CNN_Test_Latest.ipynb

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RAM Disk

```
..
drive
runs
sample_data
0_grad_cam_heatmap.jpg
0_original_image.jpg
1_grad_cam_heatmap.jpg
1_original_image.jpg
2_grad_cam_heatmap.jpg
2_original_image.jpg
3_grad_cam_heatmap.jpg
3_original_image.jpg
4_grad_cam_heatmap.jpg
4_original_image.jpg
5_grad_cam_heatmap.jpg
5_original_image.jpg
6_grad_cam_heatmap.jpg
6_original_image.jpg
7_grad_cam_heatmap.jpg
7_original_image.jpg
8_grad_cam_heatmap.jpg
8_original_image.jpg
```

Disk 54.25 GB available

[13]
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

[2]
```
!pip install segmentation-models-pytorch
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting segmentation-models-pytorch
  Downloading segmentation_models_pytorch-0.3.2-py3-none-any.whl (106 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 106.7/106.7 kB 4.3 MB/s eta 0:00:00
Requirement already satisfied: torchvision>=0.5.0 in /usr/local/lib/python3.9/dist-packages (from segmentation-models-pytorch) (0.15.1+cu118)
Requirement already satisfied: pillow in /usr/local/lib/python3.9/dist-packages (from segmentation-models-pytorch) (8.4.0)
Collecting efficientnet-pytorch==0.7.1
  Downloading efficientnet_pytorch-0.7.1.tar.gz (21 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: tqdm in /usr/local/lib/python3.9/dist-packages (from segmentation-models-pytorch) (4.65.0)
Collecting pretrainedmodels==0.7.4
  Downloading pretrainedmodels-0.7.4.tar.gz (58 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 58.8/58.8 kB 7.1 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Collecting timm==0.6.12
  Downloading timm-0.6.12-py3-none-any.whl (549 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 549.1/549.1 kB 18.5 MB/s eta 0:00:00
Requirement already satisfied: torch in /usr/local/lib/python3.9/dist-packages (from efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (2.0.0+cu118)
Collecting munch
  Downloading munch-2.5.0-py2.py3-none-any.whl (10 kB)
Collecting huggingface-hub
  Downloading huggingface_hub-0.13.4-py3-none-any.whl (200 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 200.1/200.1 kB 21.8 MB/s eta 0:00:00
Requirement already satisfied: pyyaml in /usr/local/lib/python3.9/dist-packages (from timm==0.6.12->segmentation-models-pytorch) (6.0)
Requirement already satisfied: requests in /usr/local/lib/python3.9/dist-packages (from torchvision>=0.5.0->segmentation-models-pytorch) (2.27.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.9/dist-packages (from torchvision>=0.5.0->segmentation-models-pytorch) (1.22.4)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.9/dist-packages (from torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (4.5.0)
Requirement already satisfied: triton==2.0.0 in /usr/local/lib/python3.9/dist-packages (from torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (2.0.0)
Requirement already satisfied: networkx in /usr/local/lib/python3.9/dist-packages (from torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (3.1)
Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-packages (from torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (3.11.0)
Requirement already satisfied: sympy in /usr/local/lib/python3.9/dist-packages (from torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (1.11.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.9/dist-packages (from torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (3.1.2)
Requirement already satisfied: cmake in /usr/local/lib/python3.9/dist-packages (from triton==2.0.0->torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (3.25.2)
Requirement already satisfied: lit in /usr/local/lib/python3.9/dist-packages (from triton==2.0.0->torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (16.0.1)
Requirement already satisfied: packaging>=20.9 in /usr/local/lib/python3.9/dist-packages (from huggingface-hub->timm==0.6.12->segmentation-models-pytorch) (23.1)
Requirement already satisfied: six in /usr/local/lib/python3.9/dist-packages (from munch->pretrainedmodels==0.7.4->segmentation-models-pytorch) (1.16.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/dist-packages (from requests->torchvision>=0.5.0->segmentation-models-pytorch) (2022.12.7)
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dist-packages (from requests->torchvision>=0.5.0->segmentation-models-pytorch) (2.0.12)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-packages (from requests->torchvision>=0.5.0->segmentation-models-pytorch) (3.4)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9/dist-packages (from requests->torchvision>=0.5.0->segmentation-models-pytorch) (1.26.15)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.9/dist-packages (from jinja2->torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (2.1.2)
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.9/dist-packages (from sympy->torch->efficientnet-pytorch==0.7.1->segmentation-models-pytorch) (1.3.0)
Building wheels for collected packages: efficientnet-pytorch, pretrainedmodels
  Building wheel for efficientnet-pytorch (setup.py) ... done
  Created wheel for efficientnet-pytorch: filename=efficientnet_pytorch-0.7.1-py3-none-any.whl size=16444 sha256=554dd9c769c9f76b0e28869c6fb1bef60b1a70bbddb4a628ceceba51b243afbc
  Stored in directory: /root/.cache/pip/wheels/29/16/24/752e89d88d333af39a288421e64d613b5f652918e39ef1f8e3
  Building wheel for pretrainedmodels (setup.py) ... done
  Created wheel for pretrainedmodels: filename=pretrainedmodels-0.7.4-py3-none-any.whl size=60962 sha256=949df65086217252034c8f303fa999fa8ba40c9328f153659927db8bc0032f2a
  Stored in directory: /root/.cache/pip/wheels/d1/3b/4e/2f3015f1ab76f34be28e04c4bcee27e8cabfa70d2eadf8bc3b
Successfully built efficientnet-pytorch pretrainedmodels
Installing collected packages: munch, huggingface-hub, timm, pretrainedmodels, efficientnet-pytorch, segmentation-models-pytorch
Successfully installed efficientnet-pytorch-0.7.1 huggingface-hub-0.13.4 munch-2.5.0 pretrainedmodels-0.7.4 segmentation-models-pytorch-0.3.2 timm-0.6.12
```

