Frederick National Laboratory
for Cancer Research

CURTIS R. LISLE, PH.D,
KNOWLEDGEVIS, LLC

YANLING LIU, PH.D.
FREDERICK NATIONAL LAB FOR CANCER RESEARCH

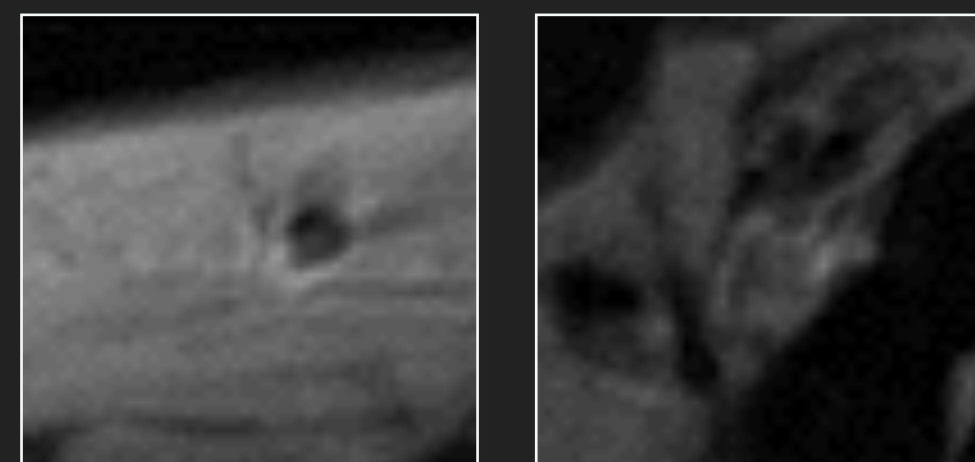
SLICER 2017 PROJECT WEEK

DEEP LEARNING FOR CANCER LESION DETECTION

PURPOSE OF THIS PROJECT

- Can we develop a binary classifier using thumbnail images from the area immediately around existing cancer lesions using MRI data?

cancer positive



cancer negative

- How to decide the effect of different data preparation strategies
- This project was an introduction to Deep Learning for the authors

