Two Goals I wanted to try and Answer this Week:

Krish's Suggestions:

1. If there are images of different sizes in a classification problem, then how are deep learning models trained with them? Is it possible to train a model with data points of different dimensions (i.e., images of different sizes)? Has it been done in any field / medical field / tissue images / cancerous tissue images? If yes, what are the tradeoffs?

Team 2's Suggestions:

2. Our stakeholder last week said that there's a potential to put multiple images together into one rectangular image to solve the larger issue of different input image sizes. I was wondering if you guys can find instances of this in histology papers or if there's another way to deal with these different sizes. Also, given that we only have 1 or 2 sox10 tissues, I wanted to know if there's a way to salvage any information for the other stains like h&e ie. if there are 3 h&e stains for a patient but 1 sox10 and 1 melanA, is there a way to use the other 2 tissues in training without the other stains?

To help narrow down my research, I broke down these objectives into small questions and expanded on them:

- What deep learning models exist that use images of different sizes to train?
    - Can you even train model with different dimensions?
    - Would stitching images together help alleviate any trade-off issues?
    - What do you do with an overrepresentation of a specific training example?
- Where has this been done, specifically in the medical field?

With this more concise and organized approach, here is ongoing literature that I found relevant to the questions posed by various stakeholders. This initial research is not exhaustive nor does it include a perfect answer to every question posed by the stakeholders, but I believe that it sets a good foundation to answer questions and help shape next steps in our projects.

[Training Convolutional Neural Networks with Multi-Size Images and Triplet Loss for Remote Sensing Scene Classification - PMC]

While the exact image extraction seems to be different in comparison to what we are doing in class, I believe that this article is a good resource to understand how to classify different image sizes as they come in. This paper uses neural networks, which was the ultimate model to use in the future as mentioned by Team 2, to classify various photos. Beyond just analyzing certain images and their sizes, another idea that this article bring to me is learning about the different stains. Initial categorization is essential for this study, and I believe with proper classification, even with stains that may be overrepresented in a patient, all samples can be used. One thing we may want to look into for next week is triplet loss and the concept of adaptive pooling to understand multi image sizes. One thing to note from this article is that while the images are different sizes, they are all squares. They are certain feature extraction processes in this article that may be beneficial in being able to deal with multi-size images. Look at sections 2.2.6 and 2.2.7 to see the most important aspect of training these models. While this shows that training a model can happen with varying size images, there is no clear indiciaton possible if this is possible in medical field based on the research shown here.

How to Handle Images of Different Sizes in a Convolutional Neural Network | dl-question-bank – Weights & Biases

While not a necessarily an extremely academic article, I believe that this gives a couple different approaches to how to solve this problem. Usage of the TensorFlow package may be helpful for this (a concept many students are currently learning in STAT 362). There are resizing features that help chang ethe image sizing without losing its quality, an issue that persisted with distortion. There are also cropping functions available in this package, which may be useful if a certain sample contains too much stroma/background. Beyond using CNNs, this article also suggests a set of networks and models to use that immune to the size of the input. With basic coding examples, I think this article is a great platform to see what exists in image manipulation to help deal with varying samples.

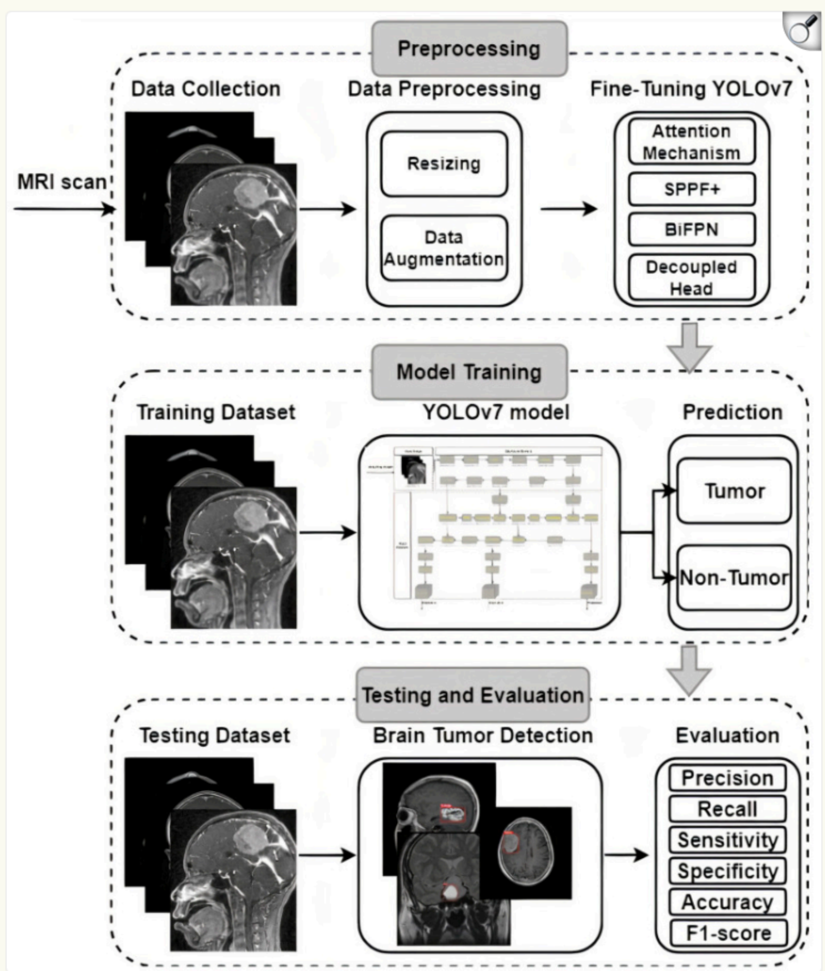
Effects of data count and image scaling on Deep Learning training - PMC

I wanted to look into this article a bit more to understand tradeoffs with image scaling. While the other research provided in this lit review shows what is possible, I want to also acknowledge what may be taken away as a result. What is also nice about this article is that it is specifically medically focuses and shows positives and negatives in the exact context we are working with. Kernel sizes of the CNN may play in an impact in the success of a training algorithm. If you look at the results, it shows how classification accuracy changes based on step-by-step data augmentation changes. One key feature this article focuses on is image interpolation, an aspect we can expand on in next week's literature review.

Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging - PMC

What is beneficial about the study shown here is the varying types of images that exist to study brain tumors. I believe that this diversity in image options can help also give context to Team 2's problem statement in addressing images with multiple stains. Using slices of an MRI scan can match a similar process as slices of one eye tissue. Like many of the other articles, resolution quality and preservation has been a key focus while manipulating images. Some CNN models to look at that seemed helpful in this context: GoogLeNet, InceptionV3, DenseNet201, AlexNet, and ResNet50. Each of these models focused on a different goal to get out of the brain tumor classification and their results were then compared together. Like many articles, and within our own research in class, it is very evident here that image preprocessing and manipulation is much more crucial in the research process than the actual model building itself. The flowchart attached below is a good reference point in deciding how we may want to go about data training. It is evident that preprocessing will be the most important aspect towards correctly classifying images.

Figure 2.



[Overview of multiplex immunohistochemistry/immunofluorescence techniques in the era of cancer immunotherapy - PMC]

I believe that this article is good insight in addressing Team 2's concerns about stains. A lot of the background information and original thought processes in this article match similar to the concerns many students have in class. I would highly suggest looking at Table 1 of the article to get a better understanding of the background and this study's stain collection processes. While this does not focus on an machine learning processes for classification of the tumors, I believe that this is a good article to skim through to consider for image preprocessing techniques beyond model manipulation and other work we have already done in QuPath.