AvengersFaceNet

May 28, 2021

1 Avengers Facial Recognition

This project uses State of the Art Facial Recognition model pruposed by Google called **FaceNet**. Facenet uses deep convolutional networks along with triplet loss to achieve state of the art accuracy.

In this project we used **NN4 Small2 v1** , an Inception model with 96x96 images as input. We have used a pretrained model from OpenFacePytorch, which was trained on OpenFace Dataset. Transfer Learning was then applied to train the classifier on the Avengers Dataset.

We have also used **MTCNN** (MultiTask Cascaded Convolution Network) from facenet-pytorch to crop and align the faces

[ ]:
```
!pip install facenet-pytorch
```

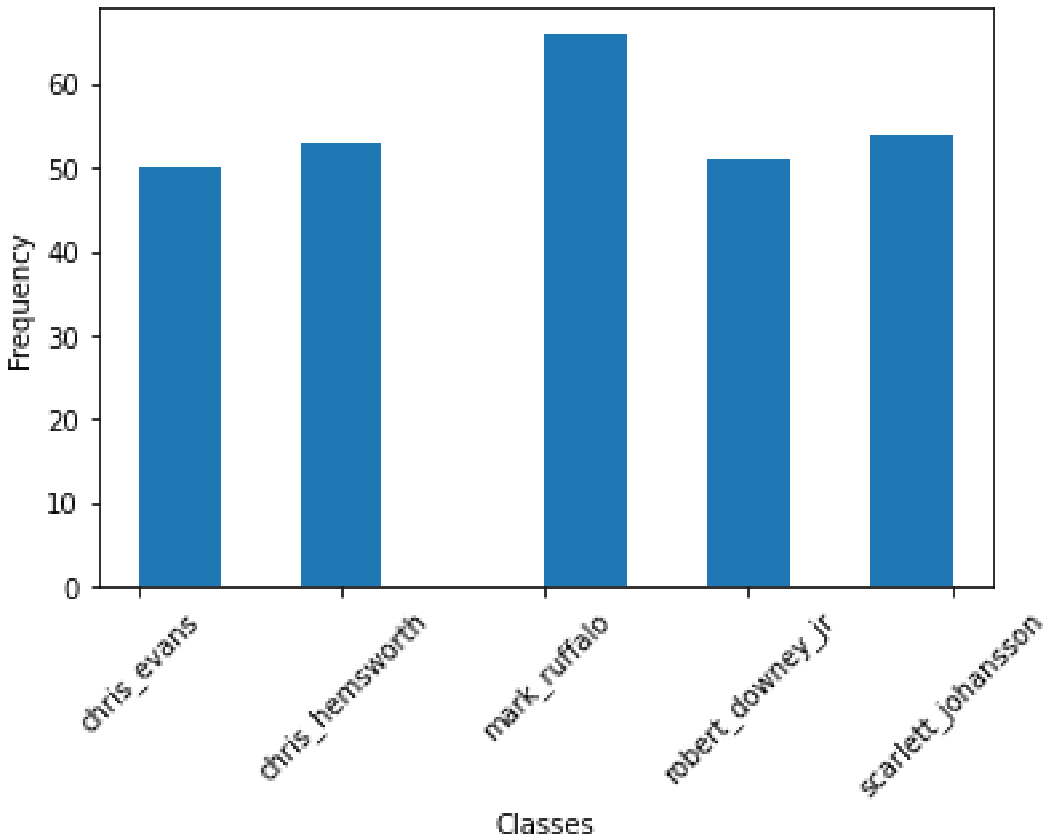
[2]:
```
import os
import torch
import numpy as np
import torchvision
from torchvision import datasets, transforms, models
import torch.optim as optim
import matplotlib.pyplot as plt
import facenet_pytorch
from facenet_pytorch import MTCNN
from tqdm.notebook import tqdm
import torch.nn as nn
import random

%matplotlib inline


# Check if CUDA GPU is available
useCuda = torch.cuda.is_available()
if useCuda:
    print('CUDA is avialable')
    device = torch.device('cuda:0')
else:
    print('CUDA is not avialable')
    device = torch.device('cpu')
```

```
CUDA is avialable
```

