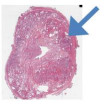
Learning Histology Slice Processing Steps

Fang-Yu Lin
Department of Electrical Engineering, Stanford University
fangyuln@stanford.edu

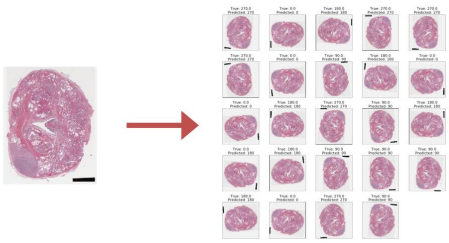
Motivation / Background

- To accelerate the process when utilizing histology slice data for further research
- Histology slice: high resolution
  + clearly indicate the existence of cancer cells
- Useful for cancer diagnosis



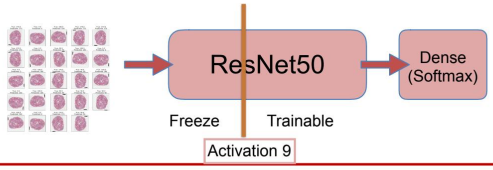
Dataset

- From: the Laboratory for Integrative Personalized Medicine
- RGB TIFF images, 5k x 5k resolution, sometimes occluded, labeled w correct angle
- Preprocessing: Rotation, Gaussian Blur, Downsample
- Augmentation:
  - Rotated in 4 angles(0, 90, 180, 270 deg)
  - Mirroring
  - Add small rotation angle (±5 deg)



Model

- ResNet50 + output layer of 4 classes



Results

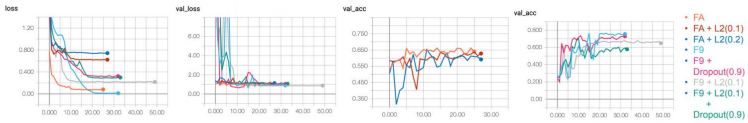


Table 3: Training and Validation Accuracy (w additional random rotation)

Model	FA	FA+L2(0.1)	FA+L2(0.2)	F9	F9+Dropout(0.9)	F9+L2(0.1)	F9+L2(0.1)+Dropout(0.9)
Training	0.9711	0.8966	0.8691	0.9986	0.8701	0.9464	0.9335
Validation	0.6402	0.6282	0.5921	0.7556	0.7284	0.6490	0.5777

Table 4: Training and Validation Accuracy (w/o additional random rotation)

Model	F9	F9+Dropout(0.9)	F9+L2(0.1)
Training	0.9593	0.9027	0.9351
Validation	0.7989	0.6691	0.7075

Results

Table 6: Confusion Matrix Table

True/Predicted	0	90	180	270
0	210	13	42	22
90	3	240	10	38
180	5	6	227	50
270	5	3	10	268

Table 7: Classification Report

True Angle	Precision	Recall	F1-Score
0	0.94	0.73	0.82
90	0.92	0.82	0.87
180	0.79	0.79	0.79
270	0.71	0.94	0.81
Ave	0.84	0.82	0.82

Results

Table 8: Example slices and classification results with different accuracy

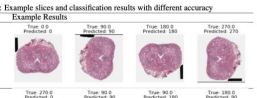
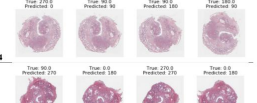
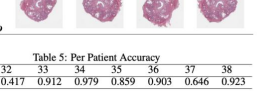
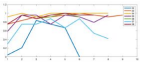
Slice #, Patient #	Example Results
(256,38), acc=1.0	
(207,32), acc=0.04	
(244,37), acc=0.29	

Table 5: Per Patient Accuracy

Patient #	32	33	34	35	36	37	38
Accuracy	0.417	0.912	0.979	0.859	0.903	0.646	0.923



Discussion

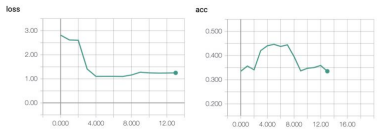
- Current regularization method doesn't work well
- Prediction quality depends on quality of original data
- High enough accuracy for our purpose

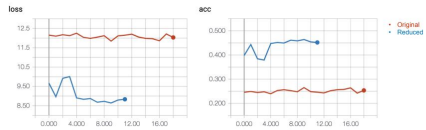
Future Work

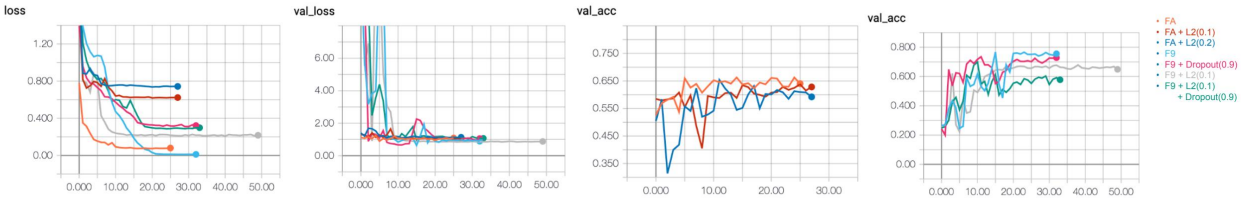
- Collect more data to avoid overfitting
- Explore different pretrained models
- Implement the model for mirroring classification

Reference

- [1] D. Saez. RotNet, 2017
- [2] P. Fischer, A. Dosovitskiy, and T. Brox. Image orientation estimation with convolutional networks. In German Conference on Pattern Recognition, pages 368–378. Springer, 2015.
- [3] U. Joshi and M. Guerzhoy. Automatic photo orientation detection with convolutional neural networks. In 2017 14th Conference on Computer and Robot Vision (CRV), pages 103–108. IEEE, 2017.


loss
acc


loss
acc
Original
Reduced


loss
val_loss
val_acc
val_acc
FA
FA + L2(0.1)
FA + L2(0.2)
F9
F9 + Dropout(0.9)
F9 + L2(0.1)
F9 + L2(0.1) + Dropout(0.9)