CHOOSE THE LEARNING INFRASTRUCTURE

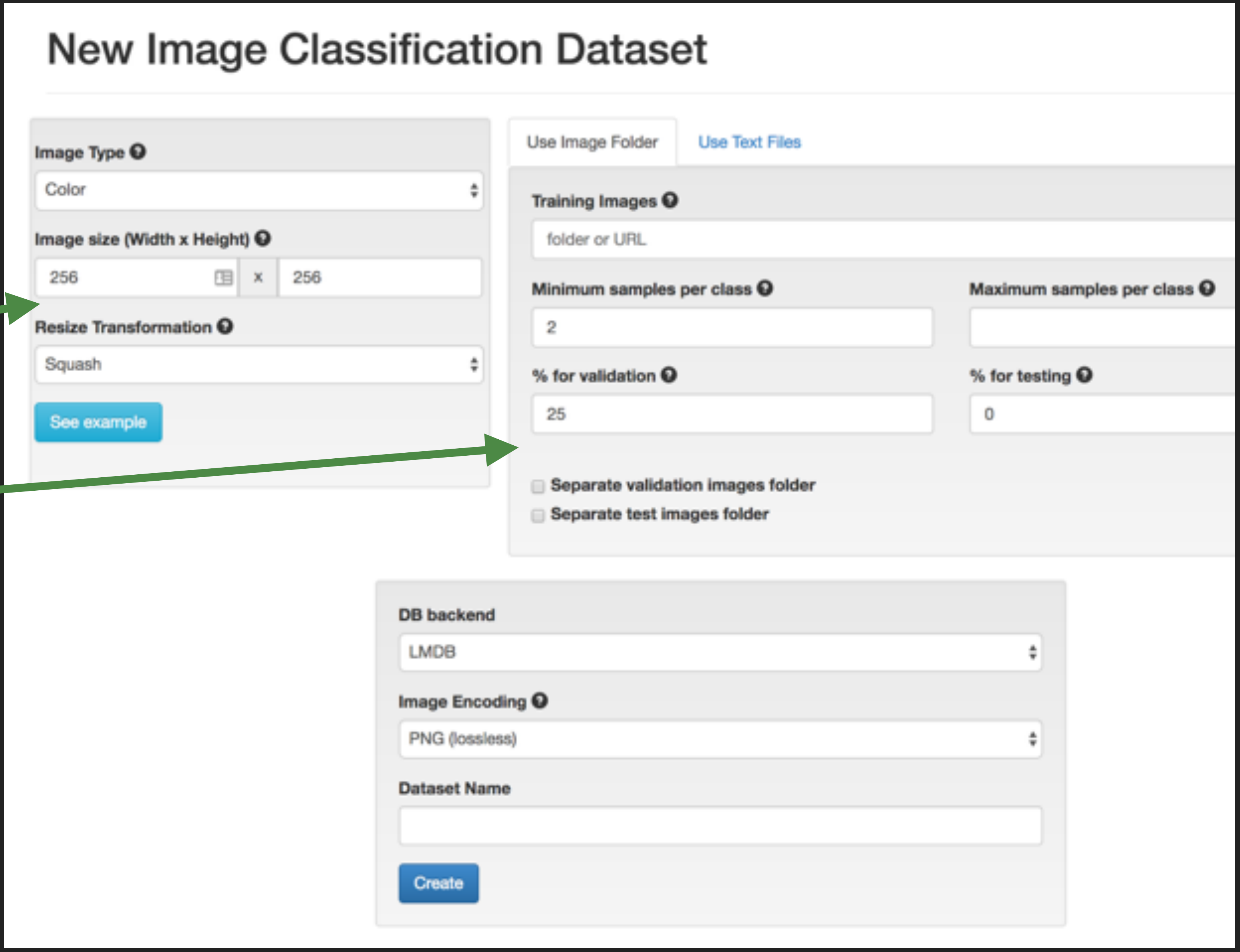
- Chose NVIDIA DIGITS
    - Seemed easiest way to start training with minimal coding required to manage data and construct the learning network
    - DIGITS offered several CNNs pre-constructed, which seemed a good match for our classification problem

ADD TRAINING DATA

- DIGITS lets users initialize training databases and then build learning models through training on a loaded database

