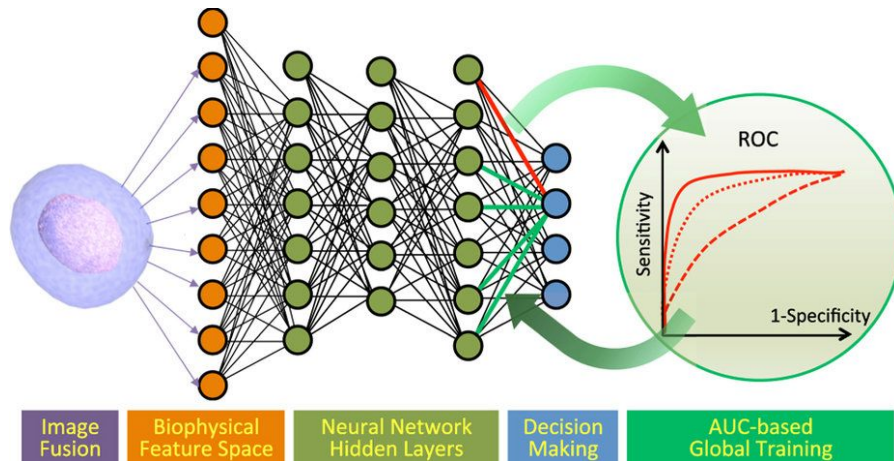
²Bates College, Lewiston, Maine

Motivation

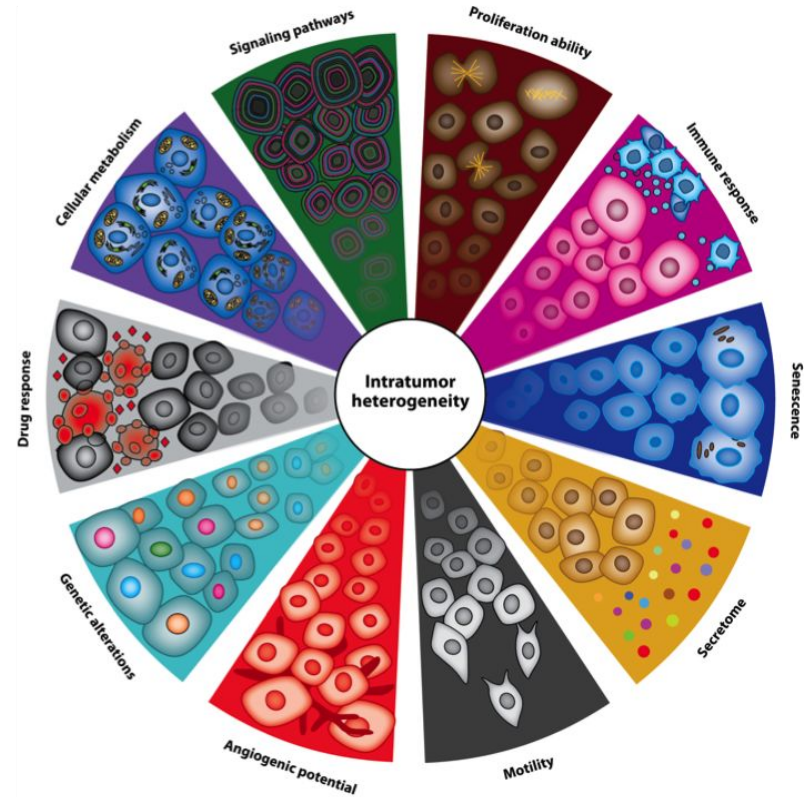
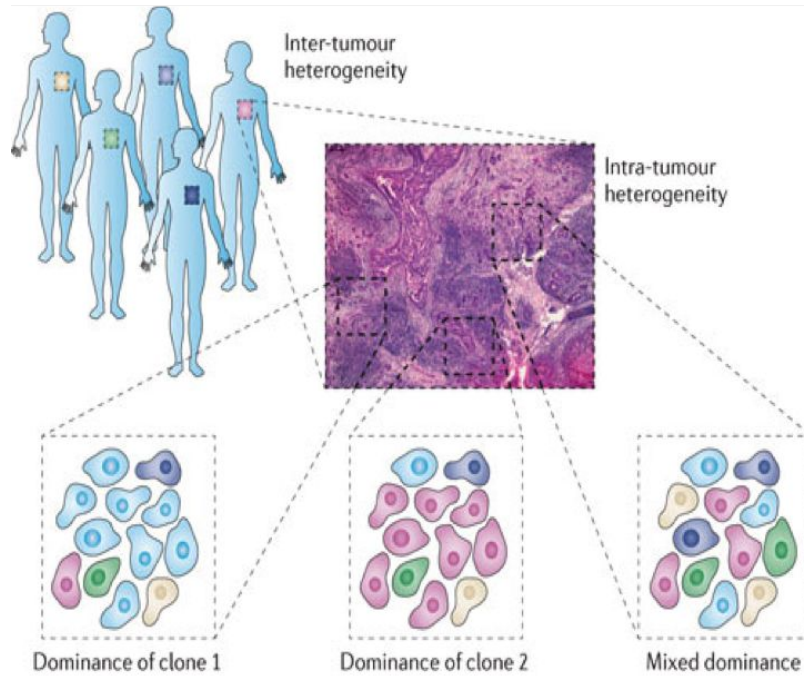
Cancer mortality compared to other diseases



