



Identifying Metastatic Cancer through Deep Learning

Stanford University
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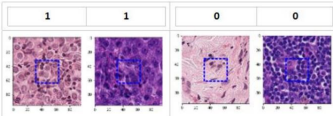
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MOTIVATION

- With over 2 million new cases in 2018, breast cancer is the second most commonly occurring cancer in the world
- Metastatic involvement of lymph nodes is a key prognostic characteristic of breast cancer
- Prognosis is poorer when cancer has spread to the lymph nodes; pathologists take exceptional care when examining and diagnosing lymph nodes
- The diagnostic procedure is tedious and time-consuming even for experienced pathologists

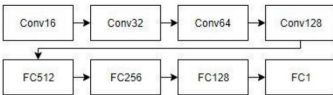
DATA

- Subset of the PatchCamelyon (PCam) benchmark
- Consists of 220,025 color images (96 x 96px) extracted from histopathologic scans of lymph node sections
- Each image is annotated with a binary label indicating presence of metastatic tissue
- A positive label means that at least one pixel of tumor tissue in the center 32 x 32 pixel region of the image
- 172K/22K/22K Split (80% Train/10% Dev/10% Test)



MODEL

- A ConvNet with 4-Convolutional and 4-Fully Connected layers trained with the Adam optimizer
- Built with PyTorch, an open-source ML library
- Trained on a Microsoft Azure Deep Learning VM



- With a Binary Cross-Entropy (BCE) loss function.

$$BCE = -\frac{1}{N} \sum_{i=0}^N y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)$$

PREDICTING METHODOLOGY AND EXPERIMENTS

Hyperparameter Tuning

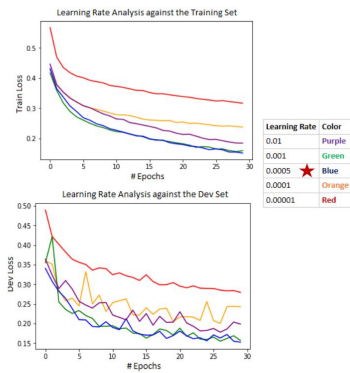
- We trained our model with different sets of hyperparameters to optimize accuracy

Batch Size Analysis

Batch Size	Train Accuracy	Dev Accuracy	Test Accuracy
8	97.0%	95.2%	96.3%
16	97.1%	95.1%	96.3%
32	97.0%	95.6%	95.1%
64	97.1%	93.8%	94.6%
128	97.0%	93.4%	94.8%
256	97.1%	94.4%	93.9%
512	97.1%	94.3%	93.5%

Batch Size Analysis Table

Learning Rate Analysis



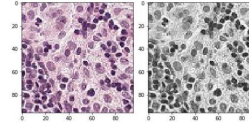
SWATS (Switching from Adams To SGD)

- Improved the performance of our model by switching to SGD after we finished training with Adam

	Previous Model		Hybrid Model	
	True Positive	True Negative	True Positive	True Negative
N = 22,003			N = 22,003	
Predicted Positive	8,489	224	8,580	234
Predicted Negative	473	12,817	382	12,807

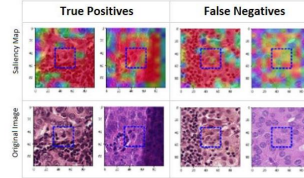
Grey-scale Input

- Explored the possibility of augmenting the data set by converting the training images to grey-scale
- Removes the bias arising due to different staining techniques used at different labs
- Unfortunately, did not generalize better than model based off color input.

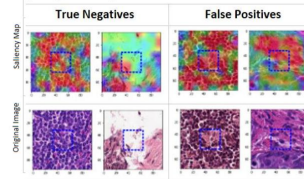


Error Analysis

- Saliency Maps from final convolutional layer with the center 32 x 32 pixels patches highlighted
- Comparing True Positive vs. False Negatives



- Comparing True Negatives vs. False Positives



RESULTS AND DISCUSSIONS

- Final model (hybrid) achieved an accuracy of 97.2%
- Replacing ReLU with SELUs (scaled exponential linear units) in our model yield negative results
- The optimal learning rate does not need to be a magnitude of 0.1
- A lack of expertise in the subject area made the error analysis especially challenging
- PyTorch is a good framework for beginners

FUTURE WORK

- Use transfer learning from an existing pre-trained model like AlexNet or VGG-16
- Try out other activation functions like Exponential Logical Unit (ELU)
- Progressive re-sizing (start by training the model on the 32 x 32 pixel center of each image and then move to the full image later)
- Apply our pre-trained model to other cancer-related problems using transfer learning (One possible use is for the Camelyon16 tasks of tumor detection and Whole-Slide Imaging diagnosis)

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