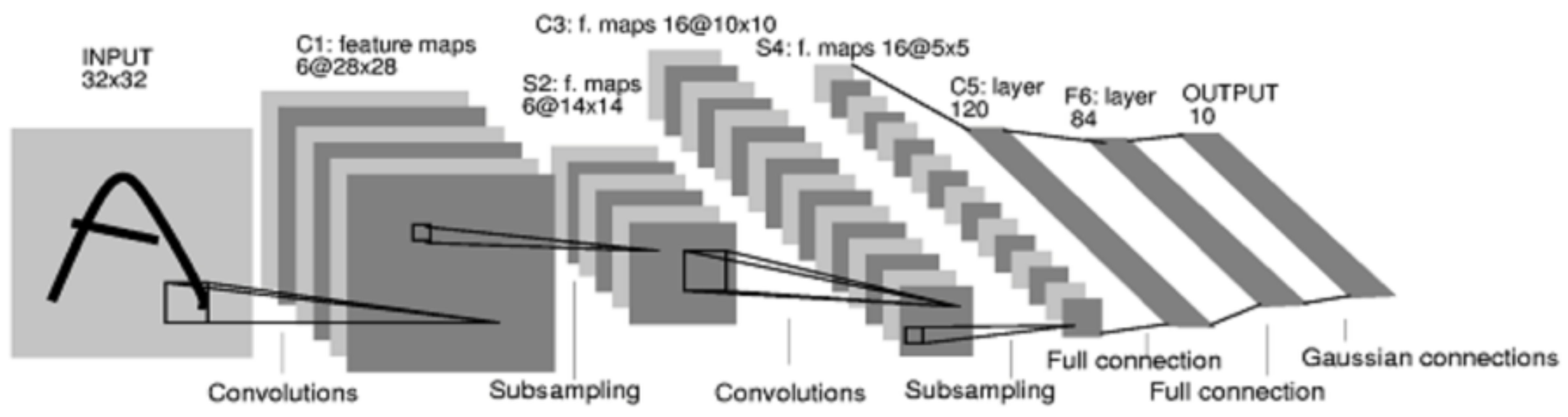
Select image dimension and color scheme

Assign training and test data



SELECT THE INITIAL CNN MODEL

- LeNet was chosen because of its simplicity, yet also the existence of convolution layers followed by fully-connected layers. Our input images are of similar size, so convolution design should be effective at feature detection.
- Convolution layers can train on lesion patterns followed by fully-connected layers combining trained detection cases