Total non-communicable diseases (including cancer, cardiovascular diseases, respiratory diseases, diabetes)



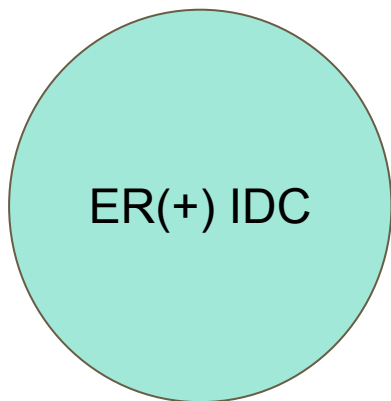
Tumor Heterogeneity



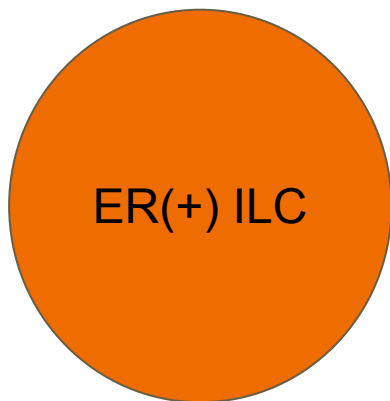
Data

Tissue microarray of 99 samples consisting of triplicate, 1mm diameter cores from 24 invasive breast tumor tissues.

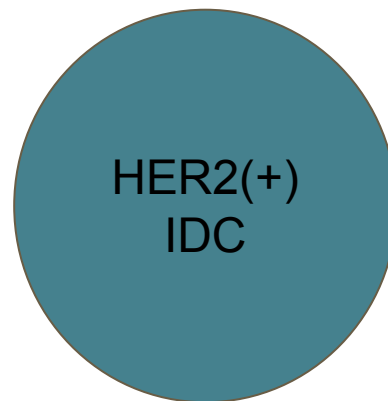
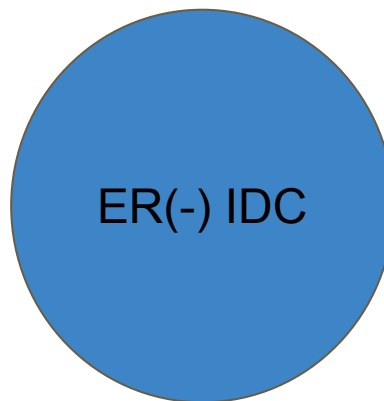
Immunohistochemical staining revealed 4 cohorts:



