

```
In [ ]: from google.colab import drive  
drive.mount('/content/gdrive')
```

Mounted at /content/gdrive

```
In [ ]: %cd '/content/gdrive/MyDrive/ML_Project_RL/images'
```

/content/gdrive/MyDrive/ML_Project_RL/images

```
In [ ]: xla_version = '1.8'
!curl https://raw.githubusercontent.com/pytorch/xla/master/contrib/scripts/env
-setup.py -o pytorch-xla-env-setup.py
!python pytorch-xla-env-setup.py --version $xla_version
```

% Total nt	% Received	% Xferd	Average Speed		Time	Time	Time	Curre
			Dload	Upload	Total	Spent	Left	Speed
100 5116	100 5116	0 0	4281	0	0:00:01	0:00:01	--:--:--	427

```

Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.7/dist-
-packages (from google-auth==1.4.1->google-api-python-client==1.8.0->cloud-tp
u-client) (4.8)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/pyt
hon3.7/dist-packages (from packaging==14.3->google-api-core<2dev,>=1.13.0->go
ogle-api-python-client==1.8.0->cloud-tpu-client) (3.0.6)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/python
3.7/dist-packages (from pyasn1-modules==0.2.1->google-auth==1.4.1->google-api
-python-client==1.8.0->cloud-tpu-client) (0.4.8)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.
7/dist-packages (from requests<3.0.0dev,>=2.18.0->google-api-core<2dev,>=1.1
3.0->google-api-python-client==1.8.0->cloud-tpu-client) (2021.10.8)
Requirement already satisfied: urllib3!=1.25.0,!1.25.1,<1.26,>=1.21.1 in /us
r/local/lib/python3.7/dist-packages (from requests<3.0.0dev,>=2.18.0->google-
api-core<2dev,>=1.13.0->google-api-python-client==1.8.0->cloud-tpu-client)
(1.24.3)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/
dist-packages (from requests<3.0.0dev,>=2.18.0->google-api-core<2dev,>=1.13.0
->google-api-python-client==1.8.0->cloud-tpu-client) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
packages (from requests<3.0.0dev,>=2.18.0->google-api-core<2dev,>=1.13.0->goo
gle-api-python-client==1.8.0->cloud-tpu-client) (2.10)
Uninstalling torch-1.10.0+cu111:
Installing collected packages: google-api-python-client, cloud-tpu-client
  Attempting uninstall: google-api-python-client
    Found existing installation: google-api-python-client 1.12.8
    Uninstalling google-api-python-client-1.12.8:
      Successfully uninstalled google-api-python-client-1.12.8
WARNING: Ignoring invalid distribution -orch (/usr/local/lib/python3.7/dist-p
ackages)
WARNING: Ignoring invalid distribution -orch (/usr/local/lib/python3.7/dist-p
ackages)
ERROR: pip's dependency resolver does not currently take into account all the
packages that are installed. This behaviour is the source of the following de
pendency conflicts.
earthengine-api 0.1.293 requires google-api-python-client<2,>=1.12.1, but you
have google-api-python-client 1.8.0 which is incompatible.
Successfully installed cloud-tpu-client-0.10 google-api-python-client-1.8.0
Done updating TPU runtime
  Successfully uninstalled torch-1.10.0+cu111
Found existing installation: torchvision 0.11.1+cu111
Uninstalling torchvision-0.11.1+cu111:
  Successfully uninstalled torchvision-0.11.1+cu111
Copying gs://tpu-pytorch/wheels/torch-1.8-cp37-cp37m-linux_x86_64.whl...
\
Operation completed over 1 objects/126.5 MiB.
Copying gs://tpu-pytorch/wheels/torch_xla-1.8-cp37-cp37m-linux_x86_64.whl...
\ [1 files][137.9 MiB/137.9 MiB]
Operation completed over 1 objects/137.9 MiB.
Copying gs://tpu-pytorch/wheels/torchvision-1.8-cp37-cp37m-linux_x86_64.wh
l...
/ [1 files][ 4.8 MiB/ 4.8 MiB]
Operation completed over 1 objects/4.8 MiB.
Processing ./torch-1.8-cp37-cp37m-linux_x86_64.whl
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/
dist-packages (from torch==1.8) (3.10.0.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-package

