Title:
Deep Learning for Non-Invasive Blood Cytometry

BACKGROUND: Current Complete Blood Count (CBC) is now achieved in an invasive way. Now an Oblique Back-illumination (OBM) capillaroscopy from Dr. Nicholas Durr's Lab makes noninvasive CBC possible. In this project, three deep learning models are proposed to analyze real-time OBM capillaroscopic video.

METHODS

1. **Mask RCNN (backbone: ResNet101)+ counting algorithm**
   - ☐ Mask RCNN for detecting cells and obtaining the masks.
   - ☐ Set a fixed ROI to calculate cells passing through.

2. **Mask-track RCNN (backbone: ResNext101)**
   - ☐ Based on Mask RCN, add tracking head to track individual cells across frames.

3. **CNN + RNN (backbone: VGG)**
   - ☐ CNN for feature extraction
   - ☐ RNN for tracking and counting cells

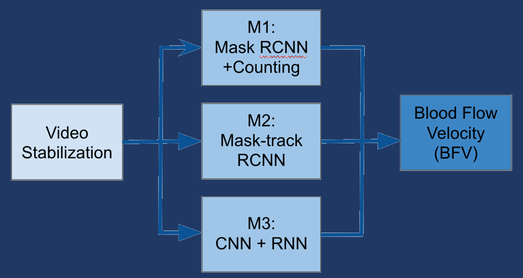


Figure 1. Workflow

RESULTS

Approaches	Count Number						BFV
	50fs			100fs			
	GT	Prediction	Error	GT	Prediction	Error	
Mask RCNN (ResNet-101)	43	43	2.63%	99	74	17.10%	118.4/s
	33	35		59	57		91.2/s
Mask-track RCNN (ResNet-101)	43	46	6.58%	99	113	12.02%	180.8/s
	33	35		59	64		102.4/s
CNN + RNN (VGG)	43	60	36.84%	99	117	27.85%	187.2/s
	33	44		59	85		136.0/s

* fs: Frames, GT: Ground Truth, BFV: Blood Flow Velocity

Mask R-CNN

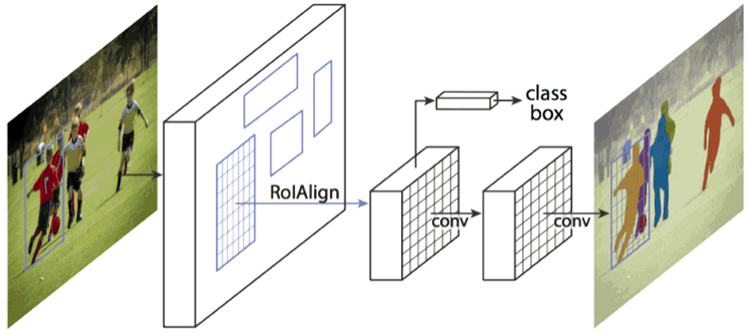


Fig1.1. Architecture

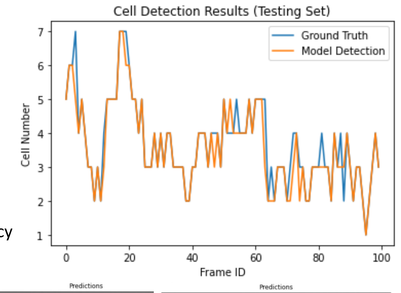
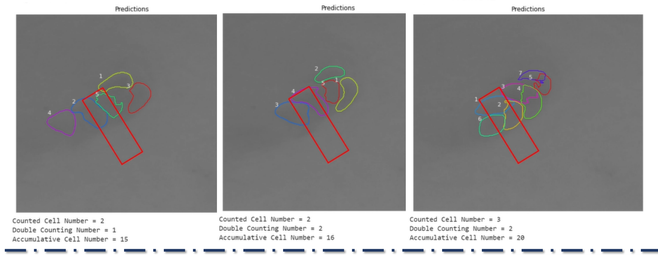
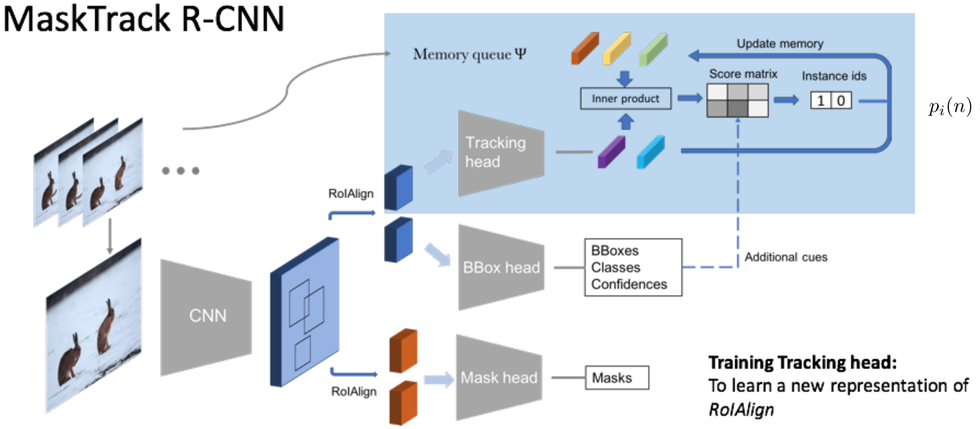