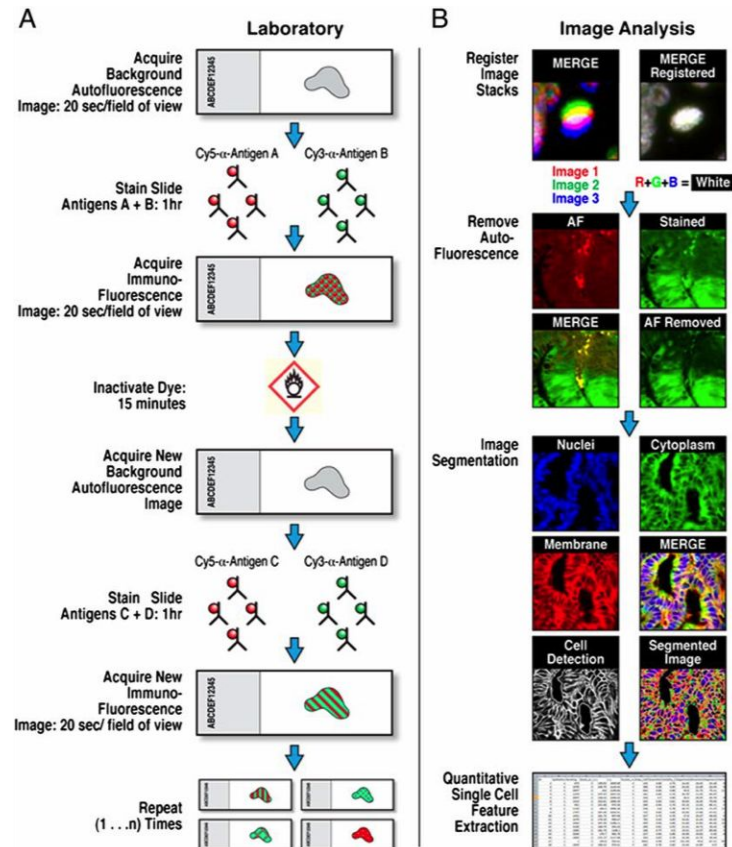
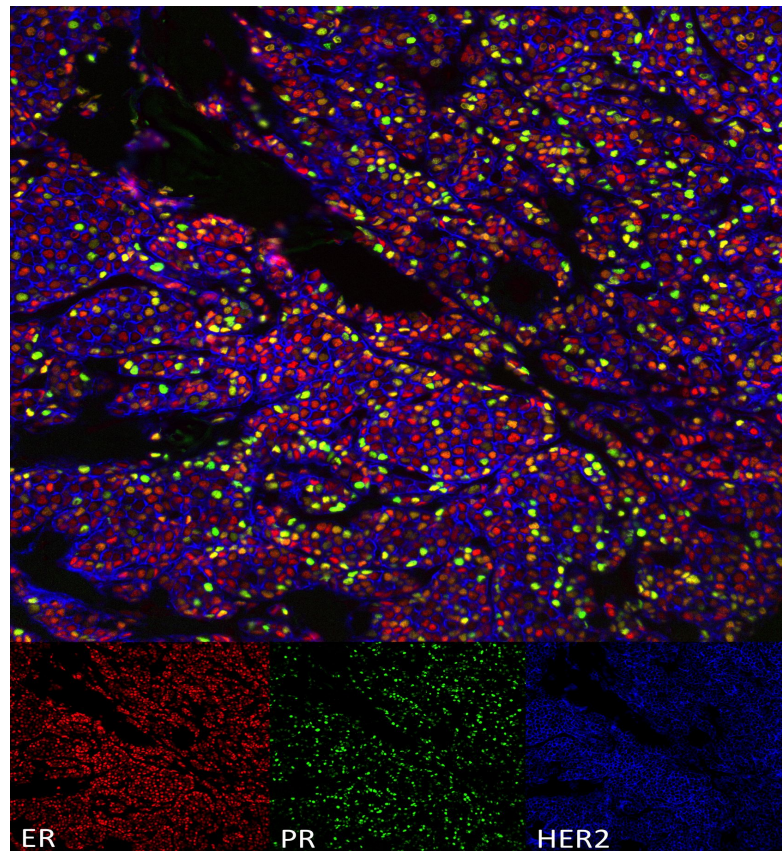
IDC - invasive ductal carcinoma



