HuBMAP + HPA - Hacking the Human Body Competition Progress Report 6

Presentation of a Report By

Group C



Overview

Changing the Model Backbone:

1. ResNext50 to EfficientNet b5

Ensemble Learning:

1. Combining the Predicted Results Of UNEXT50 And EfficientUNet

Dataset Preprocessing:

1. Balanced tile sampling for training (EDIT: masked area is balanced)

Future Plan:

1. Continue to improve the Ensembled Model



Part 1: Changing the Model Backbone

```
class EffUnet(nn.Module):
    def __init__(self. model_name. stride=1):
        super().__init__()
       cfg = efficient_net_encoders[model_name]
       stage_idxs = cfg['stage_idxs']
       out_channels = cfg['out_channels']
       self.encoder = EfficientNetEncoder(stage_idxs, out_channels, model_name)
       #aspp with customized dilatations
       self.aspp = ASPP(out_channels[-1], 256, out_c=384
                        dilations=[stride*1, stride*2, stride*3, stride*4])
       self.drop_aspp = nn.Dropout2d(0.5)
       #decoder
       self.dec4 = UnetBlock(384, out_channels[-2], 256)
       self.dec3 = UnetBlock(256, out_channels[-3], 128)
       self.dec2 = UnetBlock(128, out_channels[-4], 64)
       self.dec1 = UnetBlock(64, out_channels[-5], 32)
       self.fpn = FPN([384, 256, 128, 64], [16]*4)
       self.drop = nn.Dropout2d(0.1)
       self.final_conv = ConvLayer(32+16*4, 1, ks=1, norm_type=None, act_cls=None)
    def forward(self, x):
       enc0, enc1, enc2, enc3, enc4 = self.encoder(x)[-5:]
       enc5 = self.aspp(enc4)
       dec3 = self.dec4(self.drop_aspp(enc5), enc3)
       dec2 = self.dec3(dec3,enc2)
       dec1 = self.dec2(dec2.enc1)
       dec0 = self.dec1(dec1,enc0)
       x = self.fpn([enc5, dec3, dec2, dec1], dec0)
       x = self.final_conv(self.drop(x))
       x = F.interpolate(x,scale_factor=2,mode='bilinear')
       return x
```

Inference Trick:

1. Expansion Tile

Data Augmentation Strategy:

1. The Same As UNEXT50

[Inference]-HuBMAP fast.ai starter (EfficientNet) (version 1/16) 4 days ago by Juntuo Wang	Succeeded	0.68	
Notebook [Inference]-HuBMAP fast.ai starter (EfficientNet) Version 1			
[Inference] - FastAl Baseline (version 13/20)	Succeeded	0.66	
9 days ago by Juntuo Wang			
Notebook [Inference] - FastAl Baseline Version 13			

Part 1: Changing the Model Backbone

```
class EffUnet(nn.Module):
    def __init__(self. model_name. stride=1):
        super().__init__()
       cfg = efficient_net_encoders[model_name]
       stage_idxs = cfg['stage_idxs']
       out_channels = cfg['out_channels']
       self.encoder = EfficientNetEncoder(stage_idxs, out_channels, model_name)
       #aspp with customized dilatations
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       self.fpn = FPN([384, 256, 128, 64], [16]*4)
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    def forward(self, x):
       enc0, enc1, enc2, enc3, enc4 = self.encoder(x)[-5:]
       enc5 = self.aspp(enc4)
       dec3 = self.dec4(self.drop_aspp(enc5), enc3)
       dec2 = self.dec3(dec3,enc2)
       dec1 = self.dec2(dec2.enc1)
       dec0 = self.dec1(dec1,enc0)
       x = self.fpn([enc5, dec3, dec2, dec1], dec0)
       x = self.final_conv(self.drop(x))
       x = F.interpolate(x,scale_factor=2,mode='bilinear')
       return x
```

Pretrain The Model On Similar Dataset:

1. Hacking The Kdiney

[Inference]-HuBMAP fast.ai starter (EfficientNet) (version 1/16) 4 days ago by Juntuo Wang Notebook [Inference]-HuBMAP fast.ai starter (EfficientNet) Version	Succeeded	0.68	
1 [Inference]-HuBMAP fast.ai starter (EfficientNet)	Succeeded	0.62	
(version 8/16) 2 days ago by Juntuo Wang			
Notebook [Inference]-HuBMAP fast.ai starter (EfficientNet) Version 8			

