Name: Tahsin Reasat

VUID: Reasatt

Train.py

```
from glob import glob
import os
from albumentations import (
   Compose, Resize, Normalize, RandomBrightnessContrast,
   HorizontalFlip,RandomRotate90,RandomCrop,
CenterCrop
)
import albumentations.pytorch as albu_torch
import sys
sys.path.insert(1,r'..\utility')
sys.path.insert(1,r'..\models')
from dataloader import ISIC_Dataset
from logger import Logger
from loss import bceWithSoftmax
from torch.utils.data import DataLoader
from models import ResNet18, ResNet50, DPN92
import torch.optim as optim
import torch
import time
import argparse
import numpy as np
import pickle
import pandas as pd
from metrics import get_acc,get_recall

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
TIME_STAMP=time.strftime('%Y-%m-%d-%H-%M-%S')

parser=argparse.ArgumentParser()
parser.add_argument('--dir_project', help='project directory', default=r'..')
parser.add_argument('--dir_lf', help='directory large
files',default=r'D:\Data\cs-8395-dl')
parser.add_argument('--folderData', help='data directory', default='assignment2_data')
parser.add_argument('--encoder',help='encoder',default='resnet18')
parser.add_argument('--lr', help='learning rate', type=float, default=0.001)
parser.add_argument('--batchSize', help='batch size', type=int, default=32)
parser.add_argument('--epoch', help='epoch', type=int, default=400)
parser.add_argument('--resume_from', help='filepath to resume training')
parser.add_argument('--bottleneckFeatures', help='bottleneck the encoder Features',
type=int, default=1)
parser.add_argument('--overrideLR', help='override LR from resumed network', type=int,
default=1)
parser.add_argument('--brightness',nargs='+', type=float)
```

```
parser.add_argument('--contrast',nargs='+', type=float)
parser.add_argument('--cropSize', type=int)
parser.add_argument('--resize', type=int)
parser.add_argument('--to_ram',type=int, default=0)
parser.add_argument('--loss_weights',nargs='+', type=float)
args=parser.parse_args()

# setting up directories
DIR_LF = args.dir_lf#r'D:\Data\cs-8395-dl'
dir_data = os.path.join(DIR_LF,args.folderData)
#os.path.join(DIR_LF,'assignment1_data')
dir_model = os.path.join(args.dir_lf, 'model',TIME_STAMP)
dir_history = os.path.join(args.dir_project, 'history')
dir_log = os.path.join(args.dir_project, 'log')
dir_config = os.path.join(args.dir_project, 'config')

if os.path.exists(dir_history) is False:
   os.mkdir(dir_history)
if os.path.exists(dir_log) is False:
   os.mkdir(dir_log)
if os.path.exists(dir_config) is False:
   os.mkdir(dir_config)
if os.path.exists(os.path.join(args.dir_lf, 'model')) is False:
   os.mkdir(os.path.join(args.dir_lf, 'model'))

filepath_hist = os.path.join(dir_history, '{}.bin'.format(TIME_STAMP))
filepath_log = os.path.join(dir_log, '{}.log'.format(TIME_STAMP))
filepath_cfg = os.path.join(dir_config, '{}.cfg'.format(TIME_STAMP))

sys.stdout = Logger(filepath_log)
print(TIME_STAMP)
print(os.path.basename(__file__))
config=vars(args)
config_ls=sorted(list(config.items()))
print('--------------------------------------------------------------------------------
-------------------------------------')
for item in config_ls:
   print('{}: {}'.format(item[0],item[1]))
print('--------------------------------------------------------------------------------
-------------------------------------')
with open(filepath_cfg, 'w') as file:
   for item in config_ls:
       file.write('{}: {}\n'.format(item[0], item[1]))

if os.path.exists(dir_model)==0:
   print('creating directory to save model at {}'.format(dir_model))
   os.mkdir(dir_model)

filepath_model_best = os.path.join(dir_model, '{}_{}_best.pt'.format(TIME_STAMP,
args.encoder))  ##
```

```python
filepath_model_latest = os.path.join(dir_model, '{}_{}_latest.pt'.format(TIME_STAMP,
args.encoder))  ##

dir_data_train = os.path.join(dir_data, 'train')
dir_data_test = os.path.join(dir_data, 'test')

# get train filenames
filepath_train_label = os.path.join(dir_data, 'labels','Train_labels.csv')
df_train = pd.read_csv(filepath_train_label)
df_train.set_index('image',inplace=True)
files_train = df_train.index.values
labels_train_one_hot=[df_train.loc[flname].values for flname in files_train]
labels_train_cat = [np.argmax(label) for label in labels_train_one_hot]
# get test filenames
filepath_test_label = os.path.join(dir_data, 'labels','Test_labels.csv')
df_test = pd.read_csv(filepath_test_label)
df_test.set_index('image',inplace=True)
files_test = df_test.index.values
labels_test_one_hot=[df_test.loc[flname].values for flname in files_test]
labels_test_cat = [np.argmax(label) for label in labels_test_one_hot]

# Dataloader Parameters
aug ={
   'train': Compose([
   HorizontalFlip(),
   RandomRotate90(),
   RandomBrightnessContrast(
       brightness_limit=args.brightness,
       contrast_limit=args.contrast,
   ),
   RandomCrop(args.cropSize, args.cropSize, p=0.5),
   Resize(args.resize,args.resize),
   Normalize(),
   albu_torch.ToTensorV2()
   ]),
   'valid': Compose([
   Resize(args.resize,args.resize),
   Normalize(),
   albu_torch.ToTensorV2()
   ])
}

BATCH_SIZE=args.batchSize