ILC - invasive lobular carcinoma

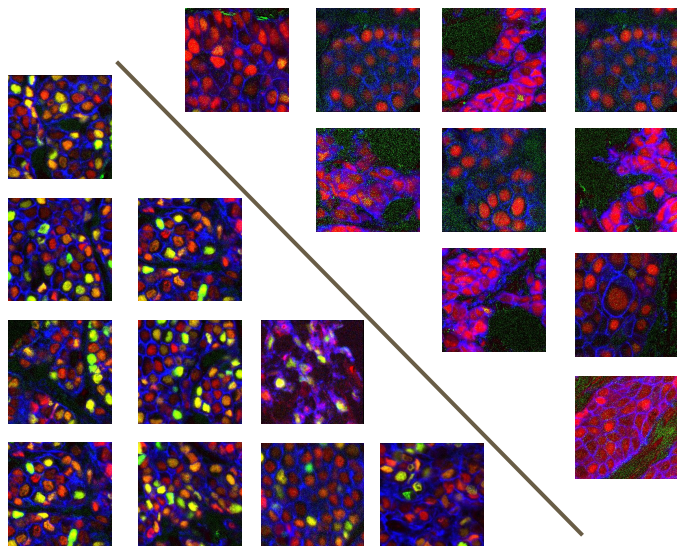


Multiplexed Immunofluorescence Imaging

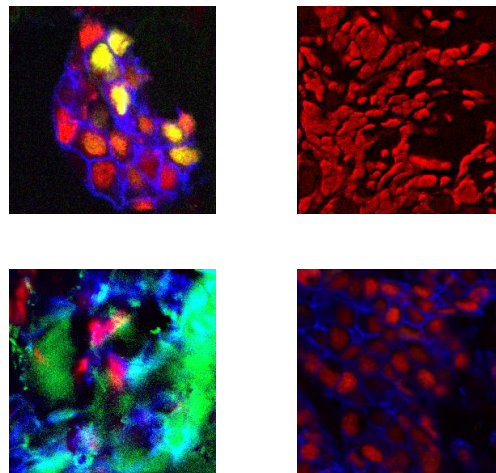


Research Goals

Develop high throughput informatics tools for integrating and analyzing cancer data obtained from a variety of imaging modalities