```

```

s (from torch==1.8) (1.19.5)
Installing collected packages: torch
ERROR: pip's dependency resolver does not currently take into account all the
packages that are installed. This behaviour is the source of the following de
pendency conflicts.
fastai 1.0.61 requires torchvision, which is not installed.
torchtext 0.11.0 requires torch==1.10.0, but you have torch 1.8.0a0+6e9f2c8 w
hich is incompatible.
torchaudio 0.10.0+cu111 requires torch==1.10.0, but you have torch 1.8.0a0+6e
9f2c8 which is incompatible.
Successfully installed torch-1.8.0a0+6e9f2c8
Processing ./torch_xla-1.8-cp37-cp37m-linux_x86_64.whl
Installing collected packages: torch-xla
Successfully installed torch-xla-1.8
Processing ./torchvision-1.8-cp37-cp37m-linux_x86_64.whl
Requirement already satisfied: pillow>=4.1.1 in /usr/local/lib/python3.7/dist
-packages (from torchvision==1.8) (7.1.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-package
s (from torchvision==1.8) (1.19.5)
Requirement already satisfied: torch in /usr/local/lib/python3.7/dist-package
s (from torchvision==1.8) (1.8.0a0+6e9f2c8)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/
dist-packages (from torch->torchvision==1.8) (3.10.0.2)
Installing collected packages: torchvision
Successfully installed torchvision-0.9.0a0+89edfaa
Reading package lists... Done
Building dependency tree
Reading state information... Done
The following NEW packages will be installed:
  libomp5
0 upgraded, 1 newly installed, 0 to remove and 37 not upgraded.
Need to get 234 kB of archives.
After this operation, 774 kB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu bionic/universe amd64 libomp5 amd64 5.
0.1-1 [234 kB]
Fetched 234 kB in 1s (320 kB/s)
Selecting previously unselected package libomp5:amd64.
(Reading database ... 155229 files and directories currently installed.)
Preparing to unpack .../libomp5_5.0.1-1_amd64.deb ...
Unpacking libomp5:amd64 (5.0.1-1) ...
Setting up libomp5:amd64 (5.0.1-1) ...
Processing triggers for libc-bin (2.27-3ubuntu1.3) ...
/sbin/ldconfig.real: /usr/local/lib/python3.7/dist-packages/ideep4py/lib/libm
kldnn.so.0 is not a symbolic link

```



```
In [ ]: import gc
import os
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision.models as models
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.autograd import Variable
from skimage import io, transform
from skimage.color import gray2rgb
from PIL import Image, ImageEnhance
import cv2
import time
import random
import copy
import seaborn as sns
import matplotlib.pyplot as plt
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms, utils
from torchsummary import summary
import torch_xla
import torch_xla.core.xla_model as xm
import torch_xla.debug.metrics as met
import torch_xla.distributed.parallel_loader as pl
import torch_xla.distributed.xla_multiprocessing as xmp
import torch_xla.utils.utils as xu
from torch.cuda.amp import GradScaler
```

WARNING:root:TPU has started up successfully with version pytorch-1.8

```

In [ ]: #Preparing the dataset
num_folds = 5
use_fold = 0

image_size = 256

batch_size = 128
batches_per_epoch = 1000
num_epochs = 10
batch_verbose = 100
num_tpu_workers = 8

eta = 0.0001
step = 1
gamma = 0.5

curr_path = os.getcwd()
train_path = os.path.join(curr_path, 'train')
test_path = os.path.join(curr_path, 'test')
class_map = {'happy': 0, 'neutral':1, 'angry': 2, 'fearful': 3, 'surprised': 4
, 'disgusted': 5, 'sad': 6}
os.environ['XLA_USE_BF16'] = '1'
os.environ['XLA_TENSOR_ALLOCATOR_MAXSIZE'] = '1000000000'