[20]
```
import torch
import math
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset
from torchvision import transforms
import numpy as np
import pandas as pd
from PIL import Image, ImageEnhance
import argparse
import os
import copy
from torch.utils.data import DataLoader
import segmentation_models_pytorch as smp
from sklearn.metrics import balanced_accuracy_score, f1_score, confusion_matrix
import cv2
import timm
import random
from torch.utils.data import WeightedRandomSampler

LABELS_Severity = {35: 0,
                   43: 0,
                   47: 1,
                   53: 1,
                   61: 2,
                   65: 2,
                   71: 2,
                   85: 2}


mean = (.1706)
std = (.2112)
normalize = transforms.Normalize(mean=mean, std=std)
train_transform = transforms.Compose([
    transforms.Grayscale(num_output_channels=3),
    transforms.Resize(size=(224,224)),
    #transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    normalize,
])
test_transform = transforms.Compose([
    transforms.Grayscale(num_output_channels=3),
    transforms.Resize(size=(224,224)),
    transforms.ToTensor(),
    normalize,
])
```

[15]
```
class OCTDataset(Dataset):
    def __init__(self, annot=None, unique_pairs=None, subset='train', transform=None, device='cpu'):
        if subset == 'train':
            self.annot = pd.read_csv("/content/drive/MyDrive/FML_Project/df_prime_train.csv")
        elif subset == 'val':
            self.annot = pd.read_csv("/content/drive/MyDrive/FML_Project/df_prime_train.csv")
            self.unique_pairs = unique_pairs
        elif subset == 'test':
            self.annot = pd.read_csv("/content/drive/MyDrive/FML_Project/df_prime_test.csv")

        # Extract "Patient_ID" and "Week_Num" columns
        self.patient_ids = self.annot["Patient_ID"]
        self.week_nums = self.annot["Week_Num"]
        self.patient_ids = self.annot["Patient_ID"]
        self.annot['Severity_Label'] = [LABELS_Severity[drss] for drss in copy.deepcopy(self.annot['DRSS'].values)]
        self.drss_class = self.annot['Severity_Label']

        if subset == 'train':
          # Create unique pairs of values
          self.unique_pairs = set(zip(self.patient_ids, self.week_nums, self.drss_class))

          # Create a list from the set of unique_pairs
          unique_pairs_list = list(self.unique_pairs)
```

```
            # Shuffle the unique_pairs_list
            random.shuffle(unique_pairs_list)

            # Calculate the index at which to split the list
            split_index = int(0.8 * len(unique_pairs_list))

            # Split the list into training and validation pairs
            self.unique_pairs = unique_pairs_list[:split_index]
            self.unique_validation_pairs = unique_pairs_list[split_index:]

        elif subset == 'test':
            # Create unique pairs of values
            self.unique_pairs = set(zip(self.patient_ids, self.week_nums, self.drss_class))

        self.root = os.path.expanduser("/content/drive/MyDrive/FML_Project/")
        self.transform = transform
        self.nb_classes=len(np.unique(list(LABELS_Severity.values())))
        self.path_list = self.annot['File_Path'].values

        self._labels = [pair[2] for pair in self.unique_pairs]
        assert len(self.unique_pairs) == len(self._labels)

        max_samples = int(len(self._labels))
        self.max_samples = max_samples
        self.device = device

    def __getitem__(self, index):
        # Get the Patient_ID and Week_Num from the indexed element in unique_pairs
        patient_id, week_num, target = list(self.unique_pairs)[index]

        # Filter the annot DataFrame to select rows that match the Patient_ID and Week_Num
        filtered_df = self.annot[(self.annot['Patient_ID'] == patient_id) & (self.annot['Week_Num'] == week_num)]

        # Extract the file paths from the filtered DataFrame and return them as a list
        file_paths = [self.root + file_path for file_path in filtered_df['File_Path'].values.tolist()]
        # Canny edge of each image blended together
        fused_image_path = os.path.dirname(file_paths[0])+"/cn_final.jpg"
        # Canny edge of each image formed as a grid
        # fused_image_path = os.path.dirname(file_paths[0])+"/grid_image_canny.jpg"
        # OCT images formed as a grid
        # fused_image_path = os.path.dirname(file_paths[0])+"/grid_image.jpg"
        # Canny edge of Alpha blended image
        # fused_image_path = os.path.dirname(file_paths[0])+"/ab_edge_image.jpg"

        img = Image.open(fused_image_path)
        img_gray = img.convert("L")
        if self.transform is not None:
            img_sharpened = self.transform(img_gray)

        return (img_sharpened, target)

    def __len__(self):
        if self.max_samples is not None:
            return min(len(self._labels), self.max_samples)
