

```
In [1]: package_paths = [
        ..../input/pytorch-image-models/pytorch-image-models-master', #'../input/efficientnet-pytorch-07/eff
icientnet_pytorch-07.07
        ]
        '..../input/image-fmix/FMIX-master'
    ]
    import sys;

    for pth in package_paths:
        sys.path.append(pth)

    from fmix import sample_mask, make_low_freq_image, binarise_mask
```

```
In [2]: from glob import glob
        from sklearn.model_selection import GroupKFold, StratifiedKFold
        import cv2
        from skimage import io
        import torch
        from torch import nn
        import os
        from datetime import datetime
        import time
        import random
        import cv2
        import torchvision
        from torchvision import transforms
        import pandas as pd
        import numpy as np
        from tqdm import tqdm

        import matplotlib.pyplot as plt
        from torch.utils.data import Dataset, DataLoader
        from torch.utils.data.sampler import SequentialSampler, RandomSampler
        from torch.cuda.amp import autocast, GradScaler
        from torch.nn.modules.loss import _WeightedLoss
        import torch.nn.functional as F

        import timm

        import sklearn
        import warnings
        import joblib
        from sklearn.metrics import roc_auc_score, log_loss
        from sklearn import metrics
        import warnings
        import cv2
        import pydicom
        #from efficientnet_pytorch import EfficientNet
        from scipy.ndimage.interpolation import zoom
```

```
In [3]: CFG = {
        'fold_num': 5,
        'seed': 719,
        'model_arch': 'tf_efficientnet_b4_ns',
        'img_size': 512,
        'epochs': 10,
        'train_bs': 16,
        'valid_bs': 32,
        'T_0': 10,
        'lr': 1e-4,
        'min_lr': 1e-6,
        'weight_decay': 1e-6,
        'num_workers': 4,
        'accum_iter': 2, # supppprt to do batch accumulation for backprop with effectively larger batch siz
        'verbose_step': 1,
        'device': 'cuda:0'
    }
```

```
In [4]: train = pd.read_csv('../input/cassava-leaf-disease-classification/train.csv')
        train.head()
```

```
Out[4]:
```

	image_id	label
0	1000015157.jpg	0
1	1000201771.jpg	3
2	1000423118.jpg	1
3	1000723321.jpg	1
4	1000812911.jpg	3

```
In [5]: train.label.value_counts()
```

```
Out[5]:
```

3	13158
4	2577
2	2386
1	2189
0	1087

Name: dtype: int64

We could do stratified validation split in each fold to make each fold's train and validation set looks like the whole train set in target distributions.

```
In [6]: submission = pd.read_csv('../input/cassava-leaf-disease-classification/sample_submission.csv')
        submission.head()
```

```
Out[6]:
```

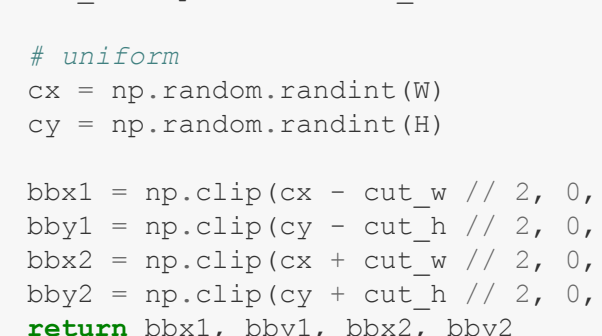
	image_id	label
0	2216849948.jpg	4

Helper Functions

```
In [7]: def seed_everything(seed):
        random.seed(seed)
        os.environ['PYTHONHASHSEED'] = str(seed)
        np.random.seed(seed)
        torch.manual_seed(seed)
        torch.cuda.manual_seed(seed)
        torch.backends.cudnn.deterministic = True
        torch.backends.cudnn.benchmark = True

        def get_img(path):
            im_bgr = cv2.imread(path)
            im_rgb = im_bgr[:, :, ::-1]
            plt.imshow(im_rgb)
            return im_rgb
```

```
img = get_img('../input/cassava-leaf-disease-classification/train_images/1000015157.jpg')
plt.imshow(img)
plt.show()
```