1.1 Visualize the Avenger Dataset

Plotting some sample images and Drawing an **histogram** of class Frequencies

[5]:
```
data_dir = 'data/cropped_images'
dataset = datasets.ImageFolder(data_dir, transform=transforms.Resize((512,␣
 ↪512)))
dataset.idx_to_class = {i:c for c, i in dataset.class_to_idx.items()}

batch_size = 32
num_workers = 0 if os.name == 'nt' else 8

# Dataloader for Visualization
vis_dataloader = torch.utils.data.DataLoader(dataset,
                                        batch_size=batch_size,
                                        num_workers=num_workers,
                                        shuffle=True,
                                        collate_fn=facenet_pytorch.training.
 ↪collate_pil)

# Load the first batch of images form the dataloader
dataiter = iter(vis_dataloader)
images, labels = dataiter.next()

# Plt the images
fig = plt.figure(figsize=(25, 4))
for i in np.arange(20):
    ax = fig.add_subplot(2, 10, i+1, xticks=[], yticks=[])
    plt.imshow(images[i])
    ax.set_title(dataset.idx_to_class[int(labels[i])])
fig.tight_layout()

## Plot the histogram of the class frequency
labels = []
for i in range(len(dataset)):
    labels.append(dataset.__getitem__(i)[1])

fig , ax = plt.subplots()
plt.xticks(range(len(dataset.idx_to_class)), dataset.idx_to_class.values(),␣
 ↪rotation=45)
ax.set_xlabel("Classes")
ax.set_ylabel("Frequency")
hist = ax.hist(labels)

del vis_dataloader
```



1.2 Use MTCNN to Crop and Align Images

In this step we apply the MTCNN model to Align and Crop images. The images are then saved in a new directory as specified in `aligned_data_dir`

[7]:
```
mtcnn = MTCNN(
    image_size=160, margin=0, min_face_size=20,
    thresholds=[0.6, 0.7, 0.7], factor=0.709, post_process=True,
    device=device
)

data_dir = 'data/cropped_images'
```

```python
aligned_data_dir = data_dir + '_aligned'

# Replace the class label with the new path for storing aligned data
dataset.samples = [(p, p.replace(data_dir, aligned_data_dir)) for p, _ in␣
 ↪dataset.samples]

batch_size = 32
num_workers = 0 if os.name == 'nt' else 8

dataloader = torch.utils.data.DataLoader(dataset,
                                         batch_size=batch_size,
                                         num_workers=num_workers,
                                         collate_fn=facenet_pytorch.training.
 ↪collate_pil)

# Run MTCNN for all the images and save them in new directory
for i, (image, path) in enumerate(tqdm(dataloader, desc="Converting")):
    mtcnn(image, save_path=path)

# Delete to save memory
del mtcnn
del dataloader
```

```
Converting:   0%|          | 0/9 [00:00<?, ?it/s]
```

1.3 Augmenting the Dataset

As the number of images per class not much, hence we are augmenting the dataset. We are doing this by simply applying **HorizontalFlip** for all the images. Thereby doubling the dataset. We have defined a custom Dataset class `AugmentDataset` which inherits from the `torchvision.datasets.ImageFolder` class.

[8]:
```python
class AugmentDataset(datasets.ImageFolder):
    def __init__(self, root, transform = None):
        super().__init__(root, transform)
        self.all_labels = [int(x[1]) for x in self.imgs]

        self.horizontalTransform = transforms.RandomHorizontalFlip(1)

    def __len__(self):
        return 2 * super().__len__()

    def __getitem__(self, item):
        if item < super().__len__():
            image, label = super().__getitem__(item)
        else:
            item -= super().__len__()
            image, label = super().__getitem__(item)
```

```
            image = self.horizontalTransform(image)

        return image, label
```

1.4 Splitting the Dataset

Here we have we split the dataset into Train and test sets. We have reserved 80% of the data for training and the rest 20% for testing the model.