LR = args.lr
EPOCH=args.epoch
Dataset_train = ISIC_Dataset(dir_data=dir_data_train, files=df_train.index.values,
label_cat=labels_train_cat, transform=aug['train'])
loader_train=DataLoader(Dataset_train,batch_size=BATCH_SIZE, shuffle=True)
print('train samples {}'.format(len(Dataset_train)))
```

```
Dataset_valid = ISIC_Dataset(dir_data=dir_data_test, files=df_test.index.values,
label_cat=labels_test_cat, transform=aug['valid'])
loader_valid=DataLoader(Dataset_valid,batch_size=BATCH_SIZE, shuffle=False)
print('validation samples {}'.format(len(Dataset_valid)))
# Model
if args.encoder == 'resnet18':
   model = ResNet18(pretrained=True,
bottleneckFeatures=args.bottleneckFeatures).to(device)
if args.encoder == 'resnet50':
   model = ResNet50(pretrained=True,
bottleneckFeatures=args.bottleneckFeatures).to(device)
if args.encoder == 'dpn92':
   model = DPN92().to(device)

# print(model)

# Optimizer
optimizer = optim.Adam(model.parameters(), lr=LR, betas=(0.9, 0.999), eps=1e-08,
weight_decay=0,
                              amsgrad=False)

# Train
if args.resume_from is not None:
   # Resume?
   print('resuming training from {}'.format(args.resume_from))
   train_states = torch.load(args.resume_from)
   model.load_state_dict(train_states['model_state_dict'])
   if args.overrideLR==0:
       optimizer.load_state_dict(train_states['optimizer_state_dict'])
   epoch_range = np.arange(train_states['epoch']+1, train_states['epoch']+1+EPOCH)
else:
   train_states = {
               'epoch': 0,
               'model_state_dict': model.state_dict(),
               'optimizer_state_dict': optimizer.state_dict(),
               'model_save_criteria': np.inf,
           }
   epoch_range = np.arange(1,EPOCH+1)

loss_train=[]
loss_valid=[]
acc_train = []
acc_valid=[]
recall_macro_valid = []
recall_micro_valid = []
compute_loss = bceWithSoftmax(weights=args.loss_weights)
for epoch in epoch_range:
   running_loss = 0
   running_acc = 0
   model.train()
```

```
    for i, sample in enumerate(loader_train):
        optimizer.zero_grad()
        img = sample[0].to(device)
        target = sample[1].to(device)
        output = model(img)
        # print(target,output)
        loss = compute_loss(output,target)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()
        running_acc += get_acc(target.cpu(),output.cpu())
        mean_loss = running_loss / (i + 1)
        mean_acc = running_acc / (i + 1)
        print('train >>> epoch: {}/{}, batch: {}/{}, mean_loss: {:.4f}, mean_acc:
{:.4f}'.format(
            epoch,
            epoch_range[-1],
            i+1,
            len(loader_train),
            mean_loss,
            mean_acc

        ))
    loss_train.append(mean_loss)
    acc_train.append(mean_acc)
    model.eval()
    running_loss = 0
    output_all=torch.FloatTensor([])
    target_all=torch.FloatTensor([])
    with torch.no_grad():
        for i, sample in enumerate(loader_valid):
            img = sample[0].to(device)
            target = sample[1].to(device)
            output = model(img)
            output_all=torch.cat((output_all,output.float().cpu()),dim=0)
            target_all=torch.cat((target_all,target.float().cpu()),dim=0)
            loss = compute_loss(output,target)
            running_loss += loss.item()
            running_acc += get_acc(target.cpu(),output.cpu())
            mean_loss = running_loss / (i + 1)

    recall_macro = get_recall(target_all, output_all, average='macro')
    recall_micro = get_recall(target_all, output_all, average='micro')
    mean_acc=get_acc(target_all, output_all)
    acc_valid.append(mean_acc)
    print('valid >>> epoch: {}/{}, mean_loss: {:.4f}, mean_acc: {:.4f}'.format(
        epoch,
        epoch_range[-1],
        mean_loss,
        mean_acc
```

```
   ))
   print('recall_micro_valid: {:.4f}, recall_macro_valid: {:4f}'.format(recall_micro,
recall_macro))

   loss_valid.append(mean_loss)
   recall_macro_valid.append(recall_macro)
   recall_micro_valid.append(recall_micro)
   # save train history
   log = {
       'loss_train':loss_train,
       'loss_valid':loss_valid,
       'acc_train': acc_train,
       'acc_valid': acc_valid,
       'recall_micro_valid':recall_micro_valid,
       'recall_macro_valid':recall_macro_valid
       }
   with open(filepath_hist, 'wb') as pfile:
       pickle.dump(log, pfile)

   # save best model
   if mean_loss<train_states['model_save_criteria']:
       print('criteria decreased from {:.4f} to {:.4f}, saving best model at
{}'.format(train_states['model_save_criteria'],

mean_loss,

filepath_model_best))
       train_states = {
           'epoch': epoch,
           'model_state_dict': model.state_dict(),
           'optimizer_state_dict': optimizer.state_dict(),
           'model_save_criteria': mean_loss,
       }
       torch.save(train_states, filepath_model_best)

# save latest model
train_states = {
   'epoch': epoch,
   'model_state_dict': model.state_dict(),
   'optimizer_state_dict': optimizer.state_dict(),
   'model_save_criteria': mean_loss,
}
torch.save(train_states, filepath_model_latest)

print(TIME_STAMP)
```