Dataset

```
In [8]: def rand_bbox(size, lam):
        W = size[0]
        H = size[1]
        cut_rat = np.sqrt(1. - lam)
        cut_w = np.int(W * cut_rat)
        cut_h = np.int(H * cut_rat)

        # uniform
        cx = np.random.randint(W)
        cy = np.random.randint(H)

        bbx1 = np.clip(cx - cut_w // 2, 0, W)
        bby1 = np.clip(cy - cut_h // 2, 0, H)
        bbx2 = np.clip(cx + cut_w // 2, 0, W)
        bby2 = np.clip(cy + cut_h // 2, 0, H)
        return bbx1, bby1, bbx2, bby2
```

```
class CassavaDataset(Dataset):
    def __init__(self, df, data_root,
                 transforms=None,
                 output_label=True,
                 one_hot_label=False,
                 do_fmfix=False,
                 fmfix_params={
                     'alpha': 1.,
                     'decay_power': 3.,
                     'shape': (CFG['img_size'], CFG['img_size']),
                     'max_soft': True,
                     'reformulate': False
                 },
                 do_cutmix=False,
                 cutmix_params={
                     'alpha': 1,
                 }
            ):
        super().__init__()
        self.df = df.reset_index(drop=True).copy()
        self.transforms = transforms
        self.data_root = data_root
        self.do_fmfix = do_fmfix
        self.fmfix_params = fmfix_params
        self.do_cutmix = do_cutmix
        self.cutmix_params = cutmix_params

        self.output_label = output_label
        self.one_hot_label = one_hot_label
```

```
        if output_label == True:
            self.labels = self.df['label'].values
            #print(self.labels)

            if one_hot_label is np.True:
                self.labels = np.eye(self.df['label'].max()+1)[self.labels]
                #print(self.labels)

        def __len__(self):
            return self.df.shape[0]

        def __getitem__(self, index: int):
```

```
            # get labels
            if self.output_label:
                target = self.labels[index]

            img = get_img("{}{}".format(self.data_root, self.df.loc[index]['image_id']))

            if self.transforms:
                img = self.transforms(image=img)['image']

            if self.do_fmfix and np.random.uniform(0., 1., size=1)[0] > 0.5:
                with torch.no_grad():
                    #lam, mask = sample_mask(**self.fmfix_params)

                    lam = np.clip(np.random.beta(self.fmfix_params['alpha'], self.fmfix_params['alpha']), 0.6,
```

```
0.7)

                    # Make mask, get mean / std
                    mask = make_low_freq_image(self.fmfix_params['decay_power'], self.fmfix_params['shape'])
                    mask = binarise_mask(mask, lam, self.fmfix_params['shape'], self.fmfix_params['max_soft'

                    fmfix_ix = np.random.choice(self.df.index, size=1)[0]
                    fmfix_img = get_img("{}{}".format(self.data_root, self.df.iloc[fmfix_ix]['image_id']))

                    if self.transforms:
                        fmfix_img = self.transforms(image=fmfix_img)['image']

                    mask_torch = torch.from_numpy(mask)

                    # mix image
                    img = mask_torch*img*(1.-mask_torch)+fmfix_img

                    #print(mask.shape)

                    #assert self.output_label==True and self.one_hot_label==True
```

```
                    # mix target
                    rate = mask.sum()/CFG['img_size']/CFG['img_size']
                    target = rate*target + (1.-rate)*self.labels[fmfix_ix]
                    #print(target, mask, img)
                    #assert False

                    if self.do_cutmix and np.random.uniform(0., 1., size=1)[0] > 0.5:
                        self.print.sum(), img.shape)
                        with torch.no_grad():
                            cmix_ix = np.random.choice(self.df.index, size=1)[0]
                            cmix_img = get_img("{}{}".format(self.data_root, self.df.iloc[cmix_ix]['image_id']))
                            if self.transforms:
                                cmix_img = self.transforms(image=cmix_img)['image']

                            lam = np.clip(np.random.beta(self.cutmix_params['alpha'], self.cutmix_params['alpha']),
```

```
0.3,0.4)

                            bbx1, bby1, bbx2, bby2 = rand_bbox((CFG['img_size'], CFG['img_size']), lam)

                            img[:, bbx1:bbx2, bby1:bby2] = cmix_img[:, bbx1:bbx2, bby1:bby2]

                            rate = 1 - ((bbx2 - bbx1) * (bby2 - bby1) / (CFG['img_size'] * CFG['img_size']))
                            target = rate*target + (1.-rate)*self.labels[cmix_ix]

                            #print('-', img.sum())
                            #print(target)
                            #assert False

                            # label smoothing
                            #print(type(img), type(target))
                            if self.output_label == True:
                                return img, target
                            else:
                                return img
```

