Untitled

April 3, 2022

[65]:
```python
import torch
import torchvision
import torchvision.transforms as transforms
import torchvision.models as models
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import time as ti
from itertools import count
import natsort
import datetime
import numpy as np
import os
import math
```

[2]:
```python
from torch.utils.data import Dataset, DataLoader, WeightedRandomSampler
import albumentations as A
from albumentations.pytorch import ToTensorV2
import cv2
import glob
import numpy
import random
import pandas as pd
import tqdm
torch.manual_seed(10)
```

[2]: <torch._C.Generator at 0x7f0cd009b5b0>

[3]:
```python
print(f"Is CUDA supported by this system? {torch.cuda.is_available()}")
print(f"CUDA version: {torch.version.cuda}")
# Storing ID of current CUDA device
cuda_id = torch.cuda.current_device()
print(f"ID of current CUDA device: {torch.cuda.current_device()}")
print(f"Name of current CUDA device: {torch.cuda.get_device_name(cuda_id)}")

device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
print(device)
```

```
Is CUDA supported by this system? True
CUDA version: 11.3
ID of current CUDA device: 0
Name of current CUDA device: NVIDIA A100-SXM4-40GB
cuda:0
```

[4]:
```python
class SurgicalDataset(Dataset):
    def __init__(self, image_paths, labels, transform=False):
        super(SurgicalDataset, self).__init__()
        self.image_paths = image_paths
        self.labels = labels    #.astype(dtype='int')
        self.transform = transform

    def __len__(self):
        return len(self.image_paths)

    def __getitem__(self, idx):
        image_filepath = self.image_paths[idx]
        image = cv2.imread(image_filepath)
        label = self.labels[idx]
        if self.transform is not None:
            image = self.transform(image=image)["image"]

        return image, label
```

[5]:
```python
def get_transform(model_name):

    if model_name == 'alexnet':
        transform = A.Compose([
            A.Resize(227, 227),
            A.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
            ToTensorV2(),
        ])

    elif model_name == 'effinet':
        transform = A.Compose([
            A.Resize(224, 224),
            A.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
            ToTensorV2(),
        ])

    else:

        transform = A.Compose([
            A.Resize(224,224),
            A.Normalize((0.5,0.5,0.5),(0.5,0.5,0.5)),
            ToTensorV2(),
```

```
        ])

    return transform
```

[6]:
```
train_image_paths = []
for i in range(1,71):
    filename = '/home/zo2151/assignments/Data/Video%i'%(i,)
    train_image_paths.append(glob.glob(filename + '/*'))
train_image_paths1 = [item for sublist in train_image_paths for item in sublist]
train_image_paths1 = natsort.natsorted(train_image_paths1)
```

[7]:
```
df = pd.read_csv("/home/zo2151/Processed_data.csv")
df1 = df.loc[:,"Phases"].to_numpy()
df2 = df1.tolist()
percentile_list = pd.DataFrame(
    {'Link': train_image_paths1,
     'Label': df2,
    })
```

[9]:
```
percentile_list1 = percentile_list.sample(frac=1, random_state=1)
train_image_paths = percentile_list1.loc[:,"Link"].to_numpy().tolist()
labels = percentile_list1.loc[:,"Label"].to_numpy().tolist()
train_image_paths, valid_image_paths = train_image_paths[:int(0.
 ↪8*len(train_image_paths))], train_image_paths[int(0.
 ↪8*len(train_image_paths)):]
train_labels, valid_labels = labels[:int(0.8*len(labels))], labels[int(0.
 ↪8*len(labels)):]
```

[10]:
```
summary = {i:0 for i in range(14)}
num_classes = 14
total_samples = 0
for i in train_labels:
    total_samples += 1
    summary[i] += 1

class_weights = [total_samples/summary[i] for i in range(num_classes)]
weights = [class_weights[train_labels[i]] for i in range(total_samples)]
sampler = WeightedRandomSampler(torch.DoubleTensor(weights), len(weights))
```