        else:
            return len(self._labels)

# Neural network architecture
class OCTClassifier(torch.nn.Module):
    def __init__(self):
        super(OCTClassifier, self).__init__()
        self.unet = smp.Unet(
            # encoder_name="resnet34",   # encoder architecture (e.g., resnet34)
            encoder_name="timm-efficientnet-b7", # encoder architecture (e.g., EfficientNet-B3)
            encoder_weights="imagenet", # pre-trained weights for the encoder
            in_channels=3,              # input channels
            classes=3,                  # number of output channels
        )
        self.avg_pool = torch.nn.AdaptiveAvgPool2d((1, 1))  # Pooling layer to get the [32, 3] output shape

    def forward(self, x):
        x = self.unet(x)               # U-Net forward pass
        x = self.avg_pool(x)           # Apply the pooling layer
        x = x.view(x.size(0), -1)      # Reshape the tensor to [batch_size, 3]
        return x

# Oversampler to use weighted random sampling for data loaders
def create_oversampler(targets):
    class_sample_counts = np.bincount(targets)
    weights = 1.0 / torch.tensor(class_sample_counts, dtype=torch.float)
    sample_weights = weights[targets]
    sampler = WeightedRandomSampler(weights=sample_weights, num_samples=len(targets), replacement=True)
    return sampler
```

```
[ ] ##############################################################################################
    #  Run this code only during Grid Search
    ##############################################################################################
    def train_model(trainloader, val_loader, testloader, model, criterion, optimizer, device, num_epochs):
        best_val_balanced_accuracy = 0
        best_val_balanced_accuracy_epoch_number = 0
        for epoch in range(num_epochs):
            running_loss = 0.0
            model.train()
            for i, (inputs, labels) in enumerate(trainloader):
                inputs = inputs.to(device)
                labels = labels.to(device)
                optimizer.zero_grad()
                outputs = model(inputs)
                loss = criterion(outputs, labels)
                loss.backward()
                optimizer.step()
                running_loss += loss.item()

            model.eval()
            val_running_loss = 0.0
            val_preds = []
            val_true_labels = []
            with torch.no_grad():
                for val_inputs, val_labels in val_loader:
                    val_inputs = val_inputs.to(device)
                    val_labels = val_labels.to(device)
                    val_outputs = model(val_inputs)
                    valdn_loss = criterion(val_outputs, val_labels)
                    val_running_loss += valdn_loss.item()

                    _, val_predicted = torch.max(val_outputs.data, 1)
                    val_preds.extend(val_predicted.cpu().numpy())
                    val_true_labels.extend(val_labels.cpu().numpy())

            train_loss = running_loss / len(trainloader)
            val_loss = val_running_loss / len(val_loader)
            val_balanced_accuracy = balanced_accuracy_score(val_true_labels, val_preds)

            if val_balanced_accuracy > best_val_balanced_accuracy:
                best_val_balanced_accuracy = val_balanced_accuracy
                best_model = model
                best_val_balanced_accuracy_epoch_number = epoch + 1

        return best_model, best_val_balanced_accuracy, best_val_balanced_accuracy_epoch_number
```

```
[16] ##############################################################################################
```

```
#  After obtaining best model parameters from Grid Search change the exit condition in below code.
#  Use this code for final run.
###############################################################################################
def train_model(trainloader, val_loader, model, criterion, optimizer, device, num_epochs):
    best_balanced_accuracy = 0
    best_balanced_accuracy_epoch_number = 0
    final_balanced_accuracy = 0
    for epoch in range(num_epochs):
        running_loss = 0.0
        model.train()
        for i, (inputs, labels) in enumerate(trainloader):
            inputs = inputs.to(device)
            labels = labels.to(device)
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()

        model.eval()
        val_running_loss = 0.0
        val_balanced_accuracy = 0.0
        val_loss = 0.0
        val_preds = []
        val_true_labels = []
        with torch.no_grad():
            for val_inputs, val_labels in val_loader:
                val_inputs = val_inputs.to(device)
                val_labels = val_labels.to(device)
                val_outputs = model(val_inputs)
                valdn_loss = criterion(val_outputs, val_labels)
                val_running_loss += valdn_loss.item()

