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

	precision	recall	f1-score
0	0.76	0.89	0.82
1	0.94	0.86	0.90
accuracy			0.87
macro avg	0.85	0.88	0.86
weighted avg	0.88	0.87	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

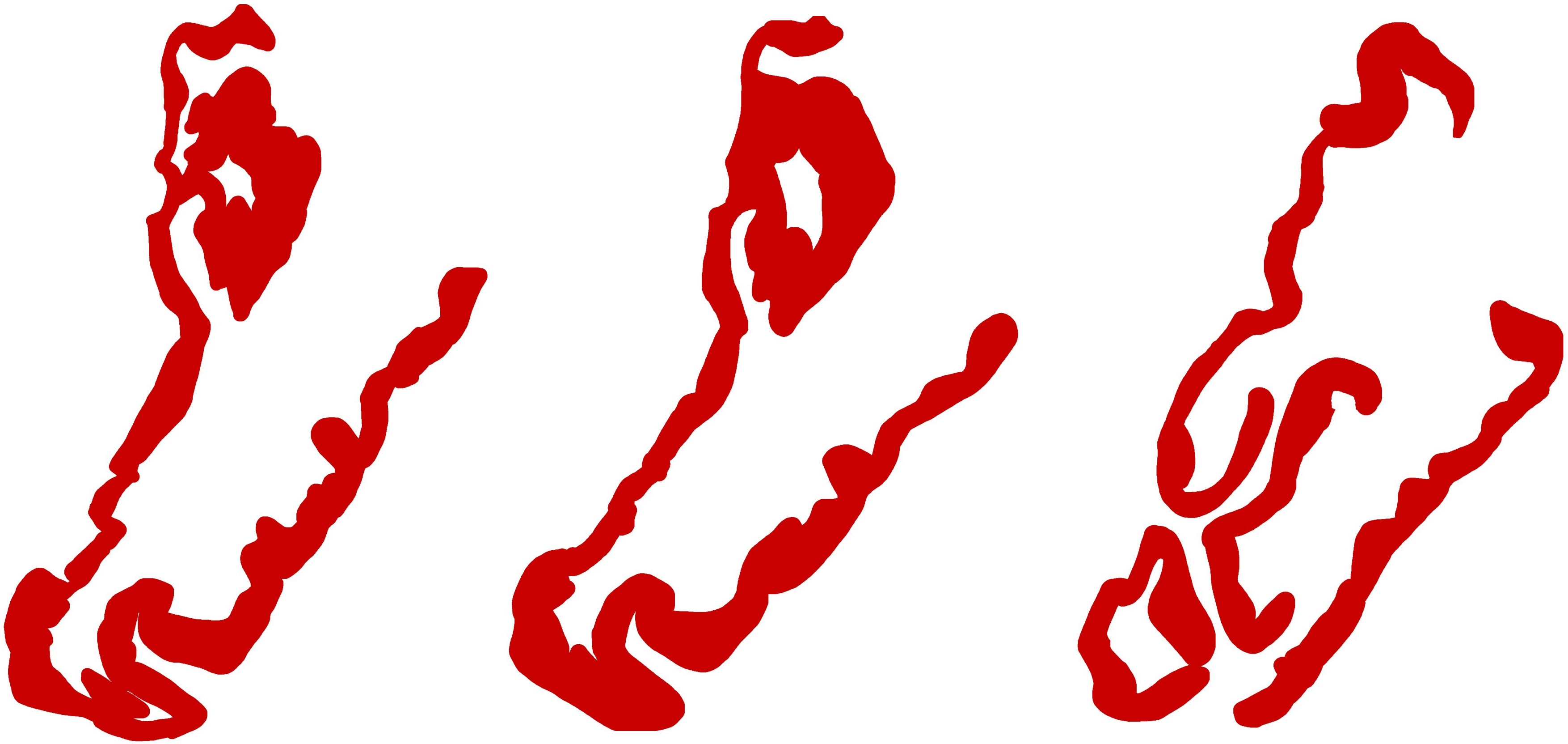
More data

	precision	recall	f1-score
0	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