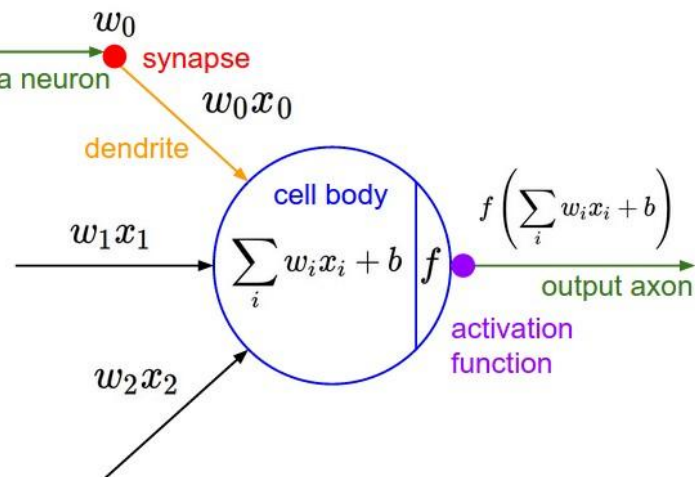
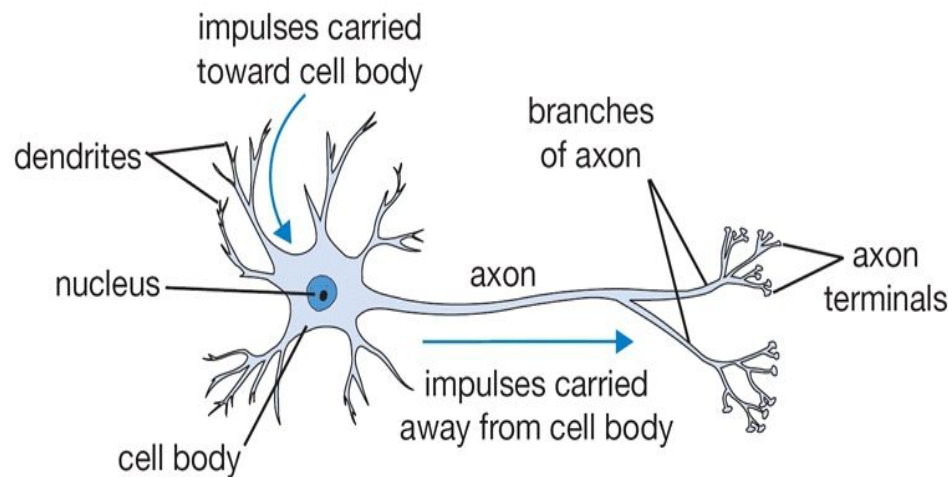


1. Cancer Classification



2. IF Signatures

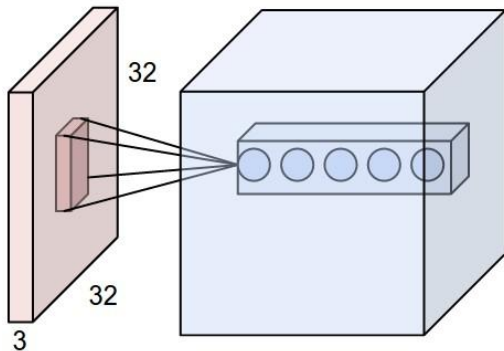
Neural Networks - Biological Motivation



Convolutional Neural Networks

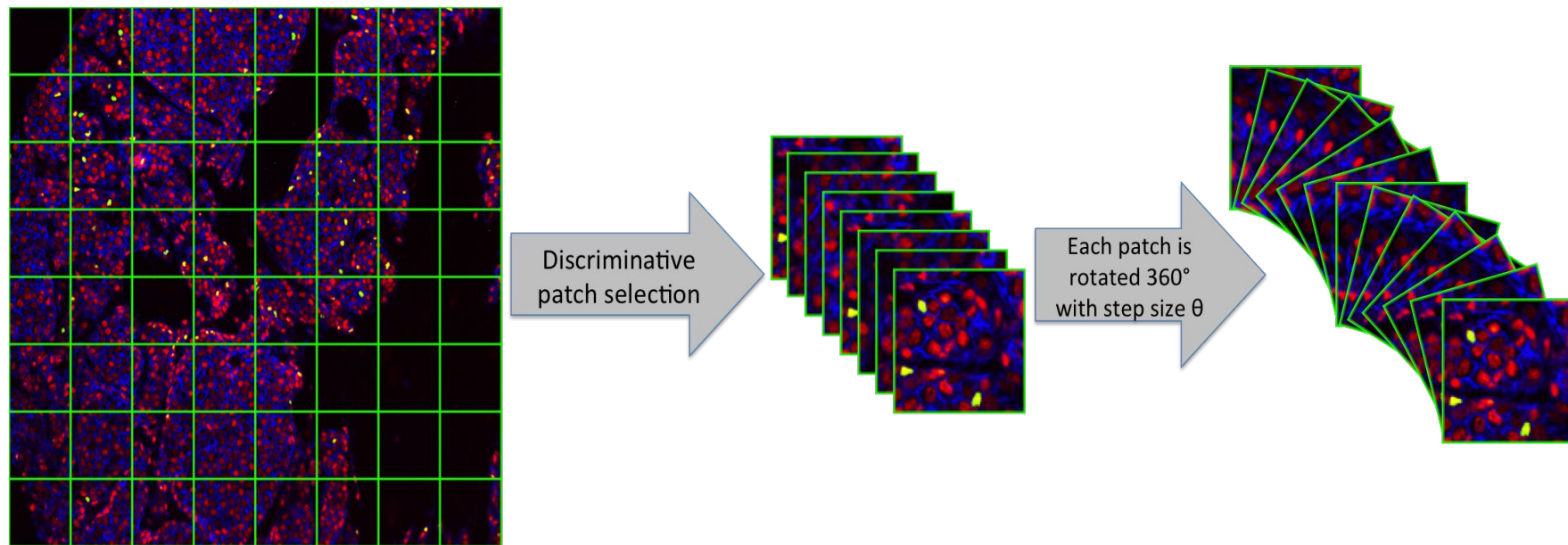
CNNs are very similar to ordinary neural networks, but...