We also initialized the respective train and test dataloaders from their respective dataset.

[9]:
```
transform = transforms.Compose([transforms.Resize(96),
                                transforms.ToTensor()])

data_dir = 'data/cropped_images'
aligned_data_dir = data_dir + '_aligned'

# dataset = datasets.ImageFolder(aligned_data_dir, transform=transform)
dataset = AugmentDataset(aligned_data_dir, transform=transform)
idx_to_class = {i:c for c, i in dataset.class_to_idx.items()}

total_count = len(dataset)
train_count = int(0.8 * total_count)
test_count = total_count - train_count

train_dataset, test_dataset = torch.utils.data.random_split(dataset,
                                                            [train_count,␣
 ↪test_count])
print('Total Images : ', total_count)
print('Num of Train Images : ', len(train_dataset))
print('Num of Test Images : ', len(test_dataset))

batch_size = 64
num_workers = 0 if os.name == 'nt' else 8

train_dataloader = torch.utils.data.DataLoader(train_dataset,␣
 ↪batch_size=batch_size,
                                              num_workers=num_workers,␣
 ↪shuffle=True)
test_dataloader = torch.utils.data.DataLoader(test_dataset,␣
 ↪batch_size=batch_size,
                                             num_workers=num_workers,␣
 ↪shuffle=True)
```

```
Total Images :  548
Num of Train Images :  438
Num of Test Images :  110
```

1.5 Triplet Loss and Triplet Generator

Here we train the model such it learns the face embeddings $f(x)$ from the image x such that the squared L2 distance between all faces of the same identity is small and the distance between a pair of faces from different identities is large.

This can be achieved with a *triplet loss* L as defined by

$$L = \sum_{i=1}^{m} [|| \ f(x_i^a) - f(x_i^p)) \ ||_2^2 - || \ f(x_i^a) - f(x_i^n)) \ ||_2^2 + \alpha]_+$$

This loss minimizes the distance between an anchor image x_i^a and a positive image x_i^p and maximizes the between the anchor image x_i^a and a negative image x_i^b

The `generate_triplets` function generates these positive and negative images for the entire batch. The current implementation randomly chooses the positive and negative images from the current batch. This can easily be enhanced to select difficult triplets to make the model train better.

The difficult triplet can be generated by selecting the positive image having the highest distance from the anchor and similarly selcting the negative image having smallest distance from the anchor

[10]:
```
# Generate triplets
def generate_triplets(images, labels):
    positive_images = []
    negative_images = []
    batch_size = len(labels)

    for i in range(batch_size):
        anchor_label = labels[i]

        positive_list = []
        negative_list = []

        for j in range(batch_size):
            if j != i:
                if labels[j] == anchor_label:
                    positive_list.append(j)
                else:
                    negative_list.append(j)

        positive_images.append(images[random.choice(positive_list)])
        negative_images.append(images[random.choice(negative_list)])

    positive_images = torch.stack(positive_images)
    negative_images = torch.stack(negative_images)

    return positive_images, negative_images

class TripletLoss(nn.Module):
```

```
    def __init__(self, alpha=0.2):
        super(TripletLoss, self).__init__()
        self.alpha = alpha

    def calc_euclidean(self, x1, x2):
        return (x1 - x2).pow(2).sum(1)

    def forward(self, anchor, positive, negative): # (batch_size , emb_size)
        distance_positive = self.calc_euclidean(anchor, positive)
        distance_negative = self.calc_euclidean(anchor, negative)
        losses = torch.relu(distance_positive - distance_negative + self.alpha)
        return losses.mean()
```

1.6 Define the Model, Optimizer and Loss Function

[11]:
```
from loadOpenFace import prepareOpenFace

model = prepareOpenFace(useCuda)
model.eval()
print("Model Loaded")

optimizer = optim.Adam(model.parameters(), lr=0.001)
loss_fn = TripletLoss()
```

```
Model Loaded
```