[11]:
```
class Classifier():

    def __init__(self, name, model, dataloaders, parameter, use_cuda=False):

        '''
        @name: Experiment name. Will define stored results etc.
        @model: Any models
```

```
        @dataloaders: Dictionary with keys train, val and test and␣
↪corresponding dataloaders
        @class_names: list of classes, where the idx of class name corresponds␣
↪to the label used for it in the data
        @use_cuda: whether or not to use cuda
        '''

        self.name = name
        if use_cuda and not torch.cuda.is_available():
            raise Exception("Asked for CUDA but GPU not found")

        self.use_cuda = use_cuda
        self.epoch = parameter['epochs']
        self.lr = parameter['lr']
        self.batch_size = parameter['batch_size']

        self.model = model.to('cuda' if use_cuda else 'cpu') # model.to('cpu')
        self.criterion = nn.CrossEntropyLoss()
        self.optimizer = optim.Adam(self.model.parameters(), lr=self.lr)
        self.train_loader, self.valid_loader = self.
↪get_dataloaders(dataloaders['train_image_paths'],
                                                                                ␣
↪dataloaders['train_labels'],
                                                                                ␣
↪dataloaders['valid_image_paths'],
                                                                                ␣
↪dataloaders['valid_labels'],
                                                                                ␣
↪train_transforms=dataloaders['transforms'],
                                                                                 batch_size␣
↪= self.batch_size,
                                                                                ␣
↪shuffle=parameter['shuffle'],
                                                                                sampler =␣
↪dataloaders['sampler'])
        self.class_names = parameter['class_names']

        self.activations_path = os.path.join('activations', self.name)
        self.kernel_path = os.path.join('kernel_viz', self.name)
        save_path = "/home/zo2151/"
        if not os.path.exists(save_path):
            os.makedirs(save_path)

        if not os.path.exists(self.activations_path):
            os.makedirs(self.activations_path)
```

```
        if not os.path.exists(self.kernel_path):
            os.makedirs(self.kernel_path)

        self.save_path = save_path

    def train(self, save=True):
        '''
        @epochs: number of epochs to train
        @save: whether or not to save the checkpoints
        '''
        best_val_accuracy = - math.inf

        for epoch in range(self.epoch):  # loop over the dataset multiple times
            self.model.train()
            t = time.time()
            running_loss = 0.0
            train_acc = 0
            val_accuracy = 0
            correct = 0
            total = 0
            count = 0
            loop = tqdm.tqdm(self.train_loader, total = len(self.train_loader),␣
↪leave = True)

            for img, label in loop:
                # get the inputs; data is a list of [inputs, labels]
                inputs, labels = img.to(device), label.to(device) #img.
↪to(device), label.to(device)

                # zero the parameter gradients
                self.optimizer.zero_grad()

                # forward + backward + optimize
                outputs = self.model(inputs)
                _, predictions = torch.max(outputs, 1)
                loss = self.criterion(outputs, labels)
                loss.backward()
                self.optimizer.step()

                # print statistics
                running_loss += loss.item()
                total += labels.shape[0]
                correct += (predictions == labels).sum().item()

                count += 1
                if count % 2000 == 1999:    # print every 2000 mini-batches
```

```
                print(f'[{epoch + 1}, {count + 1:5d}] loss: {running_loss /␣
↪2000:.3f}')
                running_loss = 0.0

        train_acc = 100 * correct / total
        print(f'Epoch:', epoch + 1, f'Training Epoch Accuracy:{train_acc}')

        # evaluate the validation dataset
        self.model.eval()
        correct_pred = {classname: 0 for classname in self.class_names}
        total_pred = {classname: 0 for classname in self.class_names}

        # again no gradients needed
        correct = 0
        total = 0
        with torch.no_grad():
            for data in self.valid_loader:
                images, labels = data[0].to(device), data[1].to(device)␣
↪#data[0], data[1]
                outputs = self.model(images)
                _, predictions = torch.max(outputs, 1)
                # collect the correct predictions for each class
                total += labels.shape[0]
                correct += (predictions == labels).sum().item()

                for label, prediction in zip(labels, predictions):
                    if label == prediction:
                        correct_pred[classes[label]] += 1
                    total_pred[classes[label]] += 1

        val_accuracy = 100 * correct / total
        print(f'Epoch:', epoch + 1, f'Validation Epoch Accuracy:
↪{val_accuracy}')

        # print the summary for each class
        print('Epoch:', epoch + 1, 'Correct predictions', correct_pred)
        print('Epoch:', epoch + 1, 'Total predictions', total_pred)
        print('Epoch:', epoch + 1, 'Correct predictions', correct_pred)
        print('Epoch:', epoch + 1, 'Total predictions', total_pred)

        # inspect the time taken to train one epoch
        d = time.time()-t
        print('Fininsh Trainig Epoch', epoch, '!', 'Time used:', d)

        if save:
            torch.save(self.model.state_dict(), os.path.join(self.
↪save_path, "model4.pt"))
```

```
            if val_accuracy > best_val_accuracy:
                torch.save(self.model.state_dict(), os.path.join(self.
↪save_path, 'best.pt'))
                best_val_accuracy = val_accuracy

        print('Done training!')


    def evaluate(self):
        # for evaluating the test dataset if there were any.
        try:
            assert os.path.exists(os.path.join(self.save_path, 'best.pt'))

        except:
            print('Please train first')
            return

        self.model.load_state_dict(torch.load(os.path.join(self.save_path,␣
↪'best.pt')))
        self.model.eval()

    def get_dataloaders(self, train_image_paths, train_labels,␣
↪valid_image_paths, valid_labels, train_transforms=False, batch_size=32,␣
↪shuffle=True, sampler = None):
        train_dataset = SurgicalDataset(train_image_paths,train_labels,␣
↪train_transforms)
        val_dataset = SurgicalDataset(valid_image_paths,valid_labels,␣
↪train_transforms)
        train_loader = DataLoader(train_dataset, batch_size, shuffle, sampler)
        valid_loader = DataLoader(val_dataset, batch_size, shuffle = True)
        return train_loader, valid_loader

    def grad_cam_on_input(self, img):

        try:
            assert os.path.exists(os.path.join(self.save_path, 'best.pt'))

        except:
            print('It appears you are testing the model without training.␣
↪Please train first')
            return

        self.model.load_state_dict(torch.load(os.path.join(self.save_path,␣
↪'best.pt')))
```

```
        self.model.eval()
        img = img.to('cuda' if self.use_cuda else 'cpu')


        out = self.model(img)

        _, pred = torch.max(out, 1)

        predicted_class = self.class_names[int(pred)]
        print(f'Predicted class was {predicted_class}')

        out[:, pred].backward()
        gradients = self.model.get_gradient_activations()

        print('Gradients shape: ', f'{gradients.shape}')

        mean_gradients = torch.mean(gradients, [0, 2, 3]).cpu()
        activations = self.model.get_final_conv_layer(img).detach().cpu()

        print('Activations shape: ', f'{activations.shape}')

        for idx in range(activations.shape[1]):
            activations[:, idx, :, :] *= mean_gradients[idx]

        final_heatmap = np.maximum(torch.mean(activations, dim=1).squeeze(), 0)

        final_heatmap /= torch.max(final_heatmap)

        return final_heatmap

    def trained_kernel_viz(self):

        all_layers = [0, 3]
        all_filters = []
        for layer in all_layers:

            filters = self.model.conv_model[layer].weight
            all_filters.append(filters.detach().cpu().clone()[:8, :8, :, :])

        for filter_idx in range(len(all_filters)):

            filter = all_filters[filter_idx]
            print(filter.shape)
            filter = filter.contiguous().view(-1, 1, filter.shape[2], filter.
↪shape[3])
            image = show_img(make_grid(filter))
            image = 255 * image
```

```python
            cv2.imwrite(os.path.join(self.kernel_path,␣
↪f'filter_layer{all_layers[filter_idx]}.jpg'), image)


    def activations_on_input(self, img):

        img = img.to('cuda' if self.use_cuda else 'cpu')

        all_layers = [0,3,6,8,10]
        all_viz = []

        # looking at the outputs of the relu
        for each in all_layers:

            current_model = self.model.conv_model[:each+1]
            current_out = current_model(img)
            all_viz.append(current_out.detach().cpu().clone()[:, :64, :, :])

        for viz_idx in range(len(all_viz)):

            viz = all_viz[viz_idx]
            viz = viz.view(-1, 1, viz.shape[2], viz.shape[3])
            image = show_img(make_grid(viz))
            image = 255 * image
            cv2.imwrite(os.path.join(self.activations_path,␣
↪f'sample_layer{all_layers[viz_idx]}.jpg'), image)
```