Define Train/Validation Image Augmentations

```
In [9]: from albumentations import (
        HorizontalFlip, VerticalFlip, IAAPerspective, ShiftScaleRotate, CLAHE, RandomRotate90,
        Transpose, ShiftScaleRotate, Blur, OpticalDistortion, GridDistortion, HueSaturationValue,
        IAASharpEN, IAABrightness, GaussianNoise, GaussNoise, MotionBlur, MedianBlur, IAAPiecewiseAffine, RandomResizedCrop
        ,
        IAASharpEN, IAABrightness, RandomBrightnessContrast, Flip, OneOf, Compose, Normalize, Cutout, CoarseDropout,
        ShiftScaleRotate, CenterCrop, Resize
    )

    from albumentations.pytorch import ToTensorV2
```

```
def get_train_transforms():
    return Compose([
        RandomResizedCrop(CFG['img_size'], CFG['img_size']),
        Transpose(p=0.5),
        HorizontalFlip(p=0.5),
        VerticalFlip(p=0.5),
        ShiftScaleRotate(p=0.5),
        HueSaturationValue(hue_shift_limit=0.2, sat_shift_limit=0.2, val_shift_limit=0.2, p=0.5),
        RandomBrightnessContrast(brightness_limit=(-0.1,0.1), contrast_limit=(-0.1, 0.1), p=0.5),
        Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225], max_pixel_value=255.0, p=
1.0),
        CoarseDropout(p=0.5),
        Cutout(p=0.5),
        ToTensorV2(p=1.0),
        ], p=1.)

def get_valid_transforms():
    return Compose([
        CenterCrop(CFG['img_size'], CFG['img_size'], p=1.),
        Resize(CFG['img_size'], CFG['img_size']),
        Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225], max_pixel_value=255.0, p=
1.0),
        ToTensorV2(p=1.0),
        ], p=1.)
```

Model

```
In [10]: class CassavaTmClassifier(nn.Module):
        def __init__(self, model_arch, n_class, pretrained=False):
            super().__init__()
            self.model = timm.create_model(model_arch, pretrained=pretrained)
            n_features = self.model.classifier.in_features
            self.model.classifier = nn.Linear(n_features, n_class)

            '''
            self.model.classifier = nn.Sequential(
                nn.Dropout(0.3),
                #nn.Linear(n_features, hidden_size,bias=True), nn.ReLU(),
                nn.Linear(n_features, n_class, bias=True)
            )
            '''

        def forward(self, x):
            x = self.model(x)
            return x
```

