5/28 Presentation

Cross-stain Model Robustness: changing test data

	precision	recall	f1-score
0	0.75	0.87	0.81
1	0.93	0.86	0.89
accuracy			0.86
macro avg	0.84	0.87	0.85
weighted avg	0.87	0.86	0.87
	. 020		(a_0)
	precision	recall	f1-score
	precision	recall	f1-score
0	precision 0.76	recall 0.89	f1-score 0.82
ø 1	•		
	0.76	0.89	0.82
	0.76	0.89	0.82
1	0.76	0.89 0.86	0.82 0.90
1 accuracy	0.76 0.94	0.89 0.86	0.82 0.90 0.87

Initial run

	precision	recall	f1-score
0	0.77	0.83	0.80
1	0.92	0.90	0.91
accuracy			0.88
macro avg	0.85	0.86	0.85
weighted avg	0.88	0.88	0.88

Cross-stain Model Robustness: adding data

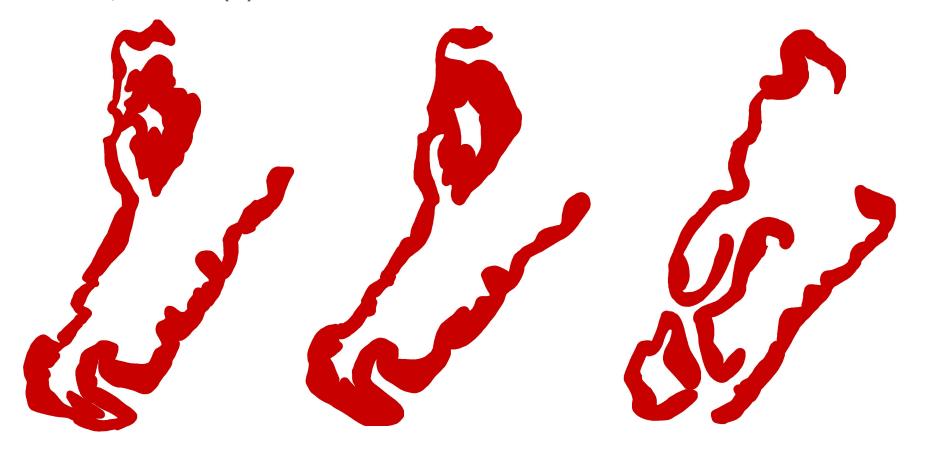
More data

	precision	recall	f1-score
ø	0.69	0.87	0.77
1	0.92	0.80	0.85
accuracy			0.82
macro avg	0.81	0.83	0.81
weighted avg	0.84	0.82	0.83

Initial run

	precision	recall	f1-score
0	0.77	0.83	0.80
1	0.92	0.90	0.91
accuracy			0.88
macro avg	0.85	0.86	0.85
weighted avg	0.88	0.88	0.88

Case 34, match 1 (B)



Final Presentation Workflows

Jeffrey and Harvey

Undersampling

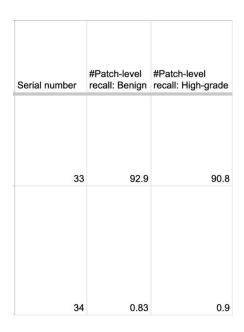
- Undersample for high grade
- Subsample from slides with lots of patches

Promising Models So Far

AlexNet

ResNet with CBAM

CoAtNet



Serial number	#Patch-level recall: Benign	#Patch-level recall: High-grade
27	0.7	0.79

Serial number	#Patch-level recall: Benign	#Patch-level recall: High-grade
16	0.55	0.93

Resizing Workflow

- 1. Determine the best model for each stain type
 - a. We test
 - i. 3 most promising models per stain
 - ii. Also resizing and pooling per stain
 - b. 18 models total
- 2. Find the best-performing model for each stain and ensemble them
 - a. Find best performing patch level model
 - b. Patch level recall: High Grade and Benign