[13]:
```python
import ssl

ssl._create_default_https_context = ssl._create_unverified_context
example_model = models.efficientnet_b7(pretrained=True)
```

```
Downloading: "https://download.pytorch.org/models/efficientnet_b7_lukemelas-
dcc49843.pth" to
/home/zo2151/.cache/torch/hub/checkpoints/efficientnet_b7_lukemelas-dcc49843.pth

  0%|          | 0.00/255M [00:00<?, ?B/s]
```

[14]:
```python
class TransferEffiNet(nn.Module):
    def __init__(self):
        super().__init__()
        self.base_effi_net = models.efficientnet_b7(pretrained=True)
        self.conv_model = self.get_conv_layers()
        self.avg_pool = self.transition_layer()
        self.fc_model = self.get_fc_layers()
        self.activate_training_layers()
```

```
    def activate_training_layers(self):
        for name, param in self.conv_model.named_parameters():
            number = int(name.split('.')[1])
            # for all layers except the last conv layer, set param.
↪requires_grad = False
            if number == 8:
                param.requires_grad = True
            else:
                param.requires_grad = False

        for name, param in self.fc_model.named_parameters():
            # for all of these layers set param.requires_grad as True
            param.requires_grad = True

    def get_conv_layers(self):
        return self.base_effi_net.features

    def transition_layer(self):
        return self.base_effi_net.avgpool

    def get_fc_layers(self):
        return nn.Sequential(
            nn.Dropout(p=0.5, inplace=False),
            nn.Linear(in_features=2560, out_features=1024, bias=True),
            nn.ReLU(inplace=True),
            nn.Dropout(p=0.5, inplace=False),
            nn.Linear(in_features=1024, out_features=512, bias=True),
            nn.ReLU(inplace=True),
            nn.Linear(in_features=512, out_features=14, bias=True),
        )

    def forward(self, x):
        x = self.conv_model(x)   #call the conv layers
        x = self.avg_pool(x)  #call the avg pool layer
        x = torch.flatten(x, 1)
        x = self.fc_model(x)  #call fully connected layers

        return x
```