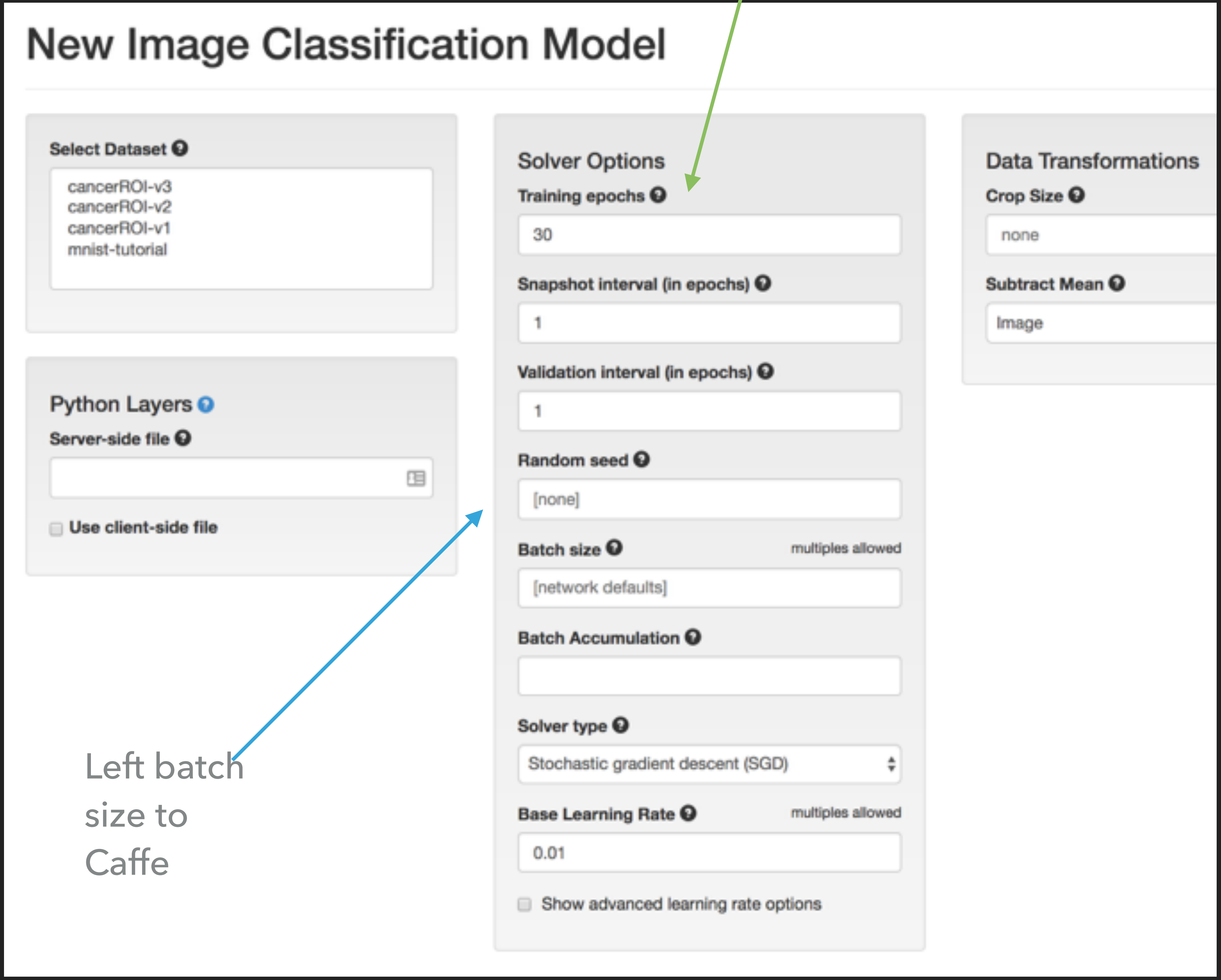


LeCun et al. 1989-1998: Handwritten Digit Recognition

TRAIN LEARNING MODEL

Select the number of epochs

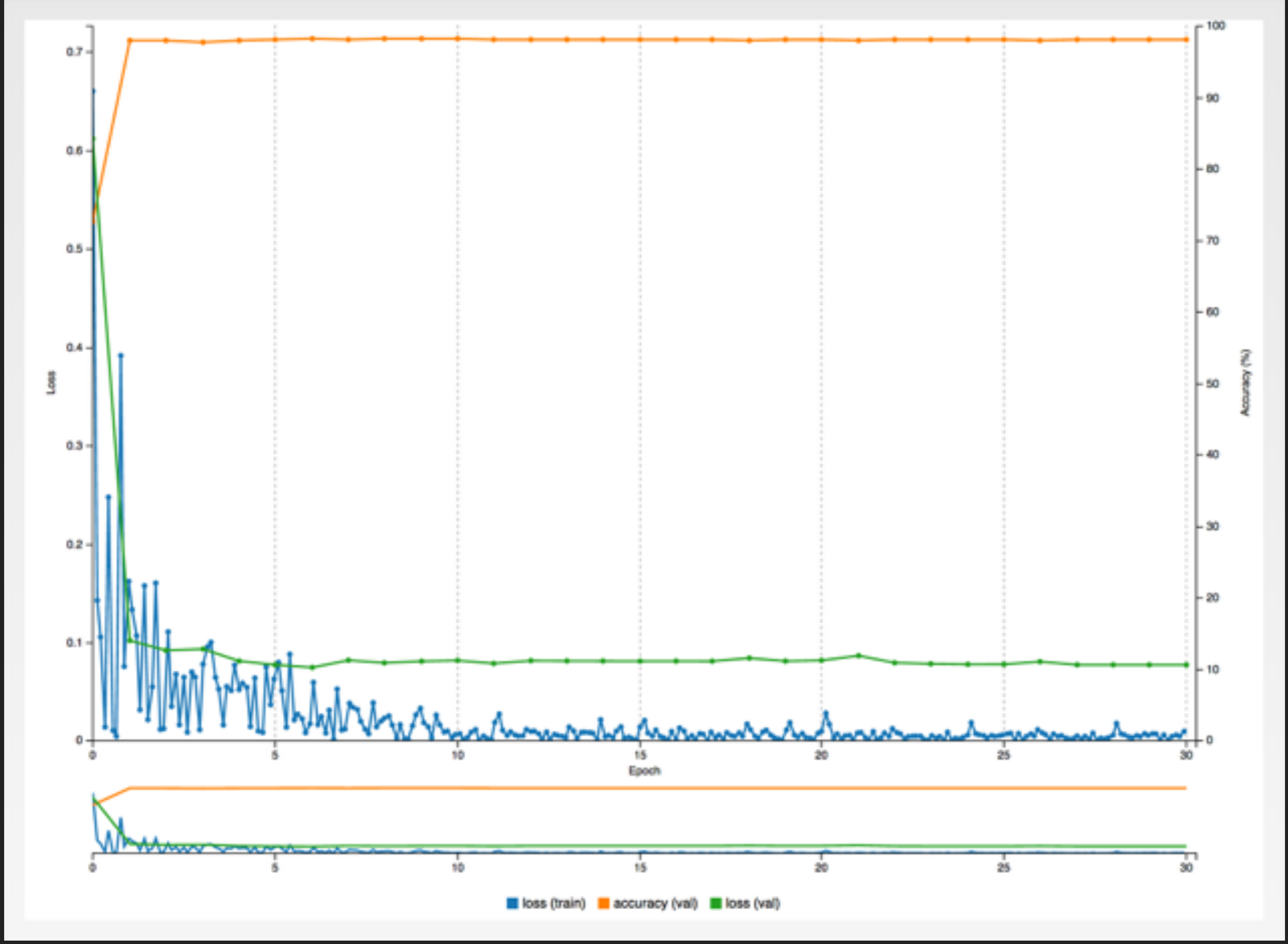
- Use the DIGITS Model Training interface
- Chose default/automatic for other training factors
- Training operation uses the Caffe framework