```

```

In [ ]: def prepare_dataset(datapath):
    list_of_classes = os.listdir(datapath)
    labels = []
    image_paths = []
    for idx, img_class in enumerate(list_of_classes):
        path = os.path.join(datapath, img_class)
        images = os.listdir(path)
        for img in images:
            image_paths.append(os.path.join(path, img))
            labels.append(class_map[img_class])

    return image_paths, labels

```

```

In [ ]: train_img_paths, train_labels = prepare_dataset(train_path)
test_img_paths, test_labels = prepare_dataset(test_path)

```

```

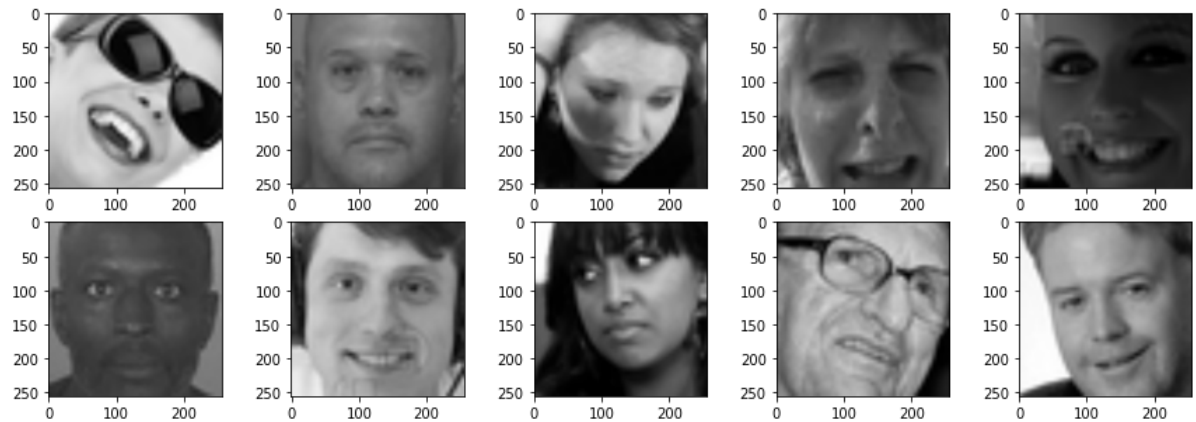
In [ ]: class_weights = []
total_size = len(train_labels)
_, counts = np.unique(np.array(train_labels), return_counts=True)
for count in counts:
    class_weights.append((count/total_size))

class_weights = torch.Tensor(class_weights)