[15]:
```
name = 'TransferEffiNet'
classes = [i for i in range(14)]
transforms = get_transform('effinet')
dataloaders = {'train_image_paths': train_image_paths, 'train_labels' :␣
↪train_labels, 'valid_image_paths': valid_image_paths, 'valid_labels':
↪valid_labels, 'transforms':transforms, 'sampler':sampler}
parameters = {'lr': 0.001, 'epochs' : 5, 'batch_size':32, 'shuffle':False,␣
↪'class_names':classes}
```

```python
model = TransferEffiNet()
classifier = Classifier(name, model, dataloaders, parameters, use_cuda=True)
classifier.train()
```

```
 37%|                                                   |
1999/5377 [10:36<17:27,  3.22it/s]

[1,  2000] loss: 0.621

 74%|                                        |
3999/5377 [20:54<07:03,  3.25it/s]

[1,  4000] loss: 0.412

100%|                                 |
5377/5377 [27:58<00:00,  3.20it/s]

Epoch: 1 Training Epoch Accuracy:83.91176727019094
Epoch: 1 Validation Epoch Accuracy:85.82488607830373
Epoch: 1 Correct predictions {0: 51, 1: 18, 2: 561, 3: 5191, 4: 195, 5: 283, 6:
9109, 7: 2103, 8: 2534, 9: 5339, 10: 244, 11: 8905, 12: 392, 13: 1990}
Epoch: 1 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Epoch: 1 Correct predictions {0: 51, 1: 18, 2: 561, 3: 5191, 4: 195, 5: 283, 6:
9109, 7: 2103, 8: 2534, 9: 5339, 10: 244, 11: 8905, 12: 392, 13: 1990}
Epoch: 1 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Fininsh Trainig Epoch 0 ! Time used: 2064.4031040668488

 37%|                                                   |
1999/5377 [10:12<17:08,  3.28it/s]

[2,  2000] loss: 0.312

 74%|                                        |
3999/5377 [20:23<06:59,  3.28it/s]

[2,  4000] loss: 0.290

100%|                                 |
5377/5377 [27:23<00:00,  3.27it/s]

Epoch: 2 Training Epoch Accuracy:90.37867999651255
Epoch: 2 Validation Epoch Accuracy:91.16060634241607
Epoch: 2 Correct predictions {0: 51, 1: 17, 2: 563, 3: 5073, 4: 190, 5: 283, 6:
10310, 7: 2116, 8: 2533, 9: 5361, 10: 247, 11: 9797, 12: 401, 13: 2268}
Epoch: 2 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Epoch: 2 Correct predictions {0: 51, 1: 17, 2: 563, 3: 5073, 4: 190, 5: 283, 6:
10310, 7: 2116, 8: 2533, 9: 5361, 10: 247, 11: 9797, 12: 401, 13: 2268}
Epoch: 2 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
```

```
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Fininsh Trainig Epoch 1 ! Time used: 2006.2973544597626

 37%|                                                           |
1999/5377 [10:13<23:57,  2.35it/s]

[3,  2000] loss: 0.261

 74%|                                               |
3999/5377 [23:39<09:18,  2.47it/s]

[3,  4000] loss: 0.241

100%|                                      |
5377/5377 [31:49<00:00,  2.82it/s]

Epoch: 3 Training Epoch Accuracy:91.92420587636956
Epoch: 3 Validation Epoch Accuracy:92.81828326978517
Epoch: 3 Correct predictions {0: 51, 1: 17, 2: 567, 3: 5233, 4: 191, 5: 282, 6:
10696, 7: 2138, 8: 2505, 9: 5458, 10: 245, 11: 9839, 12: 394, 13: 2307}
Epoch: 3 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Epoch: 3 Correct predictions {0: 51, 1: 17, 2: 567, 3: 5233, 4: 191, 5: 282, 6:
10696, 7: 2138, 8: 2505, 9: 5458, 10: 245, 11: 9839, 12: 394, 13: 2307}
Epoch: 3 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Fininsh Trainig Epoch 2 ! Time used: 2272.039259672165

 37%|                                                           |
1999/5377 [10:07<17:12,  3.27it/s]

[4,  2000] loss: 0.220

 74%|                                               |
3999/5377 [20:15<06:56,  3.30it/s]

[4,  4000] loss: 0.213

100%|                                      |
5377/5377 [27:13<00:00,  3.29it/s]

Epoch: 4 Training Epoch Accuracy:93.23316574152112
Epoch: 4 Validation Epoch Accuracy:92.2347251929694
Epoch: 4 Correct predictions {0: 52, 1: 17, 2: 573, 3: 5085, 4: 199, 5: 286, 6:
10481, 7: 2109, 8: 2657, 9: 5668, 10: 246, 11: 9516, 12: 399, 13: 2384}
Epoch: 4 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Epoch: 4 Correct predictions {0: 52, 1: 17, 2: 573, 3: 5085, 4: 199, 5: 286, 6:
10481, 7: 2109, 8: 2657, 9: 5668, 10: 246, 11: 9516, 12: 399, 13: 2384}
Epoch: 4 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Fininsh Trainig Epoch 3 ! Time used: 1996.2453582286835
```

```
 37%|                                                            |
1999/5377 [10:06<16:57,  3.32it/s]

[5,  2000] loss: 0.202

 74%|                                                   |
3999/5377 [20:13<06:57,  3.30it/s]

100%|                                         |
5377/5377 [27:11<00:00,  3.30it/s]

[5,  4000] loss: 0.190

Epoch: 5 Training Epoch Accuracy:93.93937632596123
Epoch: 5 Validation Epoch Accuracy:93.02055240398029
Epoch: 5 Correct predictions {0: 52, 1: 18, 2: 560, 3: 5325, 4: 187, 5: 281, 6:
10528, 7: 2090, 8: 2665, 9: 5674, 10: 246, 11: 9608, 12: 401, 13: 2375}
Epoch: 5 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Epoch: 5 Correct predictions {0: 52, 1: 18, 2: 560, 3: 5325, 4: 187, 5: 281, 6:
10528, 7: 2090, 8: 2665, 9: 5674, 10: 246, 11: 9608, 12: 401, 13: 2375}
Epoch: 5 Total predictions {0: 52, 1: 18, 2: 587, 3: 5470, 4: 213, 5: 288, 6:
11135, 7: 2177, 8: 3001, 9: 5799, 10: 247, 11: 10405, 12: 404, 13: 3216}
Fininsh Trainig Epoch 4 ! Time used: 1995.0119655132294
Done training!
```

[16]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
import time
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
↪classification_report, roc_curve, auc
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
import seaborn as sns
```

[17]:

```
class TransferEffiNet(nn.Module):
    def __init__(self):
        super().__init__()
        self.base_effi_net = models.efficientnet_b7(pretrained=True)
        self.conv_model = self.get_conv_layers()
        self.avg_pool = self.transition_layer()
        self.fc_model = self.get_fc_layers()
        self.activate_training_layers()

    def activate_training_layers(self):
        for name, param in self.conv_model.named_parameters():
            number = int(name.split('.')[1])
```