Fig1.2. Detection Accuracy

Fig1.3 Counting Demo



MaskTrack R-CNN



Training Tracking head:
To learn a new representation of *RoIAlign*

Fig2.1. Architecture

$$p_i(n) = \begin{cases} \frac{e^{\mathbf{f}_i^T \mathbf{f}_n}}{1+\Sigma_{j=1}^{N} e^{\mathbf{f}_i^T \mathbf{f}_j}} & n \in [1, N] \\ \frac{1}{1+\Sigma_{j=1}^{N} e^{\mathbf{f}_i^T \mathbf{f}_j}} & n = 0 \end{cases}$$

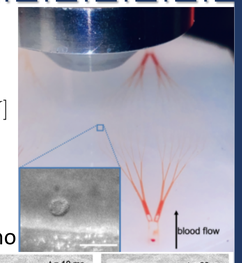
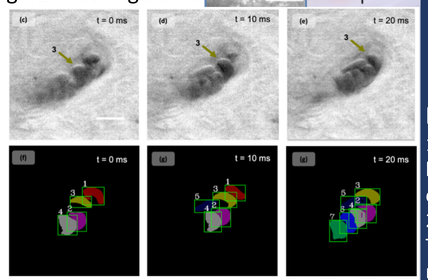


Fig2.1. Tracking Demo



CNN + RNN

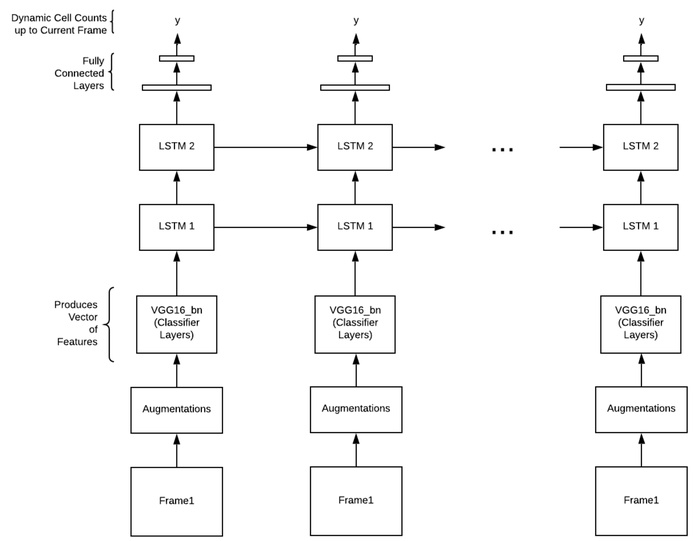


Fig3.1. Architecture

Fig3.2. Counting result on test video (100fps)

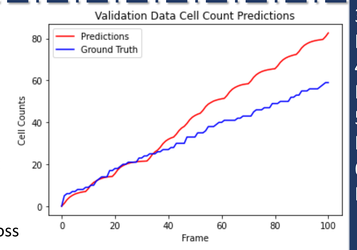
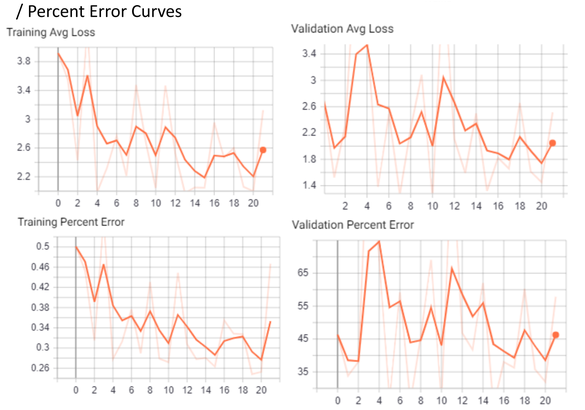


Fig3.3. Training & Validation Loss / Percent Error Curves



Discussion

Limitations

1. Mask RCNN
   The prediction accuracy is sensitive to the density of cells.
2. Mask-Track RCNN
   Modelis sensitive to cell deformation, so cells traveling through a non-linear path will result in poor results.
3. CNN + RNN
   Feature extractor was not fine-tuned due to the lack of data. More appropriate feature extractor will greatly improve performance.
4. Lack of data prevents our models from generalizing well.

Future Improvement

1. More effective object detector, such as EfficientDet
2. Add more data to train the models
3. More effective tracking strategies
4. Use features from FPN to feed RNN

Github Link: *https://github.com/Shu244/Deep-Learning-Final-Project*

References

1. McKay, Gregory, Mohan, Nela, Durr, Nicholas. Imaging human blood cells in vivo with oblique back-illumination capillaroscopy. 2020.
2. S. Ren, K. He, R. Girshick, and J. Sun. Faster R-CNN: Towards real-time object detection with region proposal networks. In NIPS, 2015.
3. Yang, Linjie, Xu, Ning. Video Instance Segmentation. In ICCV, 2019.
4. Redmon, Joseph, Farhadi, and Ali. "YOLO9000: Better, Faster, Stronger," 2016.
5. Redmon, Joseph, Farhadi, and Ali. "YOLOv3: An Incremental Improvement." April 8, 2018.
6. Mingxing, Pang, and Quoc V. "EfficientDet: Scalable and Efficient Object Detection." April 3, 2020.

Luojie Huang, **Shuhao** Lai, **Yuan** zhou

JOHNS HOPKINS UNIVERSITY