Left batch size to Caffe

FIRST TRAINING TRY

- LeNet network trained with insufficient/ biased training data (64 positive cases, 1000 negative cases, 30 epochs)
- Good match for negative cases (null classifier effect), but poor classification on positive cases (34% detection

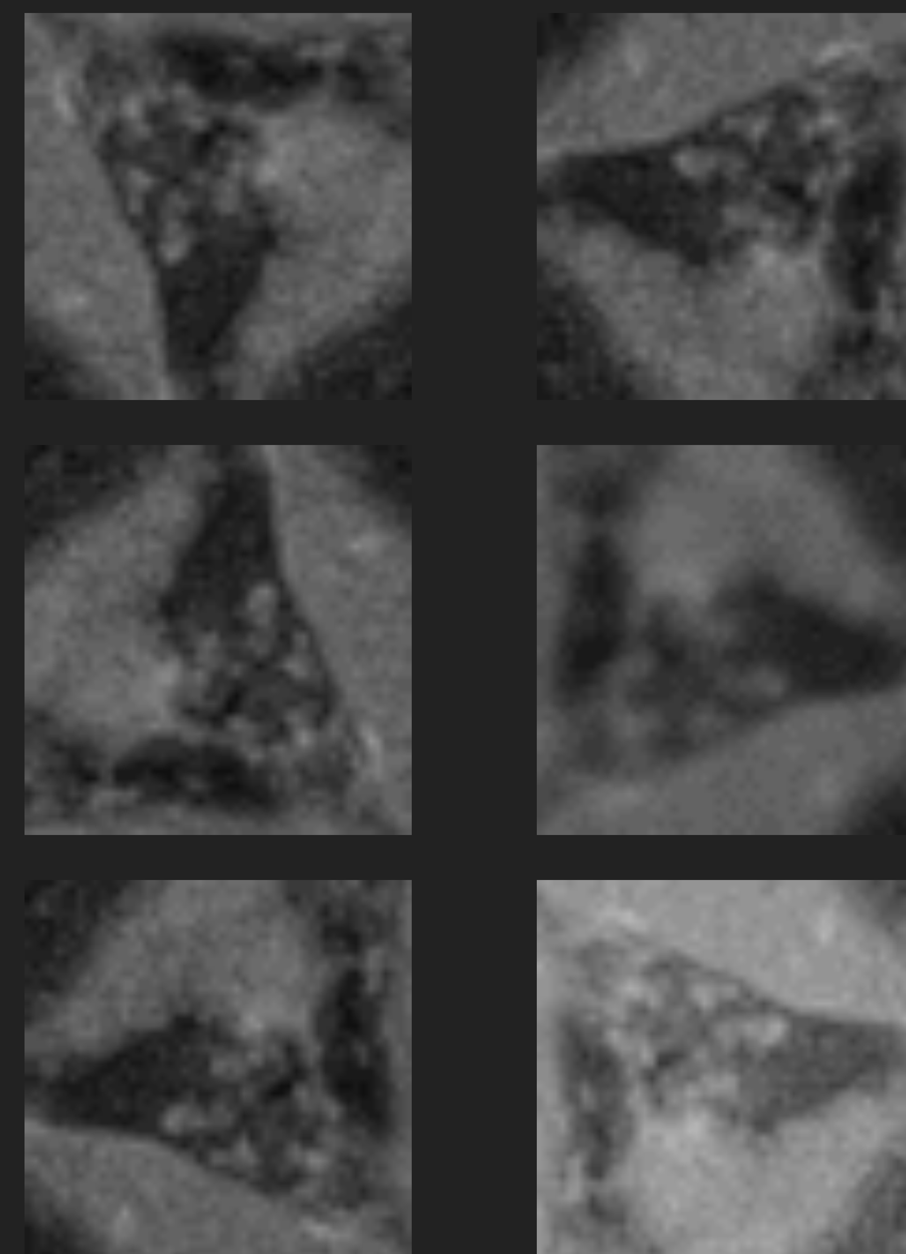