                _, val_predicted = torch.max(val_outputs.data, 1)
                val_preds.extend(val_predicted.cpu().numpy())
                val_true_labels.extend(val_labels.cpu().numpy())

        # compute the balanced accuracy
        train_loss = running_loss / len(trainloader)
        val_loss = val_running_loss / len(val_loader)
        val_balanced_accuracy = balanced_accuracy_score(val_true_labels, val_preds)

        print(f'Epoch {epoch + 1} | Train Loss: {train_loss:.3f} | Val Loss: {val_loss:.3f} | Val Balanced Accuracy: {val_balanced_accuracy:.2f}')
    return model, train_loss, val_loss, val_balanced_accuracy
```

```
[17] annot_train_prime = "/content/drive/MyDrive/FML_Project/df_prime_train.csv"
     annot_test_prime = "/content/drive/MyDrive/FML_Project/df_prime_test.csv"
     data_root = "/content/drive/MyDrive/FML_Project/"

     #set up the device (GPU or CPU)
     device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
     print('Found device:', device)

     trainset = OCTDataset(subset='train', transform=train_transform, device=device)
     valset = OCTDataset(subset='val', unique_pairs=trainset.unique_validation_pairs, transform=train_transform, device=device)
     testset = OCTDataset(subset='test', transform=test_transform, device=device)

     oversampler = create_oversampler(trainset._labels)

     Found device: cuda:0
```

```
[ ] ###############################################################################################
    #  Run this code only during Grid Search
    ###############################################################################################
    # Define parameter grid for Grid Search
    batch_sizes = [8, 16]
    learning_rates = [1e-3, 1e-4]
    num_epochs_list = [200]

    best_balanced_accuracy = 0
    best_params = None
    best_model = None

    # Perform grid search
    for batch_size in batch_sizes:
        for learning_rate in learning_rates:
            for num_epochs in num_epochs_list:
                print(f'Training with batch_size={batch_size}, learning_rate={learning_rate}, num_epochs={num_epochs}')
                trainloader = DataLoader(trainset, batch_size=batch_size, sampler=oversampler, num_workers=2)
                val_loader = DataLoader(valset, batch_size=batch_size, shuffle=True)
                testloader = DataLoader(testset, batch_size=batch_size, shuffle=False, num_workers=2)
                model = OCTClassifier().to(device)
                optimizer = optim.Adam(model.parameters(), lr=learning_rate)

                #define the loss function
                criterion = nn.CrossEntropyLoss()

                # To handle imbalanced dataset:
                class_counts = np.bincount(trainset._labels)
                print(class_counts)
                total_samples = len(trainset)

                # Adjust weights in proportion to class distribution in trainset
                class_weights = torch.FloatTensor(total_samples / (len(class_counts) * class_counts)).to(device)
                class_weights[0] = class_weights[0] * 2
                class_weights[2] = class_weights[2] * 4

                criterion = nn.CrossEntropyLoss(weight=class_weights)

                model, val_balanced_accuracy, best_balanced_accuracy_epoch_number = train_model(trainloader, val_loader, testloader, model, criterion, optimizer, device, num_epochs)
                if val_balanced_accuracy > best_balanced_accuracy:
                    best_balanced_accuracy = val_balanced_accuracy
                    best_params = (batch_size, learning_rate, num_epochs, best_balanced_accuracy_epoch_number)
                    best_model = model

    print(f'Best balanced accuracy: {best_balanced_accuracy}')
    print(f'Best parameters: batch_size={best_params[0]}, learning_rate={best_params[1]}, num_epochs={best_params[2]}, epoch_number={best_params[3]}')
```

```
[18] # Best model Hyper-parameters obtained from grid search
     batch_size = 16
     learning_rate = 1e-4
     num_epochs = 100

     best_balanced_accuracy = 0
     best_params = None
     best_model = None

     # Run this
     print(f'Training with batch_size={batch_size}, learning_rate={learning_rate}, num_epochs={num_epochs}')
     trainloader = DataLoader(trainset, batch_size=batch_size, sampler=oversampler, num_workers=2)
     val_loader = DataLoader(valset, batch_size=batch_size, shuffle=True)
     testloader = DataLoader(testset, batch_size=batch_size, shuffle=False, num_workers=2)
     model = OCTClassifier().to(device)
     optimizer = optim.Adam(model.parameters(), lr=learning_rate)

     #define the loss function
     criterion = nn.CrossEntropyLoss()

     # To handle imbalanced dataset:
     class_counts = np.bincount(trainset._labels)
     total_samples = len(trainset)
```

```python