1.7 Training the model

[12]:
```
n_epochs = 10

for epoch in tqdm(range(n_epochs), desc="epoch"):

    train_loss = 0
    count = 0

    ## Training Loop
    model.train()
    for batch, (images, labels) in enumerate(tqdm(train_dataloader, \
                                             desc="Training", leave=False)):

        positives , negatives = generate_triplets(images, labels)

        # Move tensor to device
        images, labels = images.to(device), labels.to(device)
        positives, negatives = positives.to(device), negatives.to(device)

        optimizer.zero_grad()
```

```python
        # Seaseme Network
        anchor_out = model(images)
        positive_out = model(positives)
        negative_out = model(negatives)

        # Get the loss
        loss = loss_fn(anchor_out, positive_out, negative_out)
        loss.backward()

        optimizer.step()

        train_loss += loss.detach().item()
        count =  len(labels)


    print('Epoch : %d/%d - Loss: %0.4f' %
          (epoch+1, n_epochs, train_loss / count))
    train_loss = 0.0

model.eval()
print("Training Done")
```

```
epoch:   0%|          | 0/10 [00:00<?, ?it/s]

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 1/10 - Loss: 0.0853

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 2/10 - Loss: 0.0308

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 3/10 - Loss: 0.0084

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 4/10 - Loss: 0.0095

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 5/10 - Loss: 0.0031

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 6/10 - Loss: 0.0000

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 7/10 - Loss: 0.0008

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 8/10 - Loss: 0.0011
```

```
Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 9/10 - Loss: 0.0003

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 10/10 - Loss: 0.0004
Training Done
```

1.8 Testing the Model

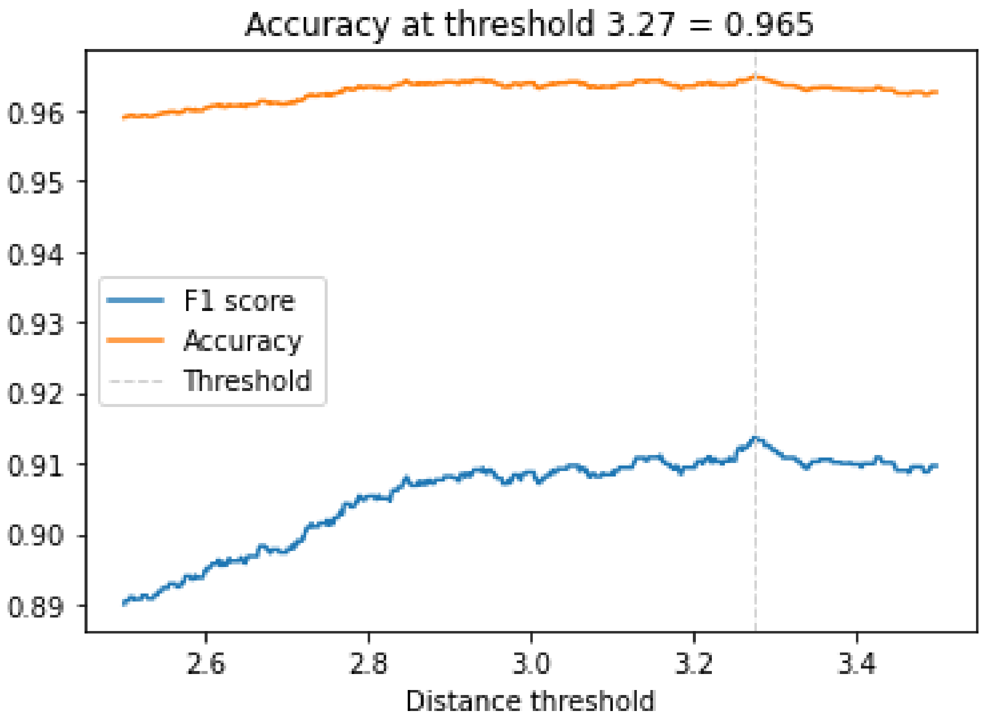
[13]:
```python
def distance(emb1, emb2):
    return torch.sum(torch.square(emb1 - emb2)).numpy()

# Generate Embeddings and label vector
test_dl = torch.utils.data.DataLoader(test_dataset,␣
 ↪batch_size=len(test_dataset))
(images, labels) = next(iter(test_dl))
positives , negatives = generate_triplets(images, labels)

images, labels = images.to(device), labels.to(device)
positives, negatives = positives.to(device), negatives.to(device)

with torch.no_grad():
    embeddings = model(images)

embeddings = embeddings.cpu()
labels = labels.cpu()
```