DATA AUGMENTATION

- We used ImageMagick to quickly create augmented cases for the TRUE cases and address training imbalance

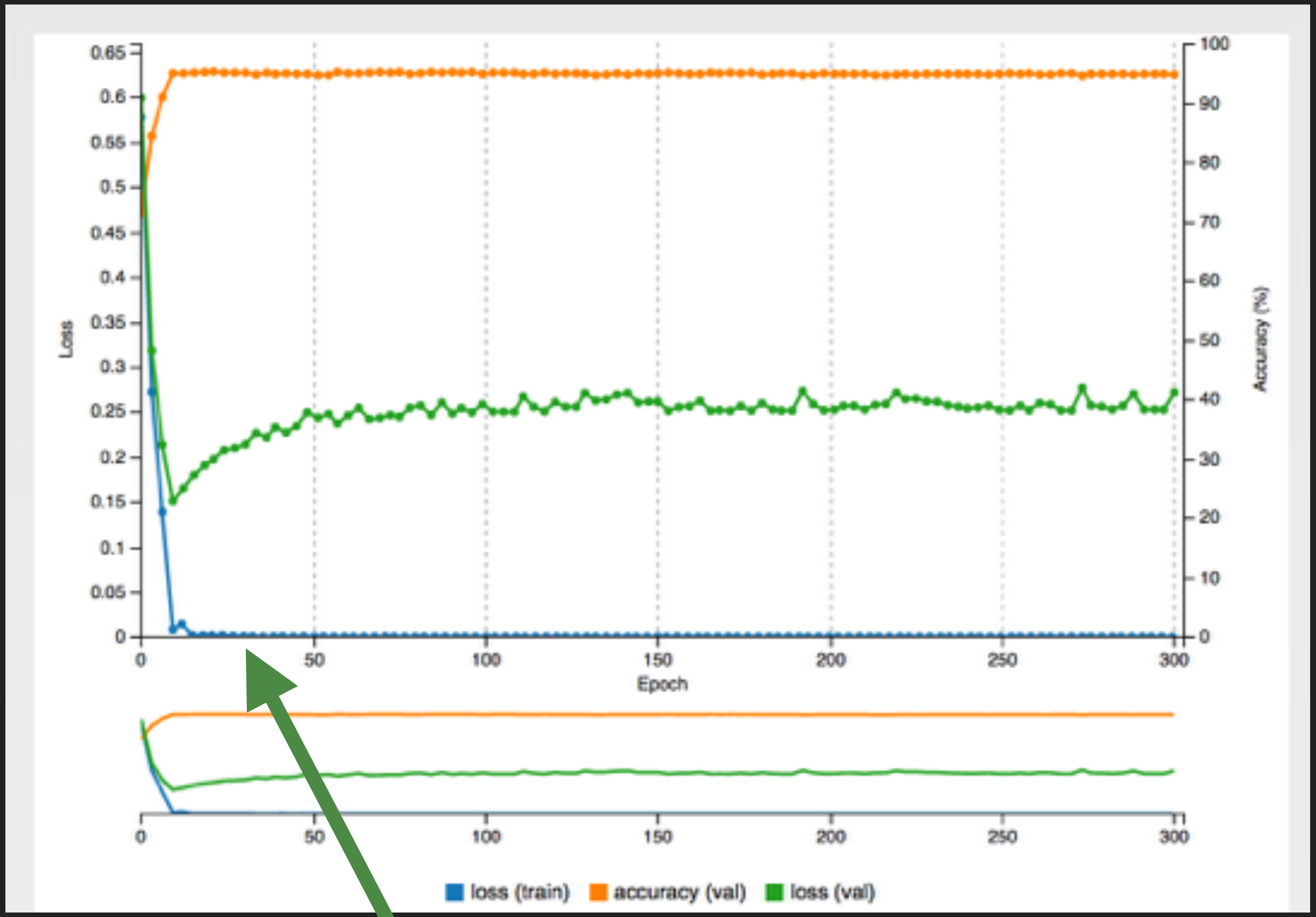
convert -flip
convert -flop
convert -rotate 90
convert -rotate 180
convert -rotate 270
convert -blur
convert -auto-gamma