```

```
In [ ]: plt.figure(figsize = (15,5))
        for i in range(10):
            index = random.randint(0, len(train_img_paths)-1)
            im = cv2.imread(train_img_paths[index])
            im_resized = cv2.resize(im, (256, 256))
            plt.subplot(2,5,i+1)
            plt.imshow(cv2.cvtColor(im_resized, cv2.COLOR_BGR2RGB))

        plt.show()
```



```
In [ ]: class EmotionDataset(Dataset):

        def __init__(self, data_labels, dataset, transform=None):
            """
            Args:
                csv_file (string): Path to the csv file with annotations.
                root_dir (string): Directory with all the images.
                transform (callable, optional): Optional transform to be applied
                    on a sample.
            """
            self.dataset = dataset
            self.data_labels = data_labels
            self.transform = transform

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

        def __getitem__(self, idx):
            img_name = self.dataset[idx]
            image = Image.open(img_name)
            #image = gray2rgb(image)
            enhancer = ImageEnhance.Sharpness(image)
            image_s = enhancer.enhance(3)

            type_p = self.data_labels[idx]
            if self.transform:
                image_s = self.transform(image_s)

            return image_s, type_p
```



```
In [ ]: transform_normal = transforms.Compose([
    transforms.Resize((224,224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5], std=[0.5])

])
transform_rotate = transforms.Compose([
    transforms.Resize((224,224)),
    transforms.RandomRotation(degrees = 20),
    transforms.ToTensor(),transforms.Normalize(mean=[0.5], std=[0.5])

])

transform_flip = transforms.Compose([
    transforms.RandomVerticalFlip(0.5),
    transforms.Resize((224,224)),
    transforms.ToTensor(),transforms.Normalize(mean=[0.5], std=[0.5])

])
transform_jitter = transforms.Compose([
    transforms.ToPILImage(),
    transforms.ColorJitter(brightness=0.4, contrast=0.4, saturation=0.2, hue=0
),
    transforms.Resize((256,256)),
    transforms.CenterCrop(240),
    transforms.Resize((224,224)),
    transforms.ToTensor()

])
```

```
In [ ]: train_datasets = []
train_datasets.append(EmotionDataset( train_labels, train_img_paths, transform
=transform_normal))
train_datasets.append(EmotionDataset( train_labels, train_img_paths, transform
=transform_rotate))
#train_datasets.append(EmotionDataset( train_labels, train_img_paths, transfor
m=transform_flip))
ds = torch.utils.data.ConcatDataset(train_datasets)
total_len = len(ds)
train_len = int(0.8*total_len)
valid_len = total_len - train_len
train_ds, val_ds = torch.utils.data.random_split(ds, [train_len, valid_len] )
```

```
In [ ]: test_datasets = []
test_datasets.append(EmotionDataset( test_labels, test_img_paths, transform=tr
ansform_normal))
test_ds = torch.utils.data.ConcatDataset(test_datasets)
```

```
In [ ]: def accuracy(outputs, labels):
    _, preds = torch.max(outputs, dim=1)
    return (torch.tensor(torch.sum(preds == labels).item())/len(preds))*100
```

```

In [ ]: #Modified Resnet34 Model
def init_model1():
    model = models.resnet34(pretrained=True)
    for param in model.parameters():
        param.requires_grad = False
    model.conv1 = nn.Conv2d(1, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3
, 3), bias=False)
    for module in model.modules():
        if isinstance(module, nn.BatchNorm2d):
            if hasattr(module, 'weight'):
                module.weight.requires_grad_(True)
            if hasattr(module, 'bias'):
                module.bias.requires_grad_(True)
    model.fc = nn.Sequential(nn.Linear(in_features=512, out_features=4096, bias=
True),
                             nn.ReLU(inplace=True),
                             nn.Dropout(0.5),
                             nn.Linear(in_features=4096, out_features=1024, bias
=True),
                             nn.ReLU(),
                             nn.Dropout(0.5),
                             nn.Linear(in_features=1024, out_features=7, bias=Tr
ue))

    model.name = "ModifiedResnet34_1"
    return model

model = init_model1()
mx= xmp.MpModelWrapper(model)

```

```

In [ ]: from torchsummary import summary
x = torch.randn(1,1,224,224)
summary(model, (1,256,256))
#print(model_x)

```

```

In [ ]: #Modified Resnet50 Model
class ModifiedResnet50(nn.Module):
    def __init__(self,trained):
        super(ModifiedResnet50, self).__init__()
        resnet = models.resnet50(pretrained=trained)
        resnet.conv1 = nn.Conv2d(1, 64, kernel_size=(7, 7), stride=(2, 2), padding
=(3, 3), bias=False)
        modules = list(resnet.children())[:-1]
        self.net = nn.Sequential(*modules)
        self.classifier = nn.Sequential(
            nn.Dropout(0.5),
            nn.Linear(in_features = 2048, out_features=4096, bias=True),
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(in_features = 4096, out_features = 1024, bias=True),
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(in_features=1024, out_features = 7, bias = True)
        )

    def forward(self,x):
        x1 = self.net(x)
        x2 = x1.view(x1.size(0), -1)
        out = self.classifier(x2)
        return out

```

```

In [ ]: from torchsummary import summary
def init_model3():
    model= ModifiedResnet50(trained=False)
    for param in model.net.parameters():
        param.requires_grad = False

    for module in model.modules():
        if isinstance(module, nn.BatchNorm2d):
            if hasattr(module, 'weight'):
                module.weight.requires_grad_(True)
            if hasattr(module, 'bias'):
                module.bias.requires_grad_(True)
    model.name = 'ModifiedResnet50'
    return model