```
            # for all layers except the last conv layer, set param.
↪requires_grad = False
            if number == 8:
                param.requires_grad = True
            else:
                param.requires_grad = False

        for name, param in self.fc_model.named_parameters():
            # for all of these layers set param.requires_grad as True
            param.requires_grad = True

    def get_conv_layers(self):
        return self.base_effi_net.features

    def transition_layer(self):
        return self.base_effi_net.avgpool

    def get_fc_layers(self):
        return nn.Sequential(
            nn.Dropout(p=0.5, inplace=False),
            nn.Linear(in_features=2560, out_features=1024, bias=True),
            nn.ReLU(inplace=True),
            nn.Dropout(p=0.5, inplace=False),
            nn.Linear(in_features=1024, out_features=512, bias=True),
            nn.ReLU(inplace=True),
            nn.Linear(in_features=512, out_features=14, bias=True),
        )

    def forward(self, x):
        x = self.conv_model(x)   #call the conv layers
        x = self.avg_pool(x)  #call the avg pool layer
        x = torch.flatten(x, 1)
        x = self.fc_model(x)  #call fully connected layers

        return x
```

[19]:
```
def get_pred(model, train_transforms, batch_size, use_cuda=True):
    val_dataset = SurgicalDataset(valid_image_paths, valid_labels,␣
↪train_transforms)
    valid_loader = DataLoader(val_dataset, batch_size, shuffle = False)
    model = model.to('cuda' if use_cuda else 'cpu')
    pr = []
    pred = []
    l = []
    # again no gradients needed
```

```
    t = time.time()
    negative_examples = []
    model.eval()
    with torch.no_grad():
        for data in valid_loader:
            images, labels = data[0].to(device), data[1].to(device)
            l.append(labels)
            outputs = model(images)
            _, predictions = torch.max(outputs, 1)
            m = F.softmax(outputs, dim=1)
            # collect the correct predictions for each class
            for label, prediction in zip(labels, predictions):
                pred.append(prediction)
            for p in m:
                pr.append(p)

    processtime = time.time()-t
    print('processtime', processtime)
    return l, pred, pr, processtime
```

[20]:
```
classes = ['adhesiolysis', 'blurry', 'catheter insertion', 'mesh placement',␣
 ↪'mesh positioning', 'out of body', 'peritoneal closure', 'peritoneal␣
 ↪scoring',
           'positioning suture', 'preperioneal dissection', 'primary hernia␣
 ↪repair', 'reduction of hernia', 'stationary idle', 'transitionary idle']
save_path = os.path.join(os.getcwd(), 'models', 'TransferEffiNet')
best_effi = TransferEffiNet()
best_effi.load_state_dict(torch.load(os.path.join(save_path, 'best.pt')))
transforms = get_transform('effinet')
batch_size = 32
y_test_true, y_test_predicted, pr, time = get_pred(best_effi, transforms,␣
 ↪batch_size)
```

```
processtime 330.7153015136719
```

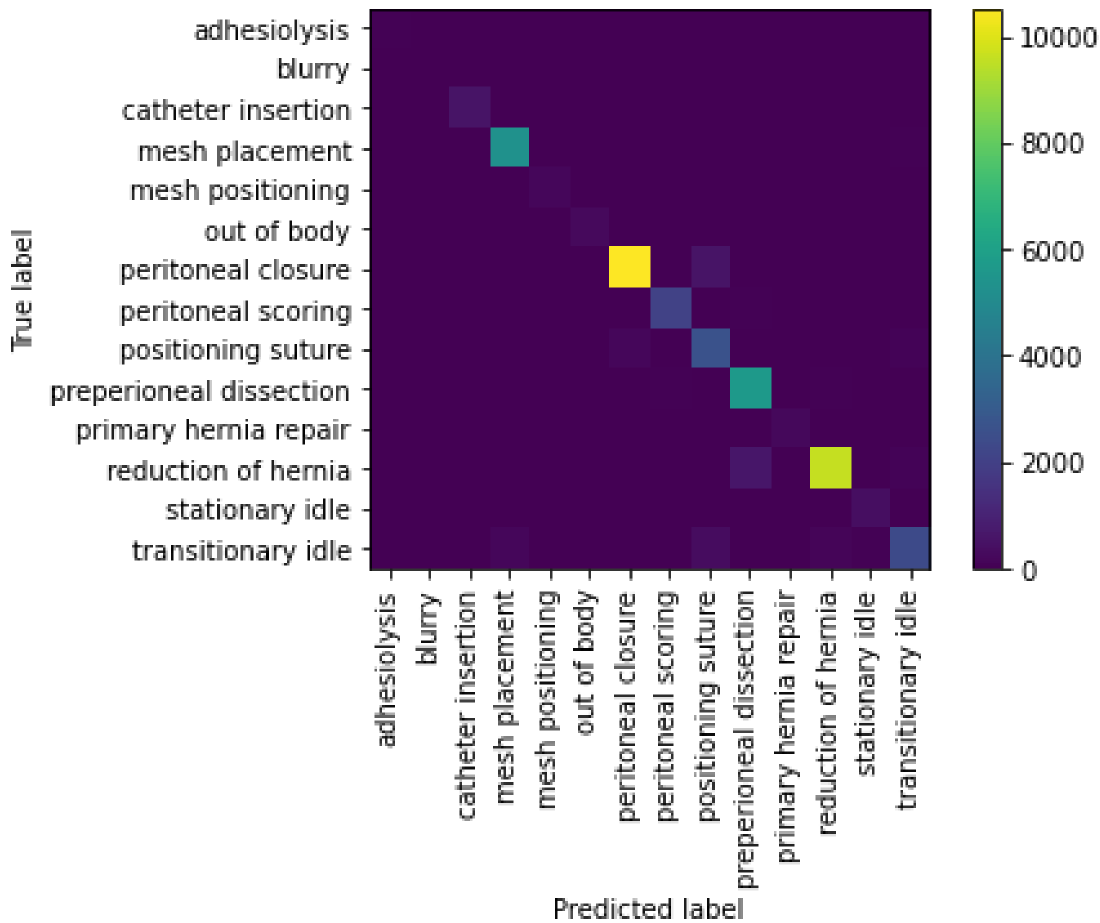
```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
/tmp/ipykernel_3609/2075712870.py in <module>
     11 batch_size = 32
     12 y_test_true, y_test_predicted, pr, time = get_pred(best_effi,␣
 ↪transforms, batch_size)
---> 13 y_test_true, y_test_predicted, pr = get_to_cpu(y_test_true,␣
 ↪y_test_predicted, pr)
     14 y_true, y_predicted = get_class_names(y_test_true, y_test_predicted,␣
 ↪classes)
```