We need to be careful here to not induce bias during augmentation…



TRAINING AFTER DATA AUGMENTATION

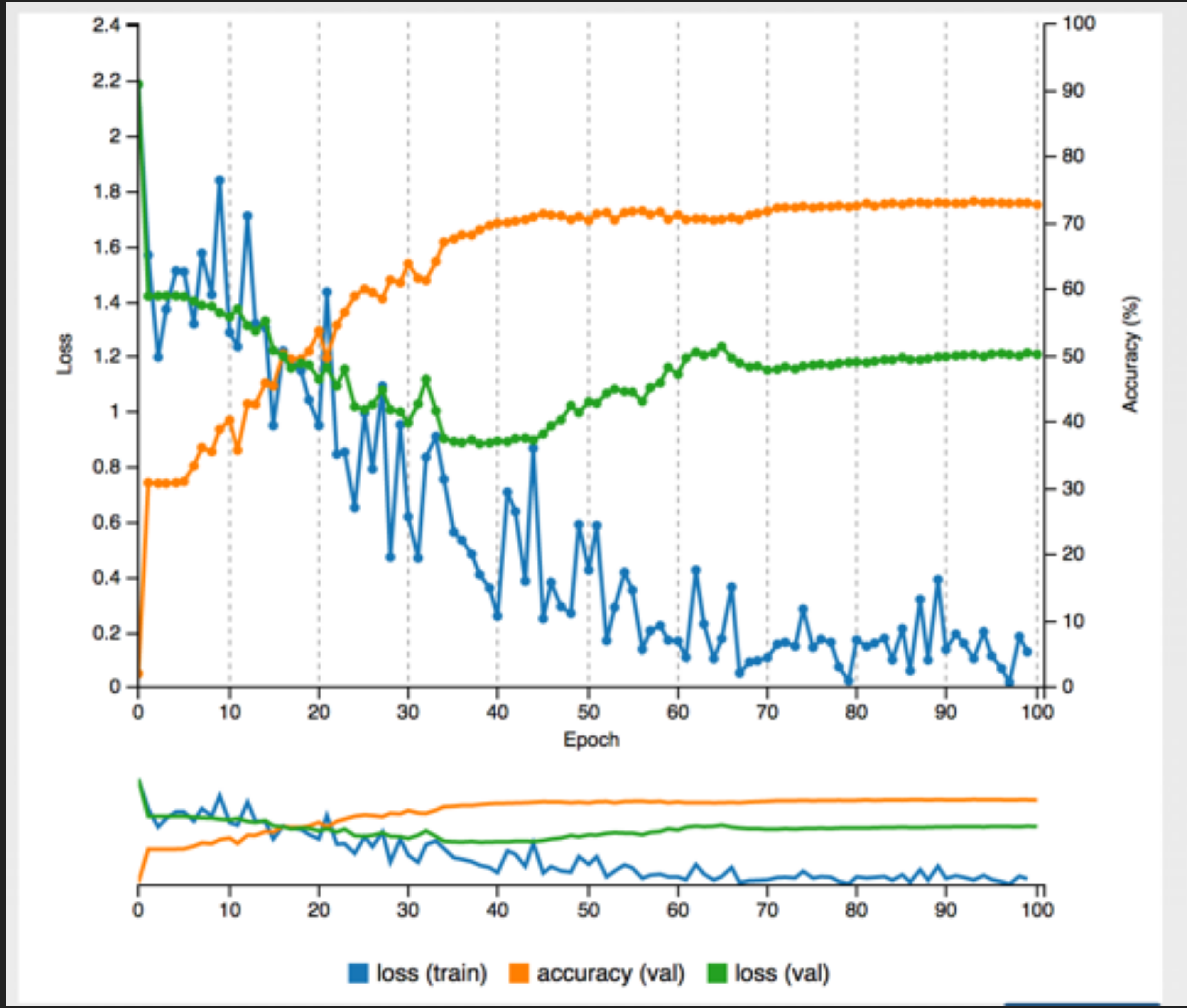
- LeNet trained for 300 epochs on more balanced training set (~900 true images, ~1000 negative images)
- Results were improved to 83% true identification
- Reviewing the training curve from DIGITS, it looks like overtraining occurred, so 300 steps (5 hours of training) was too much