Test.py

```
from glob import glob
import os
```

```
from albumentations import (
   Compose, Resize, Normalize, RandomBrightnessContrast, HorizontalFlip,
CenterCrop
)
import albumentations.pytorch as albu_torch
import sys
sys.path.insert(1,r'..\utility')
sys.path.insert(1,r'..\models')
from dataloader import ISIC_Dataset
from logger import Logger
from loss import bceWithSoftmax
from torch.utils.data import DataLoader
from models import ResNet18, ResNet50, DPN92
import torch.optim as optim
import torch
import time
import argparse
import numpy as np
import pickle
import pandas as pd
from metrics import get_acc,get_recall,conf_mat
from tqdm import tqdm
import matplotlib.pyplot as plt
from metrics import pretty_plot_confusion_matrix
from pandas import DataFrame
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

parser=argparse.ArgumentParser()
parser.add_argument('--filepath', help='project directory', required=True)
parser.add_argument('--encoder',help='encoder',default='dpn92')
parser.add_argument('--batchSize', help='batch size', type=int, default=32)
parser.add_argument('--load_from', help='filepath to load model',
default=r'D:\Data\cs-8395-dl\model\2020-02-10-22-06-20\2020-02-10-22-06-20_dpn92_best.
pt')
parser.add_argument('--resize', type=int, default=256)

args=parser.parse_args()

# setting up directories

BATCH_SIZE=args.batchSize
dir_data_part = os.path.dirname(args.filepath)
files = os.path.basename(args.filepath).split('.')[0]

# Dataloader Parameters
aug =Compose([
   Resize(args.resize,args.resize),
   Normalize(),
   albu_torch.ToTensorV2()
   ])
```

```
Dataset_valid = ISIC_Dataset(dir_data=dir_data_part, files=[files], label_cat=[ 0 ],
do_cc=True,transform=aug)
loader_valid=DataLoader(Dataset_valid,batch_size=BATCH_SIZE, shuffle=False)
# print('validation samples {}'.format(len(Dataset_valid)))
# Model
if args.encoder == 'resnet18':
   model = ResNet18(pretrained=False, bottleneckFeatures=0).to(device)
if args.encoder == 'resnet50':
   model = ResNet50(pretrained=False, bottleneckFeatures=0).to(device)
if args.encoder == 'dpn92':
   model = DPN92().to(device)
# print(model)

# print('loading model from {}'.format(args.load_from))
train_states = torch.load(args.load_from)
# print('loading model from epoch ', train_states['epoch'])
model.load_state_dict(train_states['model_state_dict'])

model.eval()
with torch.no_grad():
   for sample in loader_valid:
       img = sample[0].to(device)
       target = sample[1].to(device)
       output = model(img)
       output=torch.softmax(output,dim=1).detach().cpu().numpy()
       print(output.argmax())
```