```

```
In [ ]: class AverageMeter(object):

    def __init__(self):
        self.reset()

    def reset(self):
        self.val = 0
        self.avg = 0
        self.sum = 0
        self.count = 0

    def update(self, val, n=1):
        self.val = val
        self.sum += val*n
        self.count += n
        self.avg = self.sum/self.count
```

```
In [ ]: def train_fn(epoch, parallel_loader, optimizer, criterion, scheduler, device):
    model.train()
    trn_loss_meter = AverageMeter()

    for batch_idx, (inputs, labels) in enumerate(parallel_loader):

        inputs = inputs.to(device)
        labels = labels.to(device)

        optimizer.zero_grad()
        preds = model(inputs)
        loss = criterion(preds, labels)
        acc = accuracy(preds, labels)
        loss.backward()
        xm.optimizer_step(optimizer)

        trn_loss_meter.update(loss.detach().item(), inputs.size(0))

        if(batch_idx > 0 and (batch_idx % batch_verbose == 0)):
            xm.master_print('--batch {} | cur_loss = {:.6f}, avg_loss = {:.6f}, accuracy = {:.6f}'.format(batch_idx, loss.item(), trn_loss_meter.avg, acc.item()))

        del inputs, labels, preds, loss
        gc.collect()

        if batch_idx > batches_per_epoch:
            break

    del parallel_loader, batch_idx
    gc.collect()

    return trn_loss_meter.avg
```

```
In [ ]: def valid_fn(epoch, parallel_loader, criterion, device):

    model.eval()
    val_loss_meter = AverageMeter()

    for batch_idx, (inputs, labels ) in enumerate(parallel_loader):

        inputs = inputs.to(device)
        labels = labels.to(device)

        with torch.no_grad():
            preds = model(inputs)
            loss = criterion(preds, labels)
            acc = accuracy(preds, labels)

        val_loss_meter.update(loss.detach().item(), inputs.size(0))

        if (batch_idx > 0) and (batch_idx % batch_verbose == 0):
            xm.master_print('-- batch {} | curr_loss = {:.6f}, avg_loss = {:.6f}, acc = {:.6f}'.format(batch_idx, loss.item(), val_loss_meter.avg, acc.item()))

        del inputs, labels, preds, loss
        gc.collect()

    del parallel_loader, batch_idx
    gc.collect()

    return val_loss_meter.avg
```

```
In [ ]: def test_fn(model, parallel_loader, criterion, device):

    model.eval()
    test_loss_meter = AverageMeter()
    accuracy_meter = AverageMeter()

    for batch_idx, data in enumerate(parallel_loader):
        inputs = data[0].to(device)
        labels = data[1].to(device)

        with torch.no_grad():
            preds = model(inputs)
            loss = criterion(preds, labels)
            acc = accuracy(preds, labels)

        test_loss_meter.update(loss.detach().item(), inputs.size(0))
        accuracy_meter.update(acc.detach().item(), 1)

        xm.master_print('-- batch {} | curr_loss = {:.6f}, avg_loss = {:.6f}, accuracy_batch = {:.6f}'.format(batch_idx, loss.item(), test_loss_meter.avg, acc.item()))

        del inputs, labels, preds, loss, acc
        gc.collect()

    del parallel_loader, batch_idx
    gc.collect()

    return test_loss_meter.avg, accuracy_meter.avg
```

```

In [ ]: def _run(model):

    train_sampler = torch.utils.data.distributed.DistributedSampler(train_ds,
                                                                    num_replicas
= xm.xrt_world_size(),
                                                                    rank = xm.ge
t_ordinal(),
                                                                    shuffle = Tr
ue)
    valid_sampler = torch.utils.data.distributed.DistributedSampler(val_ds, num_
replicas=xm.xrt_world_size(), rank = xm.get_ordinal(), shuffle=False)

    train_loader = torch.utils.data.DataLoader(train_ds, batch_size = batch_size
, sampler = train_sampler,
                                                                    num_workers = 0, pin_memory = Tru
e)
    valid_loader = torch.utils.data.DataLoader(val_ds, batch_size = batch_size,
sampler = valid_sampler,
                                                                    num_workers = 0, pin_memory = Tru
e)

    device = xm.xla_device()
    model = mx.to(device)
    best_model_wts = copy.deepcopy(model.state_dict())
    scaled_data = eta * xm.xrt_world_size()

    criterion = nn.CrossEntropyLoss(class_weights)
    #optimizer = optim.Adam(model.parameters(), lr = scaled_data, weight_decay=1
e-5)
    optimizer = torch.optim.SGD(model.parameters(), lr=0.001, momentum=0.9, nest
erov=True, weight_decay=0.0001)
    #scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='mi
n', factor=0.75, patience=5, min_lr=0.00001, verbose=True)
    scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max = nu
m_epochs)

    trn_losses = []
    val_losses = []
    best_val_loss = 1

    gc.collect()
    for epoch in range(num_epochs):
        xm.master_print('-'*55)
        xm.master_print('EPOCH {}/{}'.format(epoch + 1, num_epochs))
        xm.master_print('-'*55)
        xm.master_print('- initialization | TPU cores = {}, lr = {:.6f}'.format(
            xm.xrt_world_size(), optimizer.param_groups[0]['lr']/ xm.xrt_world_siz
e()))
        epoch_start = time.time()
        gc.collect()

        train_loader.sampler.set_epoch(epoch)

        train_start = time.time()