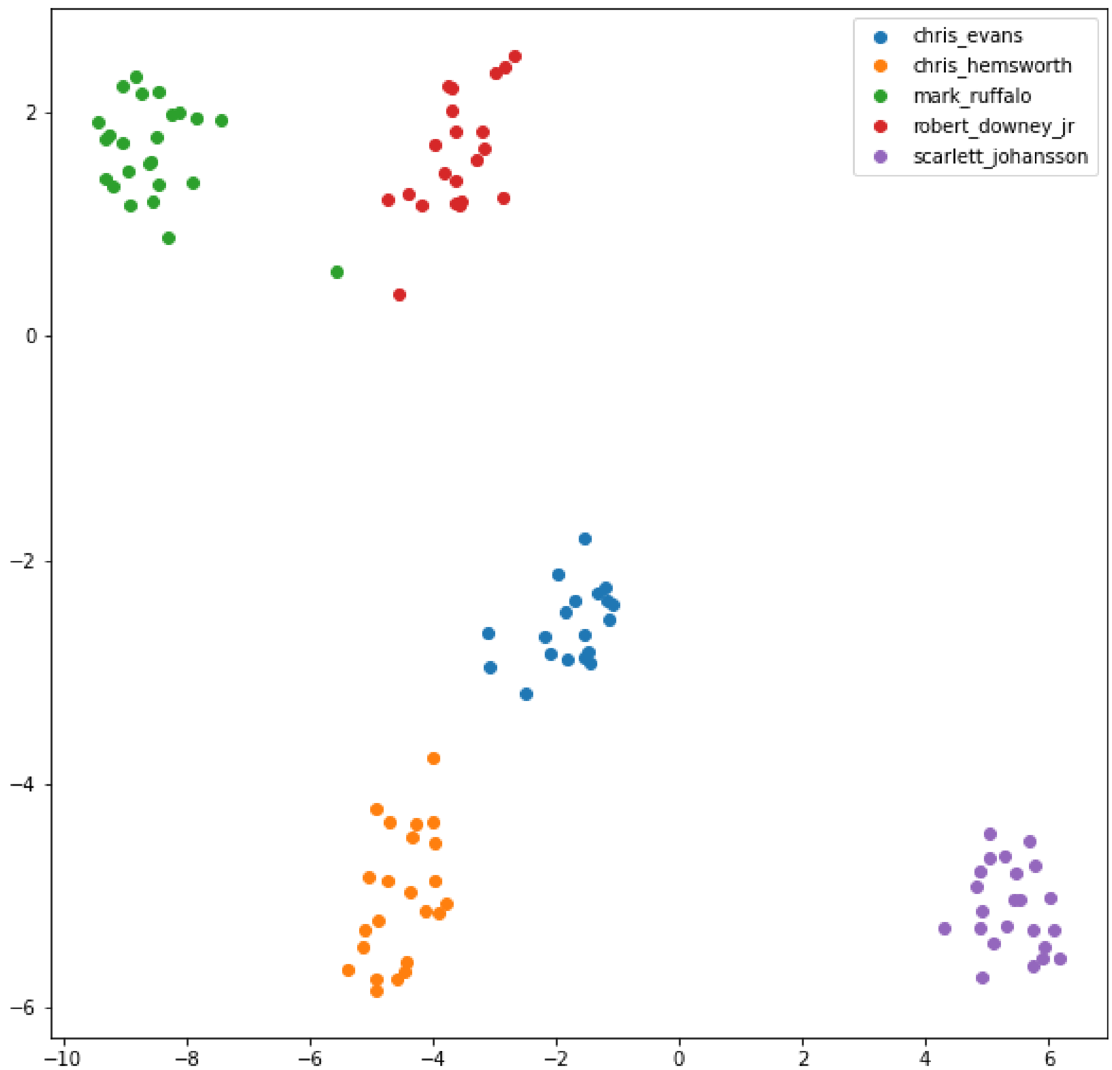
1.8.1 Visualizing the Output

As we can see the model is able to generate the face embeddings for the dataset. Now if had to use just the distance between these embeddings to predict the faces, we would get an accuracy close to **96.5%**.

[16]:
```python
from sklearn.metrics import f1_score, accuracy_score

distances = [] # squared L2 distance between pairs
identical = [] # 1 if same identity, 0 otherwise

num = len(labels)

for i in range(num-1):
    for j in range(1, num):
        distances.append(distance(embeddings[i], embeddings[j]))
        identical.append(1 if labels[i] == labels[j] else 0)

distances = np.array(distances)
identical = np.array(identical)
```

```python
thresholds = np.arange(2.5, 3.5, 0.001)

f1_scores = [f1_score(identical, distances < t) for t in thresholds]
acc_scores = [accuracy_score(identical, distances < t) for t in thresholds]

opt_idx = np.argmax(f1_scores)
# Threshold at maximal F1 score
opt_tau = thresholds[opt_idx]
# Accuracy at maximal F1 score
opt_acc = accuracy_score(identical, distances < opt_tau)

# Plot F1 score and accuracy as function of distance threshold
plt.plot(thresholds, f1_scores, label='F1 score');
plt.plot(thresholds, acc_scores, label='Accuracy');
plt.axvline(x=opt_tau, linestyle='--', lw=1, c='lightgrey', label='Threshold')
plt.title(f'Accuracy at threshold {opt_tau:.2f} = {opt_acc:.3f}');
plt.xlabel('Distance threshold')
plt.legend();

# Visualize the Result
from sklearn.manifold import TSNE

X_embedded = TSNE(n_components=2).fit_transform(embeddings)

plt.figure(figsize=(10,10))


for i, t in enumerate(set(labels.numpy())):
    idx = (t == labels.numpy())
    plt.scatter(X_embedded[idx, 0], X_embedded[idx, 1], label=idx_to_class[t])

plt.legend(bbox_to_anchor=(1, 1));
```


Accuracy at threshold 3.27 = 0.965