Dataloader.py

```
from torch.utils.data import Dataset, DataLoader
from PIL import Image
from tqdm import tqdm
import os
import random
import numpy as np
from skimage import io
import torch
from glob import glob
from skimage import io
from scipy.ndimage import gaussian_filter
from albumentations import (
Resize,HorizontalFlip,
   Compose,
   Normalize,
RandomBrightnessContrast,
CenterCrop,
)
import albumentations.pytorch as albu_torch
```

```
import pandas as pd
from matplotlib import pyplot as plt
from sampler import BalancedBatchSampler
import sys
sys.path.insert(1,r'..\preprocessing')
from color_constancy import ColorConstancy

def reverse_transform(img_t,mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]):
   img_r = np.array(img_t)
   img_r = img_r.transpose([1,2,0])
   img_r = img_r*std+mean
   img_r *=255
   img_r=img_r.astype(np.uint8)
   img_r = np.squeeze(img_r)
   return img_r

class ISIC_Dataset(Dataset):
   def __init__(self, dir_data, files, label_cat, to_ram = False, transform=None,
do_cc=False):
       self.dir_data = dir_data
       self.transform = transform
       self.files = files
       self.to_ram = to_ram
       self.image_all=[]
       self.label_cat=label_cat
       self.do_cc = do_cc
       self.color_constancy = ColorConstancy(verbose=False, thresh_bg=None)
       if self.to_ram:
           print('loading images to RAM')
           for file in tqdm(self.files):
               # file = self.files[idx]
               path_img = os.path.join(self.dir_data, file+'.jpg')
               image = io.imread(path_img)
               if self.do_cc:
                   image=self.color_constancy.comp(image)
               # print(image.shape)
               self.image_all.append(image)

   def __len__(self):
       size = len(self.files)
       return size

   def __getitem__(self, idx):
       if self.to_ram:
           image=self.image_all[idx]
       else:
           # print(self.files[idx])
           path_img = os.path.join(self.dir_data, self.files[idx] + '.jpg')
           image = io.imread(path_img)
       target=self.label_cat[idx]
```

```
        # print(self.files[idx],image.shape)
        transformed=self.transform(image=image)
        img = transformed['image']
        return img,torch.tensor(target)
```

Loss.py

```
import torch

def bceWithSoftmax(weights=None):
   # i didn't the like the official name of the loss hence the function
   if weights is not None:
       weights = torch.FloatTensor(weights).cuda()
   return torch.nn.CrossEntropyLoss(weights)
if __name__=='__main__':
   loss = bceWithSoftmax()
   input = torch.randn(2, 3, requires_grad=True)
   target = torch.empty(2, dtype=torch.long).random_(3)
   print('input',input)
   print('target',target)
   input_sm = torch.softmax(input,dim=1)
   print('softmax',input_sm)
   print(-torch.log(input_sm))
   print(-torch.log(1-input_sm))

   output = loss(input, target)
   print(output)
   # output.backward()
```

Sampler.py

```
#
https://raw.githubusercontent.com/galatolofederico/pytorch-balanced-batch/master/sampl
er.py
is_torchvision_installed = True
try:
   import torchvision
except:
   is_torchvision_installed = False
import torch.utils.data
import random
import torch


class BalancedBatchSampler(torch.utils.data.sampler.Sampler):
   def __init__(self, dataset, labels=None,shuffle=False):
       self.labels = labels
```

```
        self.dataset = dict() # keys are class labels, values are set of sample indices
associated with each label
        self.balanced_max = 0
        self.shuffle = shuffle
        # Save all the indices for all the classes
        for idx in range(0, len(dataset)):
            label = self._get_label(dataset, idx)
            if label not in self.dataset:
                self.dataset[label] = list()
            self.dataset[label].append(idx)
            self.balanced_max = len(self.dataset[label]) \
                if len(self.dataset[label]) > self.balanced_max else self.balanced_max

        # Oversample the classes with fewer elements than the max
        for label in self.dataset:
            while len(self.dataset[label]) < self.balanced_max:
                self.dataset[label].append(random.choice(self.dataset[label]))
        self.keys = list(self.dataset.keys())
        self.currentkey = 0 # keeps track of which class should be sampled
        self.indices = [-1] * len(self.keys) # keeps track of number of samples per
class
        print('balanced_max: ',self.balanced_max)
        print('number of samples in balanced dataset
{}'.format(self.balanced_max*len(self.keys)))
        # print(self.indices)

    def __iter__(self):
        if self.shuffle:
            print('shuffling dataset')
            for label in self.dataset:
                random.shuffle(self.dataset[label])
        # print(self.dataset)

        while self.indices[self.currentkey] < self.balanced_max - 1:
            self.indices[self.currentkey] += 1
            yield
self.dataset[self.keys[self.currentkey]][self.indices[self.currentkey]]
            self.currentkey = (self.currentkey + 1) % len(self.keys) # I geuss an
assertion that currentkey stays between 0 and num_class-1?
        self.indices = [-1] * len(self.keys)
    def _get_label(self, dataset, idx):
        if self.labels is not None:
            return self.labels[idx].item()
        else:
            # Trying guessing
            dataset_type = type(dataset)
            if is_torchvision_installed and dataset_type is torchvision.datasets.MNIST:
                return dataset.train_labels[idx].item()
            elif is_torchvision_installed and dataset_type is
torchvision.datasets.ImageFolder:
```

```
                return dataset.imgs[idx][1]
            else:
                raise Exception("You should pass the tensor of labels to the
constructor as second argument")

    def __len__(self):
        return self.balanced_max * len(self.keys)
```

Metrics.py

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import recall_score
from sklearn.metrics import confusion_matrix
import torch