# Adjust weights in proportion to class distribution in trainset
class_weights = torch.FloatTensor(total_samples / (len(class_counts) * class_counts)).to(device)
class_weights[0] = class_weights[0] * 2
class_weights[2] = class_weights[2] * 8

criterion = nn.CrossEntropyLoss(weight=class_weights)

model, train_loss, val_loss, val_balanced_accuracy = train_model(trainloader, val_loader, model, criterion, optimizer, device, num_epochs)
```

```
Epoch 43 | Train Loss: 0.069 | Val Loss: 1.067 | Val Balanced Accuracy: 0.57
Epoch 44 | Train Loss: 0.065 | Val Loss: 1.113 | Val Balanced Accuracy: 0.58
Epoch 45 | Train Loss: 0.145 | Val Loss: 0.824 | Val Balanced Accuracy: 0.57
Epoch 46 | Train Loss: 0.109 | Val Loss: 1.194 | Val Balanced Accuracy: 0.56
Epoch 47 | Train Loss: 0.114 | Val Loss: 1.191 | Val Balanced Accuracy: 0.62
Epoch 48 | Train Loss: 0.087 | Val Loss: 1.111 | Val Balanced Accuracy: 0.52
Epoch 49 | Train Loss: 0.063 | Val Loss: 1.076 | Val Balanced Accuracy: 0.55
Epoch 50 | Train Loss: 0.050 | Val Loss: 1.024 | Val Balanced Accuracy: 0.57
Epoch 51 | Train Loss: 0.122 | Val Loss: 1.309 | Val Balanced Accuracy: 0.57
Epoch 52 | Train Loss: 0.123 | Val Loss: 1.321 | Val Balanced Accuracy: 0.57
Epoch 53 | Train Loss: 0.055 | Val Loss: 1.318 | Val Balanced Accuracy: 0.57
Epoch 54 | Train Loss: 0.052 | Val Loss: 1.287 | Val Balanced Accuracy: 0.63
Epoch 55 | Train Loss: 0.061 | Val Loss: 1.117 | Val Balanced Accuracy: 0.63
Epoch 56 | Train Loss: 0.044 | Val Loss: 1.128 | Val Balanced Accuracy: 0.62
Epoch 57 | Train Loss: 0.043 | Val Loss: 0.971 | Val Balanced Accuracy: 0.65
Epoch 58 | Train Loss: 0.050 | Val Loss: 1.093 | Val Balanced Accuracy: 0.58
Epoch 59 | Train Loss: 0.048 | Val Loss: 1.023 | Val Balanced Accuracy: 0.63
Epoch 60 | Train Loss: 0.030 | Val Loss: 1.062 | Val Balanced Accuracy: 0.60
Epoch 61 | Train Loss: 0.030 | Val Loss: 1.296 | Val Balanced Accuracy: 0.65
Epoch 62 | Train Loss: 0.027 | Val Loss: 1.430 | Val Balanced Accuracy: 0.62
Epoch 63 | Train Loss: 0.045 | Val Loss: 1.495 | Val Balanced Accuracy: 0.64
Epoch 64 | Train Loss: 0.078 | Val Loss: 1.014 | Val Balanced Accuracy: 0.56
Epoch 65 | Train Loss: 0.100 | Val Loss: 1.142 | Val Balanced Accuracy: 0.59
Epoch 66 | Train Loss: 0.060 | Val Loss: 1.117 | Val Balanced Accuracy: 0.60
Epoch 67 | Train Loss: 0.041 | Val Loss: 1.069 | Val Balanced Accuracy: 0.61
Epoch 68 | Train Loss: 0.044 | Val Loss: 1.537 | Val Balanced Accuracy: 0.57
Epoch 69 | Train Loss: 0.061 | Val Loss: 1.181 | Val Balanced Accuracy: 0.54
Epoch 70 | Train Loss: 0.065 | Val Loss: 1.301 | Val Balanced Accuracy: 0.59
Epoch 71 | Train Loss: 0.061 | Val Loss: 1.246 | Val Balanced Accuracy: 0.60
Epoch 72 | Train Loss: 0.057 | Val Loss: 1.334 | Val Balanced Accuracy: 0.59
Epoch 73 | Train Loss: 0.047 | Val Loss: 1.146 | Val Balanced Accuracy: 0.63
Epoch 74 | Train Loss: 0.051 | Val Loss: 1.438 | Val Balanced Accuracy: 0.56
Epoch 75 | Train Loss: 0.055 | Val Loss: 1.071 | Val Balanced Accuracy: 0.57
Epoch 76 | Train Loss: 0.043 | Val Loss: 1.564 | Val Balanced Accuracy: 0.61
Epoch 77 | Train Loss: 0.027 | Val Loss: 1.881 | Val Balanced Accuracy: 0.52
Epoch 78 | Train Loss: 0.018 | Val Loss: 1.446 | Val Balanced Accuracy: 0.57
Epoch 79 | Train Loss: 0.021 | Val Loss: 1.653 | Val Balanced Accuracy: 0.56
Epoch 80 | Train Loss: 0.028 | Val Loss: 1.599 | Val Balanced Accuracy: 0.52
Epoch 81 | Train Loss: 0.029 | Val Loss: 2.206 | Val Balanced Accuracy: 0.55
Epoch 82 | Train Loss: 0.026 | Val Loss: 1.723 | Val Balanced Accuracy: 0.52
Epoch 83 | Train Loss: 0.020 | Val Loss: 1.766 | Val Balanced Accuracy: 0.61
Epoch 84 | Train Loss: 0.027 | Val Loss: 1.640 | Val Balanced Accuracy: 0.57
Epoch 85 | Train Loss: 0.031 | Val Loss: 1.857 | Val Balanced Accuracy: 0.56
Epoch 86 | Train Loss: 0.028 | Val Loss: 1.529 | Val Balanced Accuracy: 0.59
Epoch 87 | Train Loss: 0.016 | Val Loss: 1.628 | Val Balanced Accuracy: 0.52
Epoch 88 | Train Loss: 0.028 | Val Loss: 1.572 | Val Balanced Accuracy: 0.59
Epoch 89 | Train Loss: 0.023 | Val Loss: 1.126 | Val Balanced Accuracy: 0.61
Epoch 90 | Train Loss: 0.022 | Val Loss: 1.608 | Val Balanced Accuracy: 0.64
Epoch 91 | Train Loss: 0.013 | Val Loss: 2.265 | Val Balanced Accuracy: 0.58
Epoch 92 | Train Loss: 0.035 | Val Loss: 1.456 | Val Balanced Accuracy: 0.64
Epoch 93 | Train Loss: 0.018 | Val Loss: 1.870 | Val Balanced Accuracy: 0.64
Epoch 94 | Train Loss: 0.016 | Val Loss: 1.311 | Val Balanced Accuracy: 0.63
Epoch 95 | Train Loss: 0.033 | Val Loss: 1.025 | Val Balanced Accuracy: 0.64
Epoch 96 | Train Loss: 0.094 | Val Loss: 1.051 | Val Balanced Accuracy: 0.64
Epoch 97 | Train Loss: 0.130 | Val Loss: 1.267 | Val Balanced Accuracy: 0.57
Epoch 98 | Train Loss: 0.166 | Val Loss: 0.944 | Val Balanced Accuracy: 0.59
Epoch 99 | Train Loss: 0.072 | Val Loss: 1.291 | Val Balanced Accuracy: 0.56
Epoch 100 | Train Loss: 0.041 | Val Loss: 1.092 | Val Balanced Accuracy: 0.62
```