0.96
0.95
0.94
0.93
0.92
0.91
0.90
0.89
F1 score
Accuracy
Threshold
2.6
2.8
3.0
3.2
3.4
Distance threshold



2 Saving the Model

Saving the model only if the current model accuracy is better or if any previous model checkpoint doesn't exist

[17]:
```
chk_path = 'models/AvengersClassifier_FaceNet_nn4_small2_v1.pth'

def save_model(model, chk_path, current_accuracy=1.0):
    '''Saves the model only if model doesnt exist or
       if the model accuracy is better'''
    try:
        checkpoint = torch.load(chk_path)
        if(current_accuracy < checkpoint['accuracy']):
```

```
            print("Not Saving, Previous model was better")
            return

    except FileNotFoundError:
        print("Previous model not found")

    torch.save({
        'model_state_dict' : model.state_dict(),
        'accuracy' : current_accuracy
    }, chk_path)

    print("Model Saved : %s" % chk_path)

save_model(model, chk_path, opt_acc)
```

```
Not Saving, Previous model was better
```

2.0.1 Loading the Saved Model

[20]:
```
# Load the model
chk_path = 'models/AvengersClassifier_FaceNet_nn4_small2_v1.pth'

def load_model(model, chk_path):
    try:
        checkpoint = torch.load(chk_path)
        model.load_state_dict(checkpoint['model_state_dict'])
        print("Model Loaded from %s" % chk_path)
        return model
    except FileNotFoundError:
        print("Model checkpoint not found %s" % chk_path)
        return None

model = load_model(model, chk_path)
```

```
Model Loaded from models/AvengersClassifier_FaceNet_nn4_small2_v1.pth
```

3 Transfer Learning a new classifier

The current model just outputs a face embedding for the image. To create a classifer for the **Avenger Dataset** we add a new `nn.Linear` layer at the end, this layer takes in the face embedding and predicts the class label.