Training APIs

```
In [11]: def prepare_data_loader(df, trn_idx, val_idx, data_root='../input/cassava-leaf-disease-classification/tr
ain_images/'):

        from catalyst.data.sampler import BalanceClassSampler

        train = df.loc[trn_idx,:].reset_index(drop=True)
        valid = df.loc[val_idx,:].reset_index(drop=True)

        train_ds = CassavaDataset(train, data_root, transforms=get_train_transforms(), output_label=True,
one_hot_label=False, do_fmfix=False, do_cutmix=False)
        valid_ds = CassavaDataset(valid, data_root, transforms=get_valid_transforms(), output_label=True)

        train_loader = torch.utils.data.DataLoader(
            train_ds,
            batch_size=CFG['train_bs'],
            pin_memory=False,
            drop_last=False,
            shuffle=True,
            num_workers=CFG['num_workers'],
            #sampler=BalanceClassSampler(labels=train['label'].values, mode="downsampling")
        )
        val_loader = torch.utils.data.DataLoader(
            valid_ds,
            batch_size=CFG['valid_bs'],
            num_workers=CFG['num_workers'],
            shuffle=False,
            pin_memory=False,
        )
        return train_loader, val_loader
```

```
def train_one_epoch(epoch, model, loss_fn, optimizer, train_loader, device, scheduler=None, schd_batch_
update=False):
    model.train()

    t = time.time()
    running_loss = None

    pbar = tqdm(enumerate(train_loader), total=len(train_loader))
    for step, (imgs, image_labels) in pbar:
        imgs = imgs.to(device).float()
        image_labels = image_labels.to(device).long()

        #print(image_labels.shape, exam_label.shape)
        with autocast():
            image_preds = model(imgs) #output = model(input)
            #print(image_preds.shape, exam_pred.shape)

            loss = loss_fn(image_preds, image_labels)

            scaler.scale(loss).backward()

            if running_loss is None:
                running_loss = loss.item()
            else:
                running_loss = running_loss * .99 + loss.item() * .01

            if ((step + 1) % CFG['accum_iter'] == 0) or ((step + 1) == len(train_loader)):
                # may unscale here if desired (e.g., to allow clipping unscaled gradients)

                scaler.step(optimizer)
                scaler.update()
                optimizer.zero_grad()

            if scheduler is not None and schd_batch_update:
                scheduler.step()
```

```
            if ((step + 1) % CFG['verbose_step'] == 0) or ((step + 1) == len(train_loader)):
                description = f'epoch {epoch} loss: {running_loss:.4f}'

                pbar.set_description(description)

            if scheduler is not None and not schd_batch_update:
                scheduler.step()

def valid_one_epoch(epoch, model, loss_fn, val_loader, device, scheduler=None, schd_loss_update=False):
    model.eval()

    t = time.time()
    loss_sum = 0
    sample_num = 0
    image_preds_all = []
    image_targets_all = []

    pbar = tqdm(enumerate(val_loader), total=len(val_loader))
    for step, (imgs, image_labels) in pbar:
        imgs = imgs.to(device).float()
        image_labels = image_labels.to(device).long()

        image_preds = model(imgs) #output = model(input)
        #print(image_preds.shape, exam_pred.shape)
        image_preds_all += [torch.argmax(image_preds, 1).detach().cpu().numpy()]
        image_targets_all += [image_labels.detach(1).detach().cpu().numpy()]

        loss = loss_fn(image_preds, image_labels)

        loss_sum += loss.item()*image_labels.shape[0]
        sample_num += image_labels.shape[0]

        if ((step + 1) % CFG['verbose_step'] == 0) or ((step + 1) == len(val_loader)):
            description = f'epoch {epoch} loss: {loss_sum/sample_num:.4f}'
            pbar.set_description(description)

    image_preds_all = np.concatenate(image_preds_all)
    image_targets_all = np.concatenate(image_targets_all)
    print('validation multi-class accuracy = {:.4f}'.format((image_preds_all==image_targets_all).mean
()))
```

```
In [12]: # reference: https://www.kaggle.com/c/sim-isic-melanoma-classification/discussion/173733
        class MyCrossEntropyLoss(_WeightedLoss):
            def __init__(self, weight=None, reduction='mean'):
                super().__init__(weight=weight, reduction=reduction)
                self.weight = weight
                self.reduction = reduction

            def forward(self, inputs, targets):
                lsm = F.log_softmax(inputs, -1)

                if self.weight is not None:
                    lsm = lsm * self.weight.unsqueeze(-1)

                loss = -(targets * lsm).sum(-1)

                if self.reduction == 'sum':
                    loss = loss.sum()
                elif self.reduction == 'mean':
                    loss = loss.mean()

                return loss
```