#imports
from pandas import DataFrame
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.font_manager as fm
from matplotlib.collections import QuadMesh
import seaborn as sn

def get_acc(target,output):
   output_sm = torch.softmax(output, dim=1)
   output_cat = output_sm.argmax(dim=1)
   return accuracy_score(target,output_cat)
def get_recall(target,output,average):
   output_sm = torch.softmax(output, dim=1)
   output_cat = output_sm.argmax(dim=1)
   return recall_score(target,output_cat,average=average)
def conf_mat(target, output, labels=None):
   output_sm = torch.softmax(output, dim=1)
   output_cat = output_sm.argmax(dim=1)
   target=target.cpu().numpy()
   output_cat = output_cat.cpu().numpy()
   # print(output_cat)
   mat=confusion_matrix(target, output_cat, labels=labels, sample_weight=None)
   return mat
```

Color_constancy.py

```
import numpy as np
from skimage import io
import argparse
import math
from matplotlib import pyplot as plt

class ColorConstancy():
```

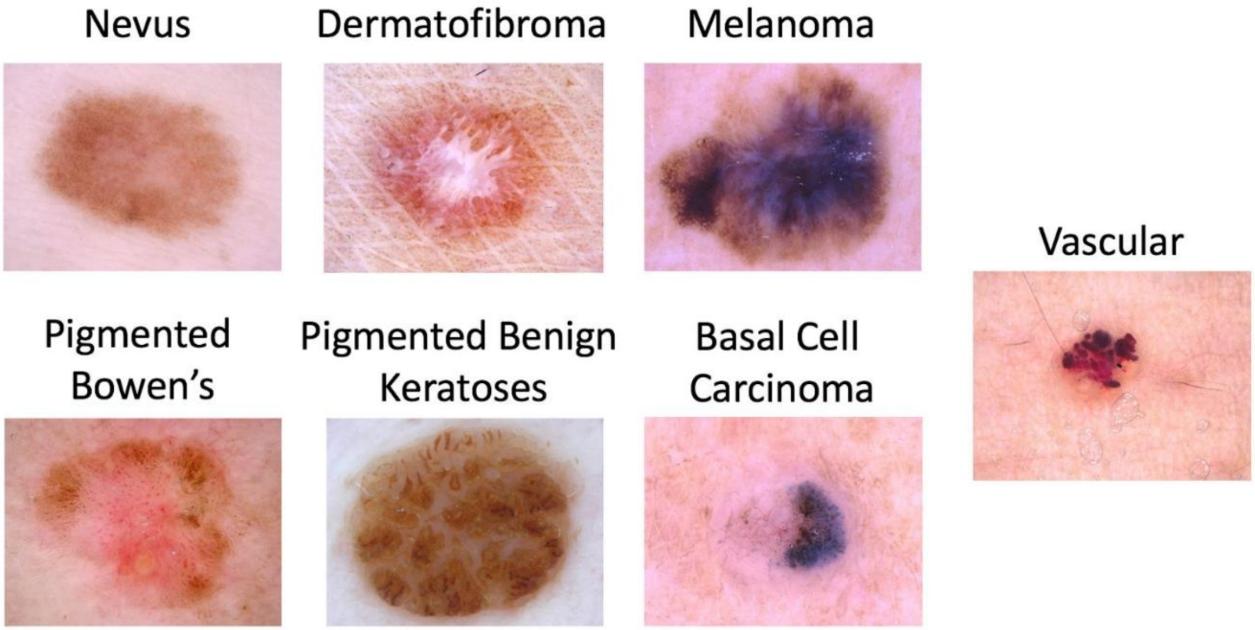
```python
def __init__(self,verbose=False, thresh_bg=None):
    self.verbose = verbose
    self.thresh_bg = thresh_bg
def thresh_img(self,img,thresh):
    red_range = thresh[0]!=img[:,:,0]
    green_range = thresh[1]!=img[:,:,1]
    blue_range = thresh[2]!=img[:,:,2]
    valid_range = np.logical_or(red_range, green_range, blue_range)
    return valid_range

def color_constancy(self,img,preserve_range=True):
    e = np.zeros([3])
    for i in range(3):
        x = img[:,:,i]
        if self.thresh_bg is not None:
            x=x[x!=0]
        e[i]=x.mean()
    if self.verbose: print('channel means',e)
    e=e/math.sqrt(sum(e*e))
    if self.verbose: print('illumination estimate',e)
    d=1/(math.sqrt(3)*e)
    if self.verbose: print('correction coefficient',d)
#     print(d)
    img_t= img*d
    for i in range(3):
        if self.verbose:
            print('transformed image channel {} max\min: {}\{}'.format(
            i+1,img_t[:,:,i].max(),img_t[:,:,i].min()))
    if preserve_range:
        if self.verbose:
            print('setting values above 255 to 255')
        img_t=img_t.flatten()
        img_t[img_t>255]=255
        img_t=img_t.reshape(img.shape)
    return img_t.astype(np.uint8)


def compute_cc(self,img,path_skin=None):