Need Further Exporetion In The Future:

Part 2: Ensemble Learning

```
models = []
for path in MODELS:
    state_dict = torch.load(path,map_location=torch.device('cpu'))
    model = EffUnet('efficientnet-b5')
    model.load_state_dict(state_dict)
    model.float()
    model.eval()
    model.to(device)
    models.append(model)
for path in MODELS1:
    state_dict = torch.load(path,map_location=torch.device('cpu'))
    model = UneXt50()
    model.load_state_dict(state_dict)
    model.float()
    model.eval()
    model.to(device)
    models.append(model)
del state dict
```

Combine The Results Of Different Model:

1. Combining the Predicted Results Of UNEXT50 And

EfficientUNet			
[Inference]-HuBMAP fast.ai starter (EfficientNet) (version 1/16) 4 days ago by Juntuo Wang	Succeeded	0.68	
Notebook [Inference]-HuBMAP fast.ai starter (EfficientNet) Version 1			
[Inference]-HuBMAP fast.ai starter (EfficientNet) (version 20/20)	Succeeded	0.70	
19 hours ago by Juntuo Wang			
Notebook [Inference]-HuBMAP fast.ai starter (EfficientNet) Version 20			

Part 3: Dataset Preprocessing

The Problem Of The Dataset:

Large empty spaces in labeled areas

Posted in hubmap-organ-segmentation 21 days ago



In preprocessing the data I noticed that there are often large empty spaces labeled as foreground. They happen most often in prostate, lung images and sometimes in intestine as well.

In my own preprocessing I am trying to discard those labels at empty pixel locations (colored blue) since they probably will confuse the model. But I am not sure if this would be the best strategy for doing inference on test data.

Has anyone tried any strategy for these "empty" labels?

Question about tiles

Posted in hubmap-organ-segmentation 10 days ago



Thanks for this https://www.kaggle.com/code/thedevastator/converting-to-256×256, I learned the way that a large medical image can be divided into small tiles.

This approach works well in some other competitions, but it doesn't work for me in this competitions.

I did spilt the large image into tiles and use them to train, but this way lead my model a negative effect, which is worse than I remain the large image.

I don't know if any one else has the same situation as me. Any advice is greatly appreciated.

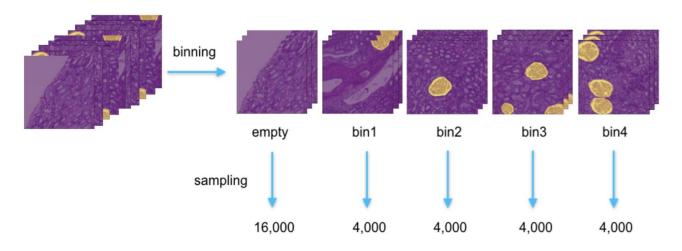
Data Imbalance:

There is an imbalance in the number of Empty tiles and Mask tiles

Part 3: Dataset Preprocessing (Further Improvment)

Possible Solution:

Balanced tile sampling for training (masked area is balanced)



Processing:

- Sample tiles from these masked and unmasked data equally
- Sample tiles from these tiles have very small masked area,
- tiles have small masked area,
 - tiles have some masked area,
- tiles have large masked area equally

Part 3: Dataset Preprocessing (Further Improvement)

The Problem Of The Dataset:

An overview: Stain Normalization Techniques Posted in hubmap-organ-segmentation 4 days ago Biology Adversarial Learning Deep Learning We might have noticed that there are not only texture differences but also color differences due to

1500

different stain protocols in the train and test set. So, I wanted to create this post to have an

overview of varying normalization techniques for histopathological images.

0 train 0 test 500 - 1000 - 1500 - 10

1500

2500

1000

2000

Color Differences:

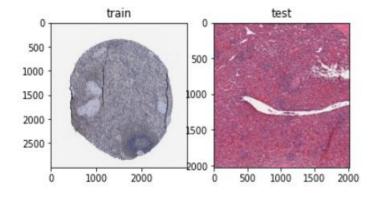
Color differences due to different stain

protocols in the train and test set

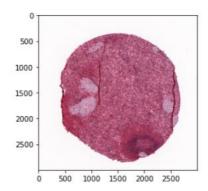
Part 3: Dataset Preprocessing (Further Improvement)

- Possible Solution
- Stain Normalization

Before



After



Part 4: Future Plan

Try to implement the Preprocessing Introduced In Part 3

Continue to Improve the Ensemble Model