Main Loop

```
In [13]: if __name__ == '__main__':
        # for training only, need nightly build pytorch

        seed_everything(CFG['seed'])

        folds = StratifiedKFold(n_splits=CFG['fold_num'], shuffle=True, random_state=CFG['seed']).split(np.
arange(train.shape[0]), train.label.values)

        for fold, (trn_idx, val_idx) in enumerate(folds):
            # we'll train fold 0 first
            if fold > 0:
                break

            print('Training with {} started'.format(fold))

            print(len(trn_idx), len(val_idx))
            train_loader, val_loader = prepare_data_loader(train, trn_idx, val_idx, data_root='../input/cass
ava-leaf-disease-classification/train_images/')

            device = torch.device(CFG['device'])

            model = CassavaTmClassifier(CFG['model_arch'], train.label.nunique(), pretrained=True).to(device)

            scaler = GradScaler()
            optimizer = torch.optim.Adam(model.parameters(), lr=CFG['lr'], weight_decay=CFG['weight_decay'

            scheduler = torch.optim.lr_scheduler.StepLR(optimizer, gamma=0.1, step_size=CFG['epochs']-1)
            scheduler = torch.optim.lr_scheduler.CosineAnnealingWarmRestarts(optimizer, T_0=CFG['T_0'], T_mu
lt=1, eta_min=CFG['min_lr'], last_epoch=-1)
            #scheduler = torch.optim.lr_scheduler.OneCycleLR(optimizer=optimizer, pct_start=0.1, div_factor
=25,
                #
                max_lr=CFG['lr'], epochs=CFG['epochs'], steps_
per_epoch=len(train_loader))

            loss_tr = nn.CrossEntropyLoss().to(device) #MyCrossEntropyLoss().to(device)
            loss_fn = nn.CrossEntropyLoss().to(device)

            for epoch in range(CFG['epochs']):
                train_one_epoch(epoch, model, loss_tr, optimizer, train_loader, device, scheduler=scheduler
, schd_batch_update=False)

                with torch.no_grad():
                    valid_one_epoch(epoch, model, loss_fn, val_loader, device, scheduler=None, schd_loss_up
date=False)

                torch.save(model.state_dict(), '{}_fold_{}_{}.format(CFG['model_arch'], fold, epoch))

                torch.save(model.cnn_model.state_dict(), '{}_cnn_model_fold_{}_{}'.format(CFG['model_path'], fo
ld, CFG['tag']))

                del model, optimizer, train_loader, val_loader, scaler, scheduler
                torch.cuda.empty_cache()
```

Training with 0 started
17117 4280
wandb: WARNING W&B installed but not logged in. Run 'wandb login' or set the WANDB_API_KEY env varia ble.
Downloading: "https://github.com/wrightman/pytorch-image-models/releases/download/v0.1-weights/tf_efficientnet_b4_ns-d6313a46.pth" to /root/.cache/torch/hub/checkpoints/tf_efficientnet_b4_ns-d6313a46.pt

epoch 0 loss: 0.3678: 100%
epoch 0 loss: 0.3678: 100%

validation multi-class accuracy = 0.8757
epoch 1 loss: 0.4044: 100%
epoch 1 loss: 0.3480: 100%

validation multi-class accuracy = 0.8790
epoch 2 loss: 0.3743: 100%
epoch 2 loss: 0.3365: 100%

validation multi-class accuracy = 0.8855
epoch 3 loss: 0.3589: 100%
epoch 3 loss: 0.3508: 100%

validation multi-class accuracy = 0.8818
epoch 4 loss: 0.3406: 100%
epoch 4 loss: 0.3210: 100%

validation multi-class accuracy = 0.8921
epoch 5 loss: 0.3095: 100%
epoch 5 loss: 0.3237: 100%

validation multi-class accuracy = 0.8932
epoch 6 loss: 0.2846: 100%
epoch 6 loss: 0.3230: 100%

validation multi-class accuracy = 0.8909
epoch 7 loss: 0.2627: 100%
epoch 7 loss: 0.3261: 100%

validation multi-class accuracy = 0.8897
epoch 8 loss: 0.2616: 100%
epoch 8 loss: 0.3193: 100%

validation multi-class accuracy = 0.8914
epoch 9 loss: 0.2400: 100%
epoch 9 loss: 0.3250: 100%

validation multi-class accuracy = 0.8902

Inference part is here: <https://www.kaggle.com/khyeh0719/pytorch-efficientnet-baseline-inference-tta>