```
NameError: name 'get_to_cpu' is not defined
```

[22]:
```
def get_to_cpu(l, pred, pr):
    for i in range(len(l)):
        l[i] = l[i].cpu()
    for i in range(len(l)):
        l[i] = l[i].data.numpy()
    l = [item for sublist in l for item in sublist]
    for i in range(len(l)):
        pred[i] = pred[i].cpu().data.numpy()
    for i in range(len(l)):
        pr[i] = pr[i].cpu().data.numpy()
    return l, pred, pr

def get_class_names(y_true, y_predicted, classes):
    yt = [classes[i] for i in y_true]
    yp = [classes[i] for i in y_predicted]
    return yt, yp
y_test_true, y_test_predicted, pr = get_to_cpu(y_test_true, y_test_predicted,␣
↪pr)
```

[30]:
```
classes = ['adhesiolysis', 'blurry', 'catheter insertion', 'mesh placement',␣
↪'mesh positioning', 'out of body', 'peritoneal closure', 'peritoneal␣
↪scoring',
           'positioning suture', 'preperioneal dissection', 'primary hernia␣
↪repair', 'reduction of hernia', 'stationary idle', 'transitionary idle']
y_true, y_predicted = get_class_names(y_test_true, y_test_predicted, classes)
```

[31]:
```
cm = confusion_matrix(y_true, y_predicted, labels=classes)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=classes)
disp.plot(include_values=False, xticks_rotation = 'vertical')
plt.show()

target_names = classes
c_report = classification_report(y_true, y_predicted, labels=classes,␣
↪target_names=target_names, output_dict=True)
print(c_report)
basic_report = classification_report(y_true, y_predicted, labels=classes)
print(basic_report)
sns.heatmap(pd.DataFrame(c_report).iloc[:-1, :].T, annot=True)

