Michael Chi Ian Tang 3035209241 Classification for pathological images using machine learning

- Digital Pathology
- Convolutional neural networks (CNN)
- From CNN to Residual Network
- First prototype
- Second prototype
- Future direction



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CONVOLUTION + RELU POOLING

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Machine Learning Model



Training



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# Digital Pathology

Highly accurate

Time-consuming, Expensive, Dependent on experience





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An image is just a collection of numbers stored in the memory



How to build a machine that recognizes objects?



How to build a machine that recognizes objects?



We model the human brain - neurons



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A neural network



Approximating human vision - Convolution Source pixel  $(-1 \times 3) + (0 \times 0) + (1 \times 1) +$  $(-2 \times 2) + (0 \times 6) + (2 \times 2) +$  $(-1 \times 2) + (0 \times 4) + (1 \times 1) = -3$ Convolution filter (Sobel Gx) Destination pixel

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Scale up the model



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### Overfitting and Underfitting



### Overfitting and Underfitting



### Overfitting and Underfitting



### Skip Connection



### Skip Connection



### Skip Connection



#### CNN to Residual Network



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Machine Learning Model



Training



Step 1: Separation of training and testing Data



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Step 2: Segmentation of images



Gardnerella Vaginosis colony

Step 3: Training using the images



Step 4: Testing using the patients images



#### The First Prototype – Model Architecture



### The First Prototype - Performance

Hold-out validation of 30% of unseen training data: 98.7% accuracy

		Prediction by the model			
		Lactobacilli	Gardnerella	Curved rods	Other
Actual type of bacteria	Lactobacilli	499	6	1	2
	Gardnerella	0	559	3	4
	Curved rods	0	2	589	0
	Other	2	5	0	63

### The First Prototype - Performance

Testing on 31 patient images:

45.1% accuracy

		Prediction by the model			
		Normal	Intermediate	BV Infection	
	Normal	8	0	0	
Actual degree of	Intermediate	5	3	0	
infection	BV Infection	6	6	3	

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#### Step 1: Collection of Data by Customized Tool "Clicklable"



#### Step 2: Regions of Interest (ROIs) Identification by Image Processing



Step 3: Image Segmentation



Step 4: Training and Validating using the images



### The Second Prototype – Model Architecture



1 Standard Convolutional Layer

7 Residual Blocks

1 Fully Connected Layer

# The Second Prototype – Performance (Provisionary)

Hold-out validation of 10% of unseen training data: 81.4% accuracy

Testing on unseen image data (not used in tuning): 72.9% accuracy

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### Future Direction

Validation accuracy < 90%  $\rightarrow$ Increase complexity, fine-tuning and further training



### Future Direction

#### Large number of unlabelled data $\rightarrow$ Exploration of other learning algorithms / architecture





YOLO algorithm for object recognition