- Now, we make the explicit assumption that input are **images**
- Since fully connected layers don't scale well - take advantage of the fact that portions of images are correlated



Example filters learned by AlexNet

Patch Selection and Augmentation



Results

Classification accuracy by configuration:

	256 × 256					512 × 512
θ step size	3	6	6	18	36	9
patch overlap	-	-	64	-	-	-
CNN Acc	0.79	0.77	0.81	0.76	0.75	0.78

Classification accuracy:

increases with patch overlap

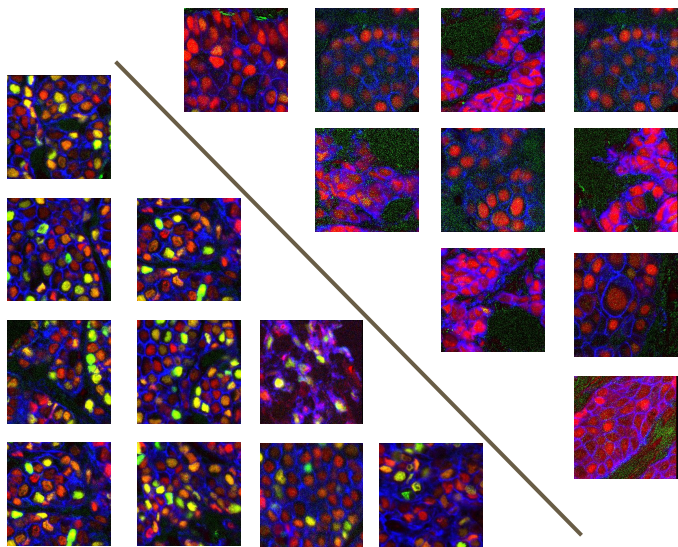
decreases with rotation step size

Ground Truth	ER(+) IDC	ER(+) ILC	ER(-) IDC	HER2(+) IDC
	0.75	0.03	0.16	0.05
	0.33	0.59	0.00	0.07
	0.08	0.02	0.87	0.03
	0.04	0.00	0.09	0.86
Predictions				
ER(+) IDC ER(+) ILC ER(-) IDC HER2(+) IDC				

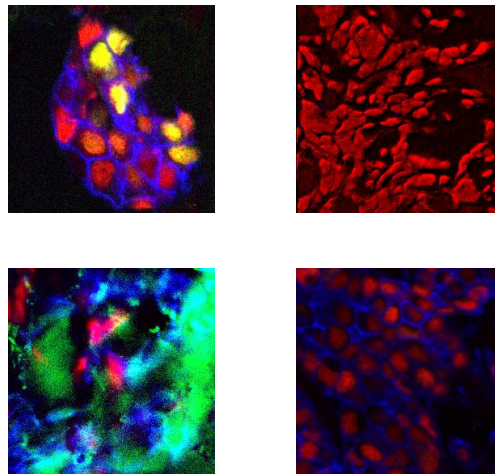
Confusion matrix for best performing configuration