```

```

xm.master_print('- training...')
para_loader = pl.ParallelLoader(train_loader, [device])
trn_loss = train_fn(epoch = epoch+1, parallel_loader=para_loader.per_device_loader(device),
                    criterion= criterion,
                    optimizer=optimizer,
                    scheduler = scheduler,
                    device = device)

del para_loader
gc.collect()

valid_start = time.time()
xm.master_print('-validation...')
para_loader = pl.ParallelLoader(valid_loader, [device])
val_loss = valid_fn(epoch = epoch+1,
                    parallel_loader = para_loader.per_device_loader(device
),
                    criterion = criterion,
                    device = device)

scheduler.step()
del para_loader
gc.collect()

if val_loss < best_val_loss:
    best_model_wts = copy.deepcopy(model.state_dict())
    best_val_loss = val_loss

xm.master_print('- elapsed time | train = {:.2f} min, valid = {:.2f} min'.format(
    (valid_start - train_start) / 60, (time.time() - valid_start) / 60
))
xm.master_print('- average loss | train = {:.6f}, valid = {:.6f}'.format(
    trn_loss, val_loss))
xm.master_print('-'*55)
xm.master_print('')

trn_losses.append(trn_loss)
val_losses.append(val_loss)
del trn_loss, val_loss
gc.collect()

xm.master_print('Best results: loss = {:.6f} (epoch {})'.format(np.min(val_losses), np.argmax(val_losses) + 1))
xm.save(best_model_wts, 'weights_{}.pt'.format(model.name))
return trn_losses, val_losses