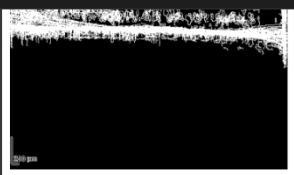
```python
[ ] torch.save(model.state_dict(), "/content/drive/MyDrive/unet_octclassifier_latest.pth")
```

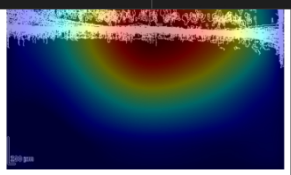
```python
[24] testset = OCTDataset(subset='test', transform=test_transform, device=device)
testloader = DataLoader(testset, batch_size=batch_size, shuffle=False, num_workers=2)

#Load model from pth file corresponding to maximum accuracy obtained from all U-Net based experiments.
#This code is commented while trying new methods and only used to lock the model weights once satisfied with trained model.
model.load_state_dict(torch.load("/content/drive/MyDrive/unet_octclassifier_0dot59.pth"))

#evaluate the model on the test set
model.eval()

# turn off gradients for evaluation
true_labels = []
pred_labels = []
with torch.no_grad():
    for i, (inputs, labels) in enumerate(testloader):
        print('Testing for batch: '+str(i))
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model(inputs)
        _, predicted = torch.max(outputs.data, 1)
        pred_labels.extend(predicted.cpu().numpy())
        true_labels.extend(labels.cpu().numpy())

# confusion matrix
conf_mat = confusion_matrix(true_labels, pred_labels)

# compute the specificivity and sensitivity
sensitivity = []
specificity = []
num_classes = conf_mat.shape[0]
for i in range(num_classes):
    tp = conf_mat[i, i]
    fp = np.sum(conf_mat[:, i]) - tp
    fn = np.sum(conf_mat[i, :]) - tp
    tn = np.sum(conf_mat) - (tp + fp + fn)

    sensitivity.append(tp / (tp + fn))
    specificity.append(tn / (tn + fp))

# compute the balanced accuracy
balanced_accuracy = balanced_accuracy_score(true_labels, pred_labels)
f1 = f1_score(true_labels, pred_labels, average='weighted')

# print the balanced accuracy
print('Balanced accuracy:', balanced_accuracy)
print('F1 score:', f1)
for i in range(num_classes):
    print(f'Sensitivity for class {i}: {sensitivity[i]:.2f}')
    print(f'Specificity for class {i}: {specificity[i]:.2f}')
```

```
Testing for batch: 0
Testing for batch: 1
Testing for batch: 2
Testing for batch: 3
Testing for batch: 4
Testing for batch: 5
Testing for batch: 6
Testing for batch: 7
Testing for batch: 8
Testing for batch: 9
Testing for batch: 10
Balanced accuracy: 0.5816583953680728
F1 score: 0.5893705052293798
Sensitivity for class 0: 0.65
Specificity for class 0: 0.72
Sensitivity for class 1: 0.57
Specificity for class 1: 0.70
Sensitivity for class 2: 0.52
Specificity for class 2: 0.93
```