Research Goals

Develop high throughput informatics tools for integrating and analyzing cancer data obtained from a variety of imaging modalities

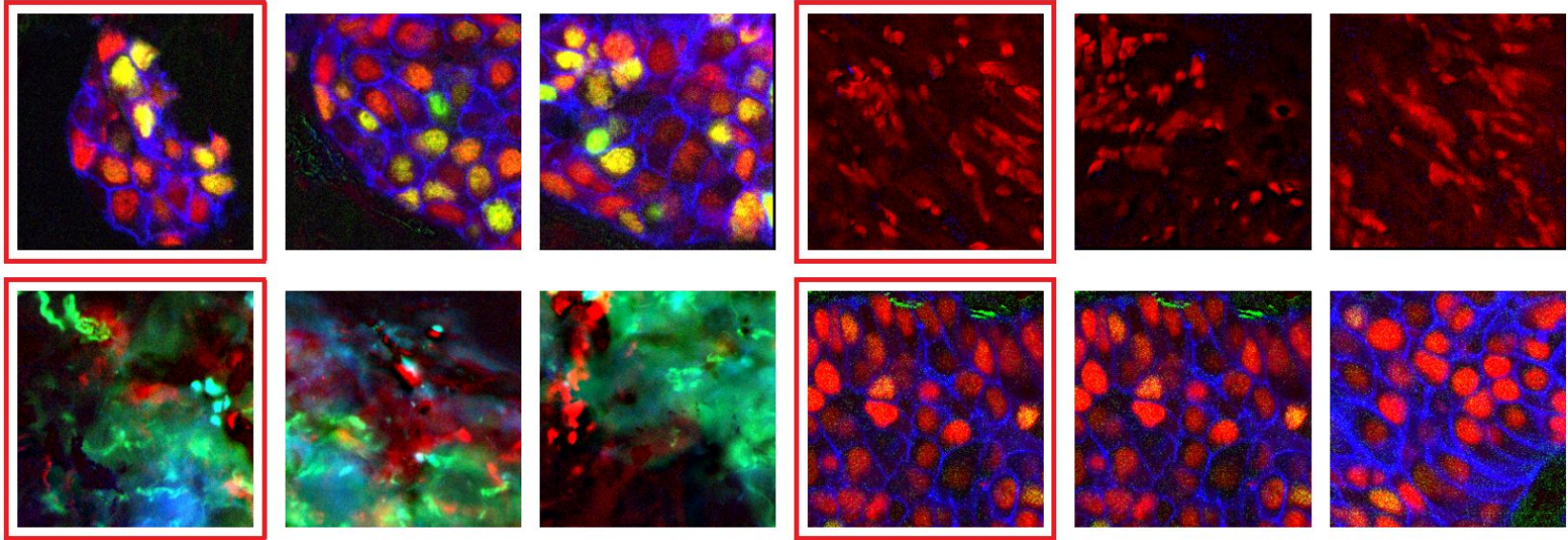


1. Cancer Classification



2. IF Signatures

Nearest Neighbor Visualization

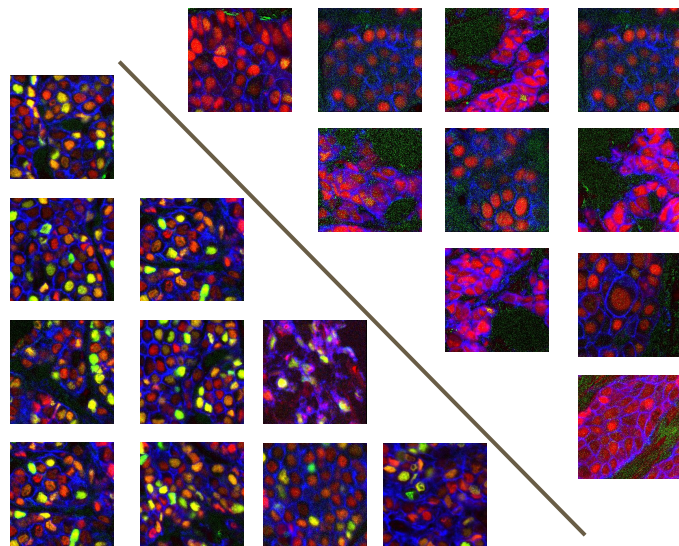


Could form the basis for a powerful and interactive visualization tool for clinicians

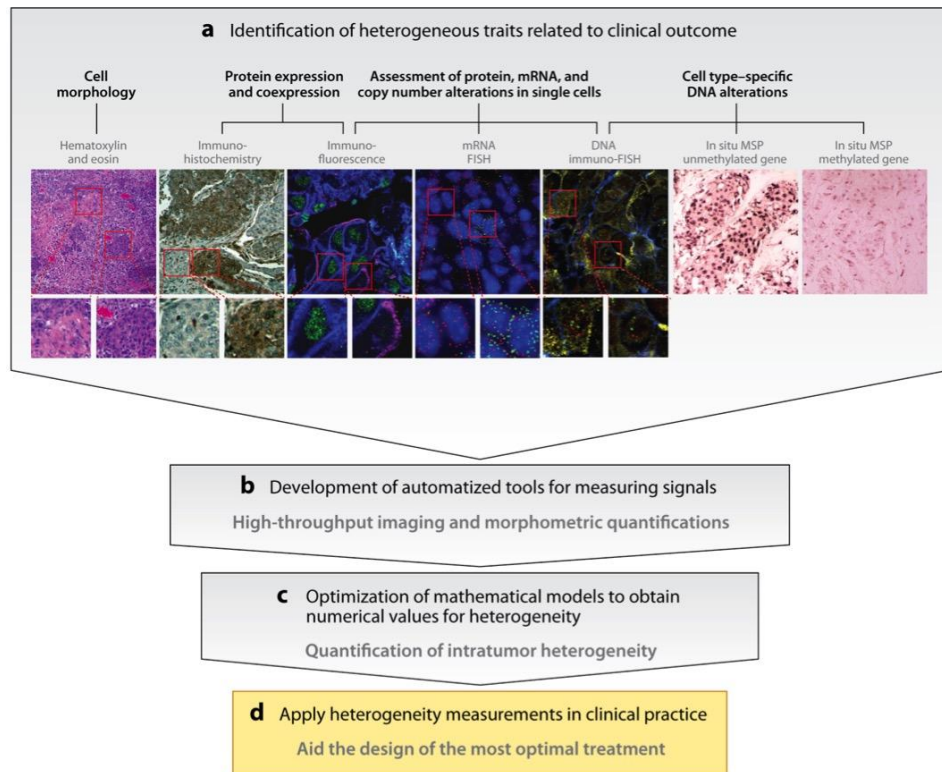
Conclusions

The main contributions of this work:

- classify cancer subtypes with respectable accuracy
- Identify immunofluorescent signatures associated with a cancer subtype



Future Work

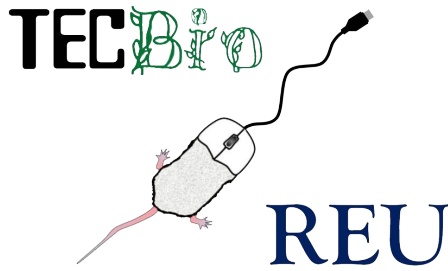


Spark

Lightning

Acknowledgements

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References

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Questions?