Ensemble Workflow

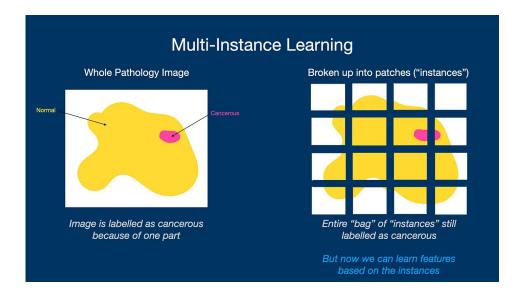
- 1. Pick best past models for each stain; ensemble these
 - a. The ensemble splits all cases into test, train, and validation sets
 - b. Each stain will get predicted by the best previously trained model per stain
 - c. A majority vote is used to determine the case level prediction
- 2. Attempt to use Akhil's SVM Case Level Classifier
 - a. Select top K confident predictions across all stains
 - b. Select top K/3 confident predictions per stain
 - c. Select most confident predictions per stain proportional to total distribution
 - d. Select top K confident prediction per stain, majority voting across stains
- 3. Compare to human level accuracy and previous results

Multiple Instance Learning

Hannah

What is it? Why use it here?

MIL is a form of supervised learning where the input data is organized into labeled bags containing multiple instances. Instead of each instance being labeled individually, only the bag as a whole has a label.



"Multiple Instance Learning (MIL) is designed to classify instances where class labels are associated with sets of instances, a common occurrence in biomedical data, especially when multiple images are derived from a single object measurement."

Data Representation

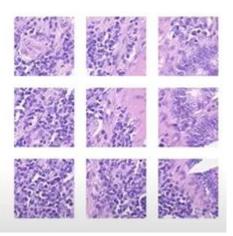
- Instances: These are the individual data points within a bag. For example, in our case, instances would be the patches of the image.
- 2. **Bags:** Each bag is a collection of instances. In our case, the bag is the case and the patches or segments of the image are the instances within that bag.
- Labels: Bags are labeled with a class label (e.g., "high grade" or "benign").

1. Data Preparation:

each case is a bag, and each patch is an instance (bag and instance construction

```
def group_patches_recursive(root_dir):
    case_patches = {}
    for root, _, files in os.walk(root_dir):
        for filename in files:
            match = re.search(r"case_(\d+)", filename)
            if match and filename.endswith(".png"):
                case_num = int(match.group(1))
                 if case_num not in case_patches:
                      case_patches[case_num] = []
                      case_patches[case_num].append(os.path.join(root, filename))
    return case_patches
```

Patches



1. Data Preparation:

- a. It builds a dataset where each item is a case (bag) made up of image patches (instances)
- b. self.bags holds lists of patch image paths, one list per case
- c. self.labels holds the corresponding bag-level (case-level) label.
- d. emergency_cap prevents memory issues by randomly sampling a fixed number of patches (e.g., 800) if a case has too many patches

```
class MILDataset(Dataset):
   def __init__(self, case_patches, labels_df, transform=None, emergency_cap=800):
       self.transform = transform
       self.emergency_cap = emergency_cap # only cap if massive
       self.bags, self.labels = [], []
       for case, paths in case_patches.items():
            raw = labels_df.loc[labels_df['Case'] == case, 'Class'].item()
            bag lbl = 0 if raw == 1 else 1
           self.bags.append(paths)
           self.labels.append(bag lbl)
   def len (self): return len(self.bags)
   def getitem (self, idx):
       paths = self.bags[idx]
       imas = []
       for p in paths:
           try:
               img = Image.open(p).convert('RGB')
               if self.transform:
                   img = self.transform(img)
               imgs.append(img)
           except:
               continue
       if len(imgs) == 0:
            raise ValueError(f"No good patches in case {paths}")
       # Only sample if emergency cap is set
       if self.emergency cap is not None and len(imgs) > self.emergency cap:
            imgs = random.sample(imgs, self.emergency cap)
       return torch.stack(imgs), torch.tensor(self.labels[idx], dtype=torch.long)
```