```



```
In [ ]: def _run_test(model):

    test_sampler = torch.utils.data.distributed.DistributedSampler(test_ds,
                                                                    num_replicas
= xm.xrt_world_size(),
                                                                    rank = xm.ge
t_ordinal(),
                                                                    shuffle = Tr
ue)
    test_loader = torch.utils.data.DataLoader(test_ds, batch_size = 64, sampler
= test_sampler,
                                                num_workers = 0)

    criterion = nn.CrossEntropyLoss()
    device = xm.xla_device()
    model = mx.to(device)

    xm.master_print('Model loaded successfully')

    para_loader = pl.ParallelLoader(test_loader, [device])
    test_loss, accuracy = test_fn(model=model, parallel_loader = para_loader.per_
device_loader(device), criterion=criterion ,device=device)

    return accuracy, test_loss
```

```
In [ ]: # wrapper function
def _mp_fn(rank, flags):
    torch.set_default_tensor_type('torch.FloatTensor')
    trn_losses, val_losses = _run(model_ensemble)
    np.save('trn_losses.npy', np.array(trn_losses))
    np.save('val_losses.npy', np.array(val_losses))

# modeling
gc.collect()
FLAGS = {}
xmp.spawn(_mp_fn, args = (FLAGS,), nprocs = num_tpu_workers, start_method = 'f
ork')
```

```
In [ ]: trn_loss = np.load('trn_losses.npy')
val_loss = np.load('val_losses.npy')
epochs = np.arange(1,101)
plt.title("Train and Validation loss with Resnet34")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.plot(epochs[1:], trn_loss[1:], label='Train Loss')
plt.plot(epochs, val_loss, color='orange', label='Validation Loss')
plt.legend()
plt.show
```

```
In [ ]: #Soft Voting Ensemble Model
num_classes = 7
class Ensemble(nn.Module):
    def __init__(self, modelA, modelB, modelC):
        super(Ensemble, self).__init__()
        self.modelA = modelA
        self.modelB = modelB
        self.modelC = modelC

    def forward(self, x):
        output = torch.zeros([x.size(0), num_classes])
        out1 = self.modelA(x.clone())
        out2 = self.modelB(x.clone())
        out3 = self.modelC(x)
        output = (out1 + out2 + out3)
        return output
```

```

In [ ]: modelA = models.vgg16_bn()
        modelB = models.resnet34()
        modelC = ModifiedResnet50(trained=False)

        modelA.features[0] = nn.Conv2d(1, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        #Modified VGG16 Model
        modelA.classifier = nn.Sequential(
            nn.Linear(in_features = 25088, out_features=4096, bias=True),
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(in_features = 4096, out_features = 1024, bias=True),
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(in_features=1024, out_features = 7, bias = True))
        modelA.load_state_dict(torch.load('weights_ModifiedVGG16BN_1.pt'))

        modelB.conv1 = nn.Conv2d(1, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
        modelB.fc = nn.Sequential(nn.Linear(in_features=512, out_features=4096, bias=True),
                                   nn.ReLU(inplace=True),
                                   nn.Dropout(0.5),
                                   nn.Linear(in_features=4096, out_features=1024, bias=True),
                                   nn.ReLU(),
                                   nn.Dropout(0.5),
                                   nn.Linear(in_features=1024, out_features=7, bias=True))
        modelB.load_state_dict(torch.load('weights_ModifiedResnet34_1.pt'))

        modelC.load_state_dict(torch.load('weights_ModifiedResnet50.pt'))

        model_ensemble = Ensemble(modelA, modelB, modelC)
        model_ensemble.name = 'Ensemble_1'
        mx= xmp.MpModelWrapper(model_ensemble)

```

```

In [ ]: #Weights of Ensemble Network after Training for 10 epochs
        model_ensemble.load_state_dict(torch.load('weights_Ensemble_1.pt'))

```

Out[]: <All keys matched successfully>

```

In [ ]: x = torch.randn(10,1,256,256)
        out = model_ensemble(x)
        print(torch.max(out,dim=1))

```

```
In [ ]: def _mp_fn(rank, flags):
    torch.set_default_tensor_type('torch.FloatTensor')
    final_acc, test_loss = _run_test(model_ensemble)
    xm.master_print('The final accuracy of the ensemble model: ',final_acc)

    # modeling
    gc.collect()
    FLAGS = {}
    xmp.spawn(_mp_fn, args = (FLAGS,), nprocs = num_tpu_workers, start_method = 'fork')
```

Calculating the Confusion Matrix for the CNN

```
In [ ]: from tqdm import tqdm
def calculate(test_loader, model):
    model.eval()
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    n = len(test_loader)
    all_preds = []
    all_labels = []
    tk0 = tqdm(test_loader)
    for _, data in enumerate(tk0):
        input = data[0].to(device)
        labels = data[1].to(device)

        output = model(input)
        output = (torch.max(torch.exp(output), 1)[1]).data.cpu().numpy()
        all_preds.extend(output) # Save Prediction
        labels = labels.data.cpu().numpy()
        all_labels.extend(labels) # Save Truth

    return all_labels, all_preds
```

```

In [ ]: import matplotlib.pyplot as plt
import numpy as np
import itertools

def plot_confusion_matrix(cm, target_names, title='Confusion matrix', cmap=None,
                           normalize=False):
    if cmap is None:
        cmap = plt.get_cmap('Blues')

    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()

    if target_names is not None:
        tick_marks = np.arange(len(target_names))
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    thresh = cm.max() / 1.5 if normalize else cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        if normalize:
            plt.text(j, i, "{:0.4f}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")
        else:
            plt.text(j, i, "{:,}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylim(len(target_names)-0.5, -0.5)
    plt.ylabel('True labels')
    plt.xlabel('Predicted labels')
    plt.savefig(title + '.png', dpi=500, bbox_inches = 'tight')
    plt.show()