overfit seems to be happening here

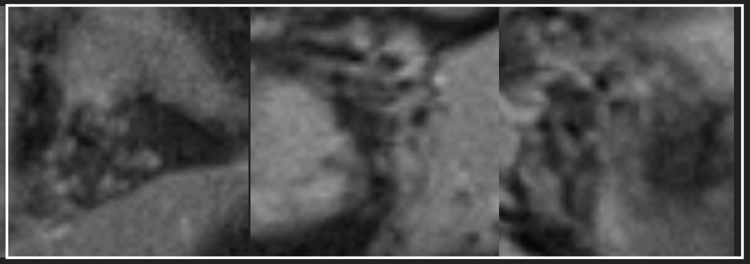
3D ALEXNET CNN CLASSIFICATION

- Augmented 2D data performs better than 2D original data alone. However the source data is available in 3D, (transaxial, sagittal,coronal) providing additional signal for training
- Original 3D only (without augmentation) produced superior results (72.7% positive detection rate) over original 2D, but not as good as augmented 2D. We theorize that augmented 3D would yield the best results
- Training chart at right seems to indicate that additional epochs of training should further improve performance. Layer depth of AlexNet seems to require additional data or higher learning rate.



DISCUSSION

- 83% positive detection rate (from augmented 2D) seems already accurate enough to be useful for some high-throughput screening applications
- Data augmentation was crucial in this application and should be further refined to further improve classification
- LeNet training was performed in 2D only. 3D imagery and proper data augmentation should yield even better results, as 3D AlexNet without augmentation was better than 2D LeNet without augmentation.
- We theorize that 3D convolution on the 3D data or presenting the three axes fused together to a 2D convolution would further improve results



axial sagital coronal

DISCUSSION

- Only ROI imagery was presented to the learning networks. Future work may investigate training simultaneously with different levels of imagery detail
- Deep Learning techniques enabled fast, high-quality classifier development when compared with traditional computer vision approaches for this dataset
- DIGITS ease of use and AWS Marketplace images allowed us to get right to training with minimal effort on data handling and system configuration