print(metrics.roc_auc_score(y_test_true, pr, multi_class = 'ovr'))
print(metrics.roc_auc_score(y_test_true, pr, multi_class = 'ovo'))
```

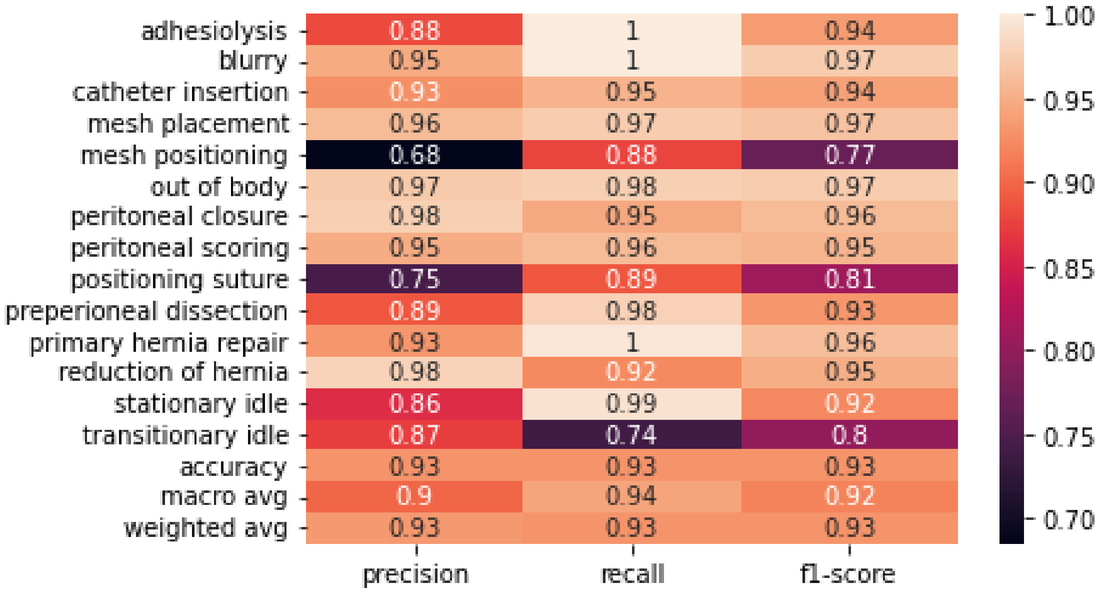


{'adhesiolysis': {'precision': 0.8813559322033898, 'recall': 1.0, 'f1-score': 0.936936936936937, 'support': 52}, 'blurry': {'precision': 0.9473684210526315, 'recall': 1.0, 'f1-score': 0.972972972972973, 'support': 18}, 'catheter insertion': {'precision': 0.9271523178807947, 'recall': 0.9540034071550255, 'f1-score': 0.9403862300587741, 'support': 587}, 'mesh placement': {'precision': 0.9596323661921067, 'recall': 0.973491773308958, 'f1-score': 0.9665123876939831, 'support': 5470}, 'mesh positioning': {'precision': 0.684981684981685, 'recall': 0.8779342723004695, 'f1-score': 0.7695473251028806, 'support': 213}, 'out of body': {'precision': 0.972318339100346, 'recall': 0.9756944444444444, 'f1-score': 0.9740034662045061, 'support': 288}, 'peritoneal closure': {'precision': 0.9754470490132493, 'recall': 0.9454872025145936, 'f1-score': 0.9602334914264866, 'support': 11135}, 'peritoneal scoring': {'precision': 0.9491371480472298, 'recall': 0.9600367478180983, 'f1-score': 0.9545558346654487, 'support': 2177}, 'positioning suture': {'precision': 0.7452460850111857, 'recall': 0.8880373208930357, 'f1-score': 0.8103998783639957, 'support': 3001}, 'preperioneal dissection': {'precision': 0.8882279273638072, 'recall': 0.9784445594067943, 'f1-score': 0.9311561499958974, 'support': 5799}, 'primary hernia repair': {'precision':

0.9318181818181818, 'recall': 0.9959514170040485, 'f1-score': 0.9628180039138944, 'support': 247}, 'reduction of hernia': {'precision': 0.9796084828711256, 'recall': 0.9234022104757328, 'f1-score': 0.9506753079701183, 'support': 10405}, 'stationary idle': {'precision': 0.8605150214592274, 'recall': 0.9925742574257426, 'f1-score': 0.92183908045977, 'support': 404}, 'transitionary idle': {'precision': 0.8725202057310801, 'recall': 0.7384950248756219, 'f1-score': 0.7999326372515999, 'support': 3216}, 'accuracy': 0.9302055240398028, 'macro avg': {'precision': 0.8982377973375744, 'recall': 0.943110902687326, 'f1-score': 0.9179978359298048, 'support': 43012}, 'weighted avg': {'precision': 0.9340204941348658, 'recall': 0.9302055240398028, 'f1-score': 0.9305808098827887, 'support': 43012}}

	precision	recall	f1-score	support
adhesiolysis	0.88	1.00	0.94	52
blurry	0.95	1.00	0.97	18
catheter insertion	0.93	0.95	0.94	587
mesh placement	0.96	0.97	0.97	5470
mesh positioning	0.68	0.88	0.77	213
out of body	0.97	0.98	0.97	288
peritoneal closure	0.98	0.95	0.96	11135
peritoneal scoring	0.95	0.96	0.95	2177
positioning suture	0.75	0.89	0.81	3001
preperioneal dissection	0.89	0.98	0.93	5799
primary hernia repair	0.93	1.00	0.96	247
reduction of hernia	0.98	0.92	0.95	10405
stationary idle	0.86	0.99	0.92	404
transitionary idle	0.87	0.74	0.80	3216
accuracy			0.93	43012
macro avg	0.90	0.94	0.92	43012
weighted avg	0.93	0.93	0.93	43012

0.9960168870834695
0.9970472448957345



[45]:
```
train_image_paths = []
for i in range(71,100):
    filename = '/home/zo2151/assignments/Data1/Test_data/001-00%i'%(i,)
    train_image_paths.append(glob.glob(filename + '/*'))
train_image_paths1 = [item for sublist in train_image_paths for item in sublist]
train_image_paths1.extend(train_image_paths4)
```

[ ]:
```
train_image_paths = []
for i in range(100,126):
    filename = '/home/zo2151/assignments/Data1/Test_data/001-0%i'%(i,)
    train_image_paths.append(glob.glob(filename + '/*'))
train_image_paths2 = [item for sublist in train_image_paths for item in sublist]
train_image_paths1.extend(train_image_paths4)
```

[ ]:
```
train_image_paths = []
for i in range(1,5):
    filename = '/home/zo2151/assignments/Data1/Test_data/002-000%i'%(i,)
    train_image_paths.append(glob.glob(filename + '/*'))
train_image_paths3 = [item for sublist in train_image_paths for item in sublist]
train_image_paths1.extend(train_image_paths4)
```

[51]:
```
train_image_paths = []
for i in range(1,2):
    filename = '/home/zo2151/assignments/Data1/Test_data/003-000%i'%(i,)
    train_image_paths.append(glob.glob(filename + '/*'))
train_image_paths4 = [item for sublist in train_image_paths for item in sublist]
train_image_paths1.extend(train_image_paths4)
```

[52]:
```
len(train_image_paths1)
```

[52]: 180191

[53]:
```
train_image_paths1 = natsort.natsorted(train_image_paths1)
```

[56]:
```
names = []
for i in range(len(train_image_paths1)):
    a = os.path.basename(train_image_paths1[i])
    a1 = a[:-4]
    names.append(a1)
```

[58]:
```
train_transforms = A.Compose(
    [
        A.Resize(224,224),
        A.Normalize((0.5,0.5,0.5),(0.5,0.5,0.5)),
        ToTensorV2(),
    ]
)
```

[63]:
```
class SurgicalDataset1(Dataset):
    def __init__(self, image_paths, transform=False):
        super(SurgicalDataset1, self).__init__()
        self.image_paths = image_paths
        self.transform = transform