2. Feature Extraction

- base_model.features:
 Convolutional layers from
 DenseNet extract features
 from each patch
- AdaptiveAvgPool2d((2,2)):
 Each feature map is pooled into a 2×2 grid (4 vectors per patch)
- c. patch_projector: Those 4 vectors are flattened and projected into a shared embedding space of dimension 512 (i.e., your embed_dim)

```
class AttnMIL(nn.Module):
   def __init__(self, base_model, num_classes=2, embed_dim=512):
       super().__init__()
       # grabbing the convolutional feature extractor from the pretrained model
       self.features = base_model.features
       # applying adaptive average pooling to compress to feature map of 2x2 grid
       # you get 4 spatial vectors per patch
       self.pool = nn.AdaptiveAvgPool2d((2,2)) # richer than (1,1)
       # meaning that you'll get 4 vectors per patch which will then be flattened
       self.patch projector = nn.Linear(base model.classifier.in features * 4, embed dim)
       self.attention_pool = AttentionPool(embed_dim)
       self.classifier = nn.Linear(embed_dim, num_classes)
    def forward(self, x, return_patch_logits=False, return_attn_weights=False):
       if x.dim() == 4:
           x = x.unsqueeze(0)
       # typically after CNN you get 3D tensor with num channels, height and width of image
       # but we packed the patches into a bag by case (the tensor), so B is batch size, M is number of patches per bag
       B, M, C, H, W = x.shape
       x = x.view(B*M, C, H, W)
       features = self.features(x) # exxtracting cnn features for each patch
       pooled = self.pool(features).view(B*M, -1) # pool each feature map to a 2x2 grid and flatten
       embedded = self.patch_projector(pooled).view(B, M, -1) # project each patch into shared embedding space --
       # just ensuring all the patches are transformed into vectors of the same length for attention
       # in order to get patch level predictions
       if return_patch_logits:
           logits = self.classifier(embedded) # (B, M, 2)
           return logits
       # returning attention weights for visualization
       if return_attn_weights:
           bag_emb, attn_weights = self.attention_pool(embedded, return_weights=True)
           logits = self.classifier(bag_emb)
           return logits, attn weights # bag prediction + per-patch attention scores
       # applying attention
                                     ddings using attention, and then is passed through the classifier to get bag level prediction
       bag_emb = self (variable) classifier: Any
       logits = self.classifier(bag_emb)
        return logits
```

3. Attention pooling

- a. Learns importance weights for each patch
- b. Applies softmax to normalize across patches
- Uses weighted average to get a single bag embedding
- d. Outputs interpretable attention scores per patch

```
# this pools the patch level features into single bag level representation for MIL
class AttentionPool(nn.Module):
    def __init__(self, input_dim, hidden_dim=128):
        super().__init__()
       # creates small neural network to compute attention scores for each patch
       # each patch embedding is passed through a linear layer, tanh for nonlinearity, and another linear layer to get a scalar score
        self.attention = nn.Sequential(
           nn.Linear(input_dim, hidden_dim),
           nn.Tanh(),
           nn.Linear(hidden_dim, 1)
    def forward(self, x, return_weights=False):
       # x is of shape (B, M, D) where B is batch size or number of cases,
       # M is number of patches per bag, and D is the embedding dimensions for each patch
       weights = self.attention(x) # (B, M, 1)
       weights = torch.softmax(weights, dim=1)
       # outputs attention scores for each patch and normalized with softmax
       # D is the embedding dimension which is size of feature vector for each patch after going through the patch classifier
       weighted x = (weights * x).sum(dim=1) # (B, D)
       # returning the raw attention weights per patch just to help with visualization of the weights for each patch
        if return_weights:
            return weighted_x, weights.squeeze(-1) # (B, D), (B, M)
        return weighted_x
```

$$ext{Bag embedding} = \sum_{i=1}^5 lpha_i \cdot \mathbf{x}_i$$

where:

- \mathbf{x}_i is the feature vector for the i-th patch
- α_i is the attention weight for the *i*-th patch (from softmax)
- $\sum \alpha_i = 1$

Next steps: Grouping by Slice instead of Case

- 1. Treat each slice as a bag during MIL
 - a. I.e. case_9_unmatched_1 is one bag, case_9_unmatched_2 is another
- 2. Use MIL as usual: attention to get slice-level prediction
- 3. Aggregate slice predictions into case level prediction
 - a. Average slice softmax probabilities
 - b. Max probability for high-grade
 - c. Majority vote over slices