    if img.shape[2]>3:
        img=img[:,:,:3]
    if path_skin is not None:
        mask_skin=io.imread(path_skin)
        mask_skin = mask_skin/mask_skin.max()
        if len(mask_skin.shape)<3:
            mask_skin = np.repeat(mask_skin[:, :, np.newaxis], 3, axis=2)
        img = (img*mask_skin).astype(np.uint8)

    if self.thresh_bg is not None:
```

```
    mask = self.thresh_img(img,self.thresh)
    mask = np.repeat(mask[:, :, np.newaxis], 3, axis=2)
    img = img*mask
img_tx = self.color_constancy(img)
return img_tx
```

Assignment 2
Skin Lesion Classification

Tahsin Reasat
VUID: reasatt

Task - Multi Class Classification



Network Architecture

ISIC Challenge 2018 Leaderboards

TASK 1: LESION BOUNDARY SEGMENTATION | TASK 2: LESION ATTRIBUTE DETECTION | TASK 3: LE

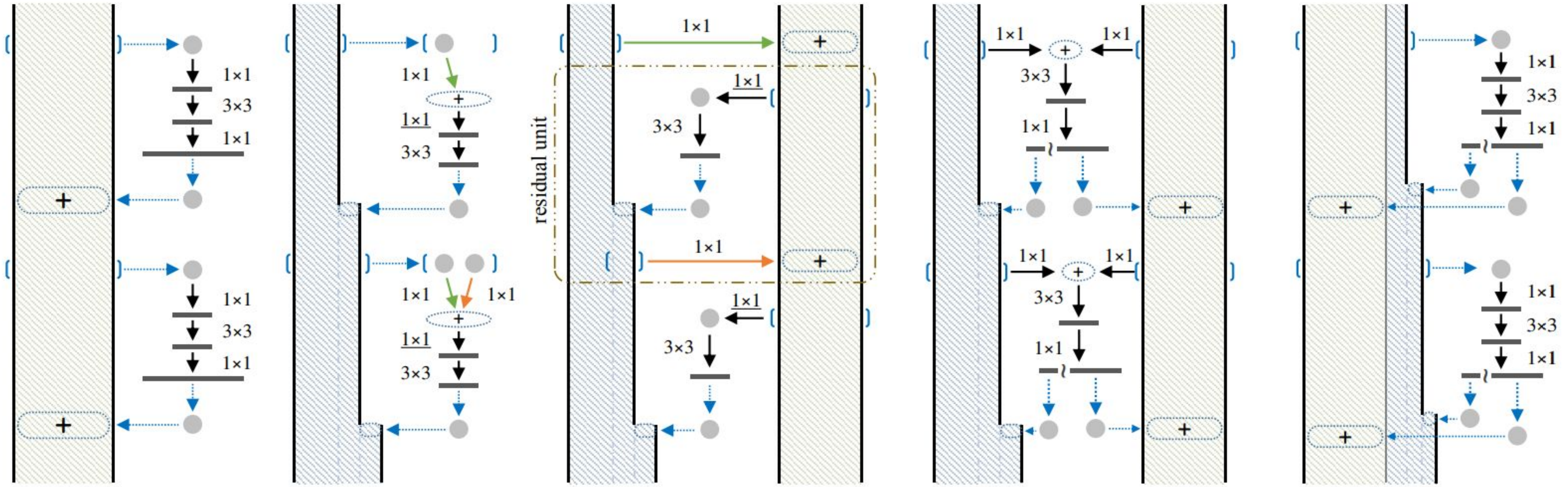
Rank <140 total> ↑	Team (Submitter User) <77 unique teams>	Approach Name	Manuscript
1	MetaOptima Technology Inc. *(Jordan Yap)*	Top 10 Models Averaged	
2	MetaOptima Technology Inc. *(Jordan Yap)*	Meta Ensemble	
3	MetaOptima Technology Inc. *(Jordan Yap)*	Best Single Model	

TABLE II
MODELS USED IN ENSEMBLE

Model	Input Size	Loss	Balanced Accuracy
DPN-92(5k)	224×224	0.331	0.787
DPN-92(5k)	224×224	0.333	0.786
Resnet-152	224×224	0.333	0.770
Densenet-161	224×224	0.334	0.771
Inceptionv3	299×299	0.334	0.770
Inceptionv3*	299×299	0.359	0.757
seresneXt-50	224×224	0.345	0.774
ResNet-50	224×224	0.350	0.772
ResNet-34	224×224	0.356	0.762
ResNet-34	224×224	0.358	0.759
ResNet-50**	224×224	0.364	0.766
seresneXt-50†	224×224	0.366	0.793
seresneXt-50†	224×224	0.372	0.801
seresnet-50	224×224	0.393	0.720
ResNet-18	224×224	0.381	0.736
ResNet-50	224×224	0.437	0.721
ResNet-18‡	224×224	0.438	0.774
Squeezenet1.1	224×224	0.558	0.555
histogram	NA	0.797	0.323

https://challenge2018.isic-archive.com/leaderboards/

Network Architecture - Dual Path Network (DPN)



(a) Residual Network (b) Densely Connected Network (c) Densely Connected Network (with shared connections) (d) Dual Path Architecture (e) DPN

The residual path implicitly reuses features, but it is not good at exploring new features.

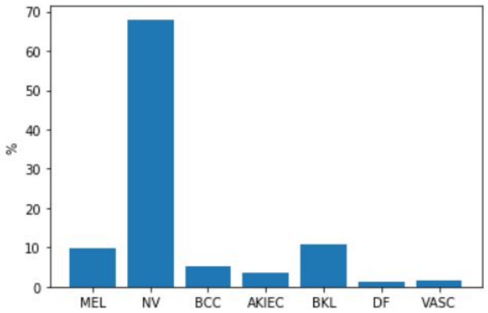
The densely connected network keeps exploring new features but suffers from higher redundancy.

Paper: https://arxiv.org/abs/1707.01629

Pretrained model: https://github.com/Cadene/pretrained-models.pytorch

Handling Imbalance

Train Set Statistics