    def __len__(self):
        return len(self.image_paths)

    def __getitem__(self, idx):
        image_filepath = self.image_paths[idx]
        image = cv2.imread(image_filepath)

        if self.transform is not None:
            image = self.transform(image=image)["image"]

        return image
```

[72]:
```
def get_pred1(model, train_transforms, batch_size, use_cuda=True):
    val_dataset = SurgicalDataset1(train_image_paths1, train_transforms)
    valid_loader = DataLoader(val_dataset, batch_size, shuffle = False)
    model = model.to('cuda' if use_cuda else 'cpu')
    pred = []
    # again no gradients needed
    t = ti.time()
    model.eval()
    with torch.no_grad():
```

```
        for data in valid_loader:
            images= data.to(device)
            outputs = model(images)
            _, predictions = torch.max(outputs, 1)
            # collect the correct predictions for each class
            for prediction in predictions:
                pred.append(prediction)

    processtime = ti.time()-t
    print('processtime', processtime)
    return pred, processtime
```

[73]:
```
save_path = os.path.join(os.getcwd(), 'models', 'TransferEffiNet')
best_effi = TransferEffiNet()
best_effi.load_state_dict(torch.load(os.path.join(save_path, 'best.pt')))
transforms = get_transform('effinet')
batch_size = 32
y_test_predicted, time = get_pred1(best_effi, transforms, batch_size)
```

```
processtime 1381.637146949768
```

[76]:
```
for i in range(len(y_test_predicted)):
    y_test_predicted[i] = y_test_predicted[i].cpu().data.numpy()
```

[77]:
```
d = {'Id': names, 'Predicted': y_test_predicted}
```

[78]:
```
df = pd.concat([pd.Series(v, name=k) for k, v in d.items()], axis=1)
```

[80]:
```
df.to_csv("Predicted.csv", index = False)
```

[81]:
```
some_csv = pd.read_csv("kaggle_template.csv")
```

[82]:
```
names1 = some_csv["Id"]
```

[92]:
```
names1 = some_csv["Id"].values.tolist()
```

[93]:
```
names2 = []
y_test_predicted1 = []
```

[94]:
```
for i in range(len(names)):
    if names[i] in names1:
        names2.append(names[i])
        y_test_predicted1.append(y_test_predicted[i])
```

[130]:
```
len(y_test_predicted1)
```

[130]:
```
179928
```

[149]:
```
d1 = {'Id': names3, 'Predicted': y_test_predicted2}
```

[150]:
```
df = pd.concat([pd.Series(v, name=k) for k, v in d1.items()], axis=1)
```

[151]:
```
df.to_csv("Predicted.csv", index = False)
```

[141]:
```
names3=[]
```

[142]:
```
# The labels are using 0-based index, which is different from the final␣
↪prediction label example. Only one set of labels
# were submitted due to time constraint.
for i in range(len(names2)):
    if names2[i][-2] == "-":
        n = int(names2[i][-1:])
        na = names2[i][0:-1]+"0000%i"%(n)
        names3.append(na)
    elif names2[i][-3] == "-":
        n = int(names2[i][-2:])
        na = names2[i][0:-2]+"000%i"%(n)
        names3.append(na)
    elif names2[i][-4] == "-":
        n = int(names2[i][-3:])
        na = names2[i][0:-3]+"00%i"%(n)
        names3.append(na)
    elif names2[i][-5] == "-":
        n = int(names2[i][-4:])
        na = names2[i][0:-4]+"0%i"%(n)
        names3.append(na)
```

[148]:
```
y_test_predicted2 = []
for i in range(len(y_test_predicted1)):
    if y_test_predicted1[i] == 0:
        y_test_predicted2.append("adhesiolysis")
    elif y_test_predicted1[i] == 1:
        y_test_predicted2.append("blurry")
    elif y_test_predicted1[i] == 2:
        y_test_predicted2.append("catheter insertion")
    elif y_test_predicted1[i] == 3:
        y_test_predicted2.append("mesh placement")
    elif y_test_predicted1[i] == 4:
        y_test_predicted2.append("mesh positioning")
    elif y_test_predicted1[i] == 5:
        y_test_predicted2.append("out of body")
    elif y_test_predicted1[i] == 6:
        y_test_predicted2.append("peritoneal closure")
    elif y_test_predicted1[i] == 7:
        y_test_predicted2.append("peritoneal scoring")
```

```python
    elif y_test_predicted1[i] == 8:
        y_test_predicted2.append("positioning suture")
    elif y_test_predicted1[i] == 9:
        y_test_predicted2.append("preperioneal dissection")
    elif y_test_predicted1[i] == 10:
        y_test_predicted2.append("primary hernia repair")
    elif y_test_predicted1[i] == 11:
        y_test_predicted2.append("reduction of hernia")
    elif y_test_predicted1[i] == 12:
        y_test_predicted2.append("stationary idle")
    elif y_test_predicted1[i] == 13:
        y_test_predicted2.append("transitionary idle")
```

[ ]:

```python

```