```

```

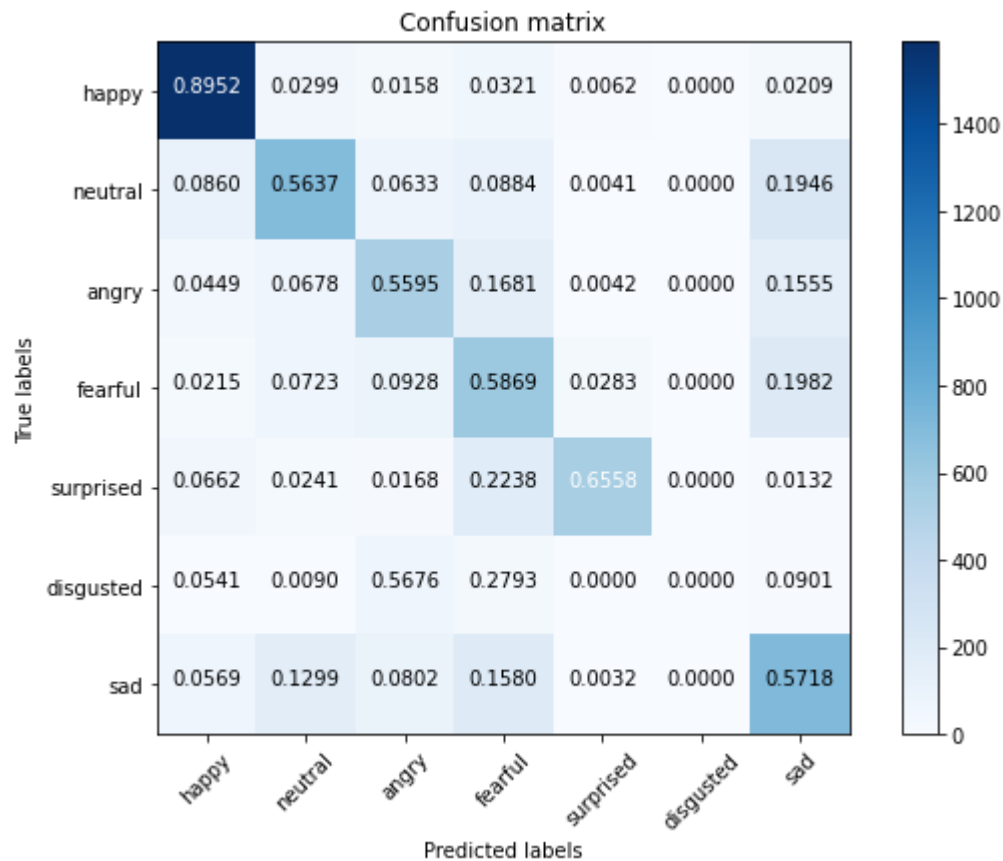
In [ ]: from sklearn.metrics import confusion_matrix
test_loader = DataLoader(test_ds, batch_size=1, shuffle=True)
targets, preds = calculate(test_loader, model_ensemble)
cm = confusion_matrix(targets, preds)
print(type(cm))

```

100%|██████████| 7178/7178 [57:44<00:00, 2.07it/s]

<class 'numpy.ndarray'>

```
In [ ]: target_names = ['happy', 'neutral', 'angry', 'fearful', 'surprised', 'disgusted', 'sad']
plot_confusion_matrix(cm, target_names, title='Confusion matrix', normalize=True)
```



```
In [ ]: from sklearn.metrics import f1_score, precision_score, accuracy_score
print('Precision score for Ensemble Model: ', precision_score( targets, preds
, average='weighted'))
print('F1 score for Ensemble Model: ', f1_score(targets, preds, average='weig
hted'))
print('Accuracy score for Ensemble Model: ', accuracy_score(targets, preds))
```

```
In [ ]:
```