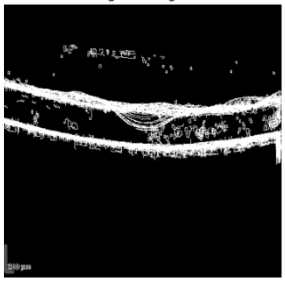
Specificity for class 2: 0.92

[40]
```
#Heat-map generation based on explainability assignment
import torch.nn.functional as F
import matplotlib.pyplot as plt

def grad_cam(device, model, input_image_path, target_layer):
    model.eval()

    # transforms
    preprocess = transforms.Compose([
        transforms.Resize((224, 224)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ])
    img = cv2.imread(input_image_path)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)  # Convert BGR (OpenCV default) to RGB
    img_pil = Image.fromarray(img)  # Convert NumPy array to PIL Image
    input_tensor = preprocess(img_pil).unsqueeze(0)
    input_tensor = input_tensor.to(device)

    # Forward and backward hooks
    feature_maps = []
    gradients = []

    def forward_hook(_, input, output):
        feature_maps.append(output)

    def backward_hook(_, grad_in, grad_out):
        gradients.append(grad_out[0])

    handle_forward = target_layer.register_forward_hook(forward_hook)
    handle_backward = target_layer.register_backward_hook(backward_hook)

    # Forward pass
    model.zero_grad()
    output = model(input_tensor)

    # Backward pass
    target_class = output.argmax(1).item()
    output[:, target_class].backward()

    # Remove hooks
    handle_forward.remove()
    handle_backward.remove()

    # Grad-CAM computation
    feature_map = feature_maps[0].detach()
    gradient = gradients[0].detach()
    weights = F.adaptive_avg_pool2d(gradient, 1)

    grad_cam_map = torch.mul(feature_map, weights).sum(dim=1, keepdim=True).relu()
    grad_cam_map = F.interpolate(grad_cam_map, (224, 224), mode='bilinear', align_corners=False).squeeze().cpu().numpy()

    # Normalize the heatmap
    grad_cam_map = grad_cam_map - np.min(grad_cam_map)
    grad_cam_map = grad_cam_map / np.max(grad_cam_map)

    return grad_cam_map

#Image list containing images from each DRSS severity category
input_image_list = []
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/01-027/W52/OS/cn_final.jpg")
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/02-031/W100/OD/cn_final.jpg")
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/01-002/W40/OD/cn_final.jpg")
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/01-002/W4/OD/cn_final.jpg")
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/01-013/W92/OD/cn_final.jpg")
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/01-026/W92/OD/cn_final.jpg")
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/01-026/W0/OD/cn_final.jpg")
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/01-020/W0/OS/cn_final.jpg")
input_image_list.append("/content/drive/MyDrive/FML_Project/Prime_FULL/01-026/W0/OD/cn_final.jpg")

#Iterates over list of images
for idx, input_image in enumerate(input_image_list):
    # Create heat-map for every image
    heatmap = grad_cam(device, model, input_image, model.unet.decoder.blocks[4].conv2)

    # Combine image with heatmap
    img = cv2.imread(input_image)
    heatmap = cv2.resize(heatmap, (img.shape[1], img.shape[0]))
    heatmap = np.uint8(255 * heatmap)
    heatmap = cv2.applyColorMap(heatmap, cv2.COLORMAP_JET)
    superimposed_img = cv2.addWeighted(img, 0.6, heatmap, 0.4, 0)

    # Write original image and corresponding grad cam heatmap
    original_image_output_path = f"{idx}_original_image.jpg"
    superimposed_image_output_path = f"{idx}_grad_cam_heatmap.jpg"
    cv2.imwrite(original_image_output_path, img)
    cv2.imwrite(superimposed_image_output_path, superimposed_img)

    plt.figure(figsize=(10, 5))
    plt.subplot(1, 2, 1)
    plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
    plt.title(f'Original Image {idx}')
    plt.axis('off')

    plt.subplot(1, 2, 2)
    plt.imshow(cv2.cvtColor(superimposed_img, cv2.COLOR_BGR2RGB))
    plt.title(f'Grad-CAM Heatmap {idx}')
    plt.axis('off')

    plt.show()
```