Serial number	#Patch-level recall: Benign	#Patch-level recall: High-grade
33	92.9	90.8
34	0.83	0.9

ResNet with CBAM

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

CoAtNet

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

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
3. Compare to human level accuracy and previous results

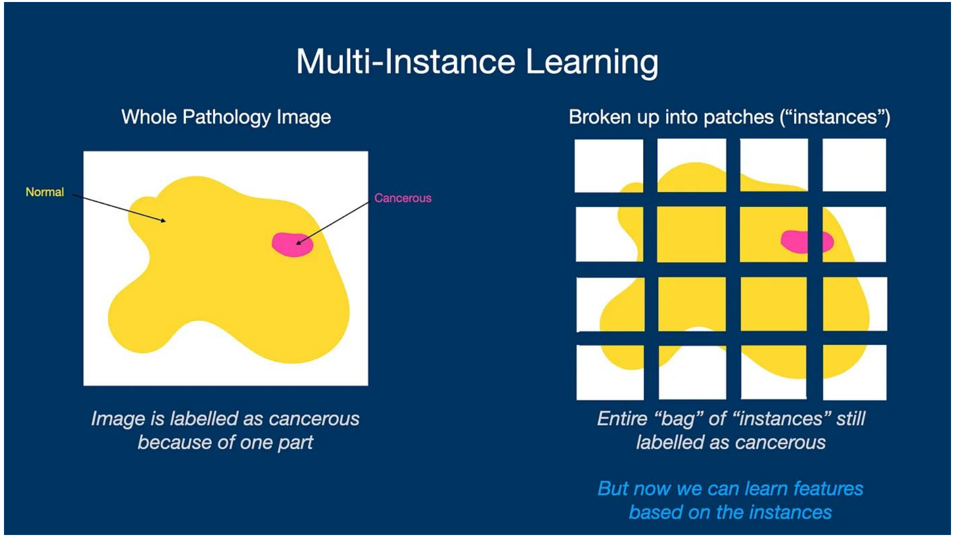
Multiple Instance Learning

Hannah

https://www.sciencedirect.com/science/article/abs/pii/S1746809423013071
https://medium.com/@gulernilay088/multi-instance-learning-a-gentle-introduction-and-practical-guide-23b8b9be46f2

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

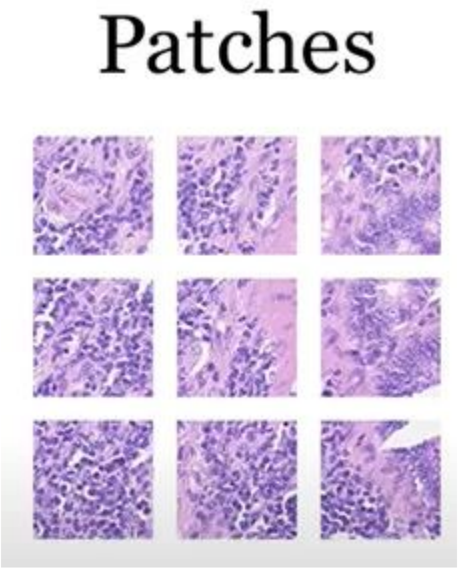
1. **Instances**: These are the individual data points within a bag. For example, in our case, instances would be the patches of the image.
2. **Bags:** Each bag is a collection of instances. In our case, the bag is the case and the patches or segments of the image are the instances within that bag.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

Application Process

1. Data Preparation:
    a. 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 = group_patches_recursive(filtered_patches_dir)
```



Application Process

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

```python
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]
        imgs = []
        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)
```

Application Process

2. Feature Extraction

a. base_model.features: Convolutional layers from DenseNet extract features from each patch

b. 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)

```python
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
        #computing a w (variable) classifier: Any eddings using attention, and then is passed through the classifier to get bag level prediction
        bag_emb = self
        logits = self.classifier(bag_emb)
        return logits
```

Application Process

3. Attention pooling

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

```python
# 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
```

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

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