```
MEL, count: 887, 9.84%
NV, count: 6130, 68.00%
BCC, count: 480, 5.32%
AKIEC, count: 317, 3.52%
BKL, count: 972, 10.78%
DF, count: 101, 1.12%
VASC, count: 128, 1.42%
```

a) Sampling:

1) Undersampling
2) **Oversampling**

Balanced Mini Batch

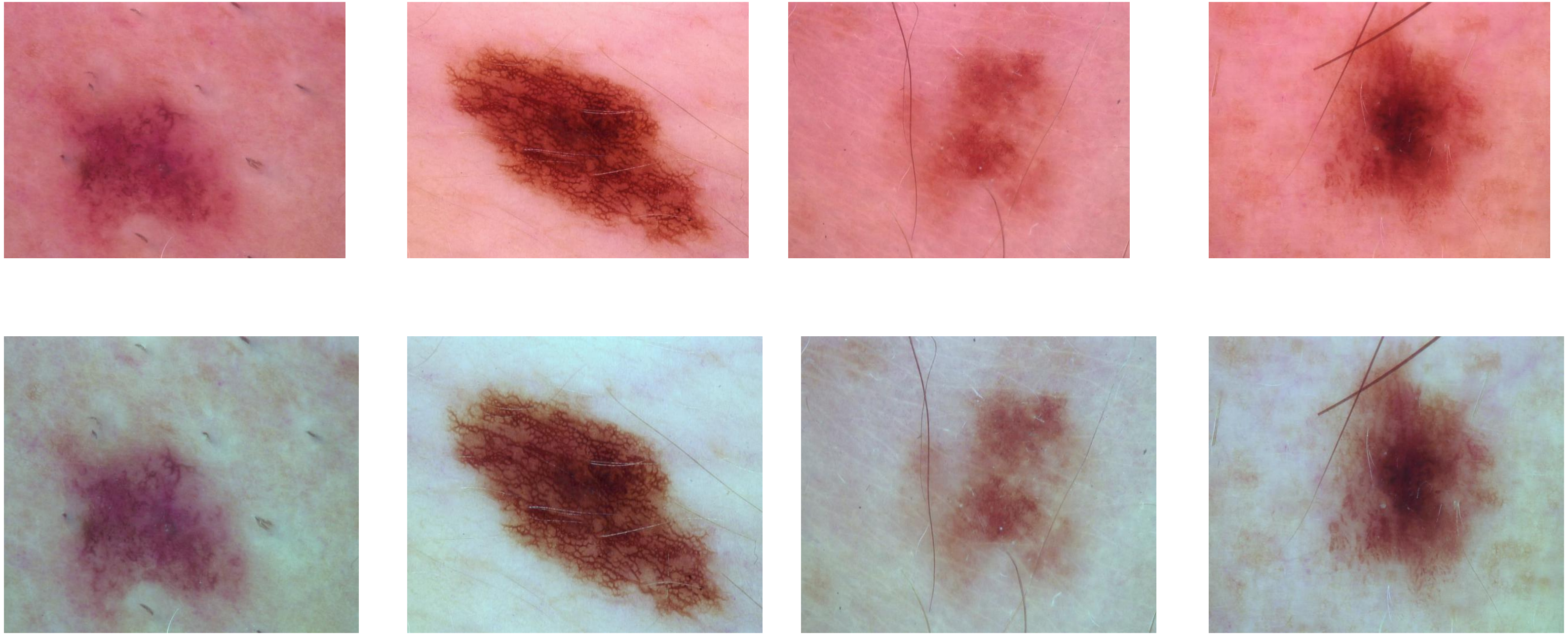
MEL	NV	BCC	AKIEC	BKL	DF	VASC

Batch size 7, 14, or 21 etc.

b) Weighted loss

$$-w_0 y log(p) - w_1 (1-y) log(1-p)$$

Color Constancy



What would the image look like if it was taken under white light
(Under Gray World Assumption)

https://ieeexplore.ieee.org/document/6866131

Augmentations

- HorizontalFlip(),
- RandomRotate90(),
- RandomBrightnessContrast(

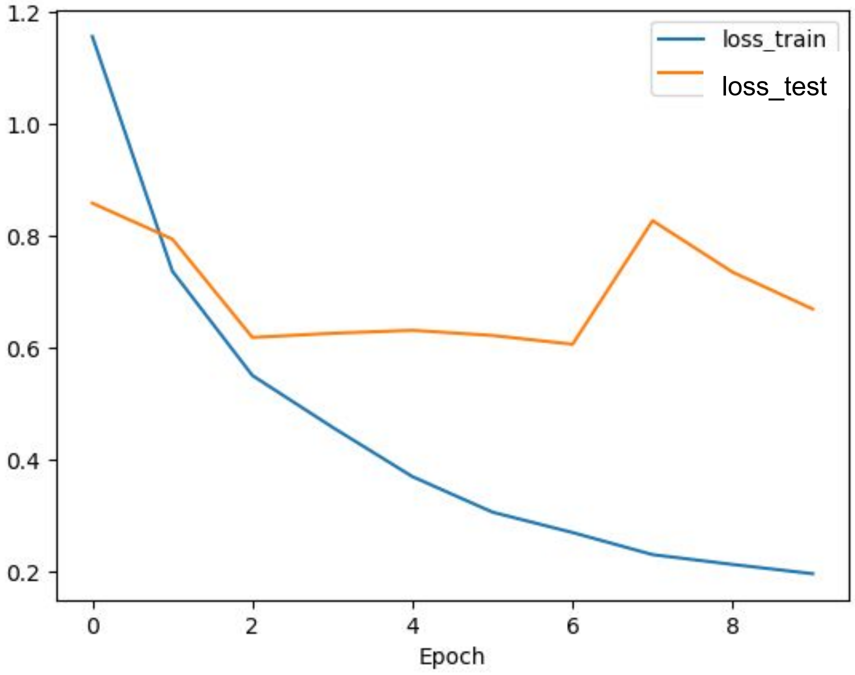
    brightness_limit= [-0.2, 0.2],

    contrast_limit=[-0.2, 0.2]   ),
- RandomCrop(400, 400, p=0.5),
- Resize(256, 256),
- Normalize() (mean and std taken from imagenet)

Training parameters

- Epoch number : 10
- Batch size: 21-24
- Learning rate: 0.00001
- Loss function: (Weighted) Cross Entropy