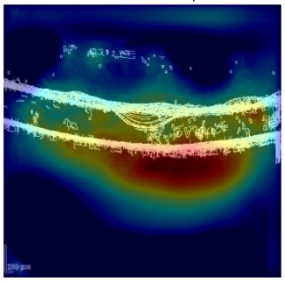


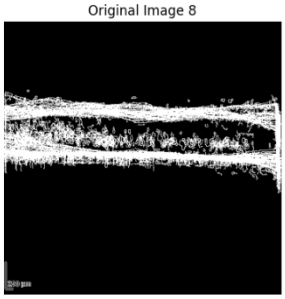


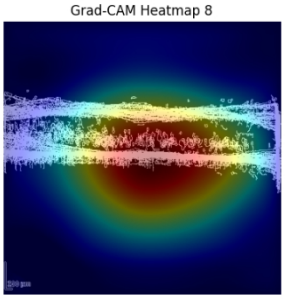
Original Image 7



Grad-CAM Heatmap 7





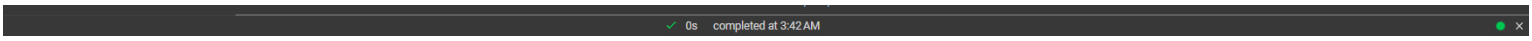



```
[42] pip install tensorboard
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: tensorboard in /usr/local/lib/python3.9/dist-packages (2.12.2)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (0.7.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (3.4.3)
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (67.6.1)
Requirement already satisfied: absl-py>=0.4 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (1.4.0)
Requirement already satisfied: wheel>=0.26 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (0.40.0)
Requirement already satisfied: grpcio>=1.48.2 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (1.53.0)
Requirement already satisfied: numpy>=1.12.0 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (1.22.4)
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (2.17.3)
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (2.2.3)
Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (1.0.0)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (1.8.1)
Requirement already satisfied: protobuf>=3.19.6 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (3.20.3)
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.9/dist-packages (from tensorboard) (2.27.1)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.9/dist-packages (from google-auth<3,>=1.6.3->tensorboard) (4.9)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/python3.9/dist-packages (from google-auth<3,>=1.6.3->tensorboard) (5.3.0)
Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.9/dist-packages (from google-auth<3,>=1.6.3->tensorboard) (1.16.0)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.9/dist-packages (from google-auth<3,>=1.6.3->tensorboard) (0.2.8)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.9/dist-packages (from google-auth-oauthlib<1.1,>=0.5->tensorboard) (1.3.1)
Requirement already satisfied: importlib-metadata>=4.4 in /usr/local/lib/python3.9/dist-packages (from markdown>=2.6.8->tensorboard) (6.4.1)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/dist-packages (from requests<3,>=2.21.0->tensorboard) (2022.12.7)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9/dist-packages (from requests<3,>=2.21.0->tensorboard) (1.26.15)
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dist-packages (from requests<3,>=2.21.0->tensorboard) (2.0.12)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-packages (from requests<3,>=2.21.0->tensorboard) (3.4)
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.9/dist-packages (from werkzeug>=1.0.1->tensorboard) (2.1.2)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.9/dist-packages (from importlib-metadata>=4.4->markdown>=2.6.8->tensorboard) (3.15.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/python3.9/dist-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->tensorboard) (0.4.8)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.9/dist-packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<1.1,>=0.5->tensorboard) (3.2.2)
```

```
#Print the model summary - each layer within the model
from torchsummary import summary
from torch.utils.tensorboard import SummaryWriter
summary(model, input_size=(3, 224, 224))
```

```
        Attention-1041         [-1, 336, 28, 28]               0
            Conv2d-1042         [-1, 128, 28, 28]         387,072
       BatchNorm2d-1043         [-1, 128, 28, 28]             256
              ReLU-1044         [-1, 128, 28, 28]               0
            Conv2d-1045         [-1, 128, 28, 28]         147,456
       BatchNorm2d-1046         [-1, 128, 28, 28]             256
              ReLU-1047         [-1, 128, 28, 28]               0
          Identity-1048         [-1, 128, 28, 28]               0
         Attention-1049         [-1, 128, 28, 28]               0
      DecoderBlock-1050         [-1, 128, 28, 28]               0
          Identity-1051         [-1, 176, 56, 56]               0
         Attention-1052         [-1, 176, 56, 56]               0
            Conv2d-1053          [-1, 64, 56, 56]         101,376
       BatchNorm2d-1054          [-1, 64, 56, 56]             128
              ReLU-1055          [-1, 64, 56, 56]               0
            Conv2d-1056          [-1, 64, 56, 56]          36,864
       BatchNorm2d-1057          [-1, 64, 56, 56]             128
              ReLU-1058          [-1, 64, 56, 56]               0
          Identity-1059          [-1, 64, 56, 56]               0
         Attention-1060          [-1, 64, 56, 56]               0
      DecoderBlock-1061          [-1, 64, 56, 56]               0
          Identity-1062        [-1, 128, 112, 112]              0
         Attention-1063        [-1, 128, 112, 112]              0
            Conv2d-1064         [-1, 32, 112, 112]         36,864
       BatchNorm2d-1065         [-1, 32, 112, 112]             64
              ReLU-1066         [-1, 32, 112, 112]              0
            Conv2d-1067         [-1, 32, 112, 112]          9,216
       BatchNorm2d-1068         [-1, 32, 112, 112]             64
              ReLU-1069         [-1, 32, 112, 112]              0
          Identity-1070         [-1, 32, 112, 112]              0
         Attention-1071         [-1, 32, 112, 112]              0
      DecoderBlock-1072         [-1, 32, 112, 112]              0
            Conv2d-1073         [-1, 16, 224, 224]          4,608
       BatchNorm2d-1074         [-1, 16, 224, 224]             32
              ReLU-1075         [-1, 16, 224, 224]              0
            Conv2d-1076         [-1, 16, 224, 224]          2,304
       BatchNorm2d-1077         [-1, 16, 224, 224]             32
              ReLU-1078         [-1, 16, 224, 224]              0
          Identity-1079         [-1, 16, 224, 224]              0
         Attention-1080         [-1, 16, 224, 224]              0
      DecoderBlock-1081         [-1, 16, 224, 224]              0
       UnetDecoder-1082         [-1, 16, 224, 224]              0
            Conv2d-1083          [-1, 3, 224, 224]            435
          Identity-1084          [-1, 3, 224, 224]              0
          Identity-1085          [-1, 3, 224, 224]              0
        Activation-1086          [-1, 3, 224, 224]              0
              Unet-1087          [-1, 3, 224, 224]              0
AdaptiveAvgPool2d-1088             [-1, 3, 1, 1]               0
================================================================
Total params: 65,452,099
Trainable params: 65,452,099
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 3848290695650.88
Params size (MB): 249.68
Estimated Total Size (MB): 3848290695901.13
----------------------------------------------------------------
```


0s completed at 3:42 AM