- Loss weights: [0.8, 0.2, 1.0, 1.0, 0.8, 1.0, 1.0]
- Optimizer: adam
- Network depth: 92 trainable layers
- Input number of channels: 3
- Output number of channels: 7
- OS: Windows
- GPU: RTX 2070

Loss Plot



Results - (Accuracy)

Sampling → Random (RS), Balanced Sampling (BS)

Color → Original Color (OC), Color Constancy (CC)

Loss → Weighted Loss(WL), Unweighted Loss (UL)

RS+WL+ OC	BS+UL+ OC	RS+WL+ CC	BS+UL+ CC
0.8200	0.8260	0.8280	0.7880

Accuracy measured at minimum test loss

Metrics

Accuracy: 0.8280

Recall: 0.7820

Precision: 0.7720

Confusion matrix

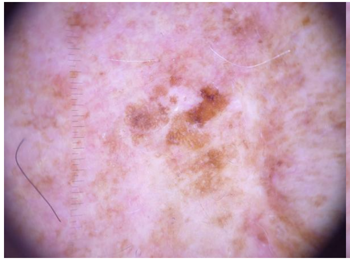
Conclusion

A few duplicate images in the train set.

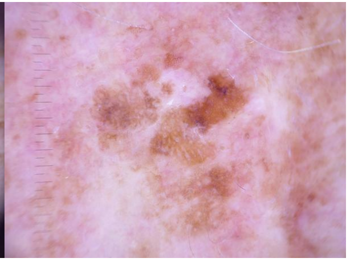
Better Hyper parameter tuning

Exploring more architectures

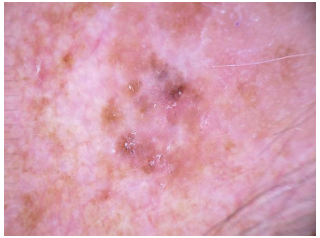
More advance techniques, few shot learning or meta learning can be explored for rare diseases.



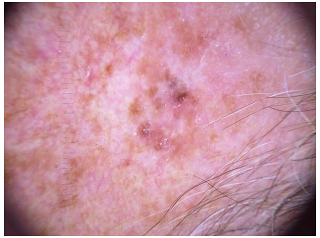
ISIC_0025030



ISIC_0027419



ISIC_0026769



ISIC_0025661

Duplicates