Since we only need to train the final layer, we freeze the parameters for all layers except the final layer.

We also defined the **optimizer** to take only the final layer parameters and a `CrossEntropyLoss` function

[21]:
```
from collections import OrderedDict

n_classes = len(dataset.class_to_idx)

classifier_model = nn.Sequential(OrderedDict([
                                    ("nn4_small_v2", model),
                                    ("fc",  nn.Linear(736, n_classes))
                                ]))

classifier_model = classifier_model.to(device)

# Freeze the parameters in the nn4_small_v2 layer
for param in classifier_model.parameters():
    param.requires_grad = False

for param in classifier_model.fc.parameters():
    param.requires_grad = True


optimizer = optim.Adam(classifier_model.fc.parameters(), lr=0.01)
loss_fn = torch.nn.CrossEntropyLoss()
```

3.0.1 Training the Classifier

[22]:
```
def train(n_epochs, dataloader, model, optimizer, loss_fn):
    '''returns Trained classifier model'''

    for epoch in tqdm(range(n_epochs), desc="epoch"):

        train_loss = 0.0
        count = 0

        # Training loop
        model.train()
        for batch, (images, labels) in enumerate(tqdm(dataloader, \
                                                  desc="Training", leave=False)):

            # Move Tensor to appropriate device
            images, labels = images.to(device), labels.to(device)

            optimizer.zero_grad()

            out = model(images)

            # Get the loss
            loss = loss_fn(out, labels)
            loss.backward()
```

```
            optimizer.step()

            train_loss += loss.detach().item()
            count =  len(labels)


        print('Epoch : %d/%d - Loss: %0.4f' %
              (epoch+1, n_epochs, train_loss / count))
        train_loss = 0.0

    model.eval()
    print("Training Done")
    return model

classifier_model = train(10 , train_dataloader, classifier_model, optimizer,␣
 ↪loss_fn)
```

```
epoch:   0%|          | 0/10 [00:00<?, ?it/s]

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 1/10 - Loss: 0.1476

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 2/10 - Loss: 0.0591

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 3/10 - Loss: 0.0287

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 4/10 - Loss: 0.0186

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 5/10 - Loss: 0.0114

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 6/10 - Loss: 0.0094

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 7/10 - Loss: 0.0079

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 8/10 - Loss: 0.0079

Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 9/10 - Loss: 0.0060
```

```
Training:   0%|          | 0/7 [00:00<?, ?it/s]

Epoch : 10/10 - Loss: 0.0065
Training Done
```

3.0.2 Testing the Classifier

[24]:
```python
def test(dataloader, model, loss_fn):

    test_loss = 0.0
    total = 0
    correct = 0

    # Testing loop
    model.eval()
    for batch, (images, labels) in enumerate(tqdm(dataloader, \
                                              desc="Testing")):

        # Move Tensor to appropriate device
        images, labels = images.to(device), labels.to(device)

        with torch.no_grad():
            out = model(images)

        loss = loss_fn(out, labels)
        test_loss += loss.detach().item()

        # Get the class with max probability
        pred = out.data.max(1, keepdim=True)[1]
        # Compare predictions with true label
        correct += np.sum(np.squeeze(pred.eq(labels.view_as(pred))).cpu().
↪numpy())
        total += labels.size(0)

    print('Test Loss: {:.6f}\n'.format(test_loss/total))
    print('Test Accuracy : %d%% (%d/%d)' % (
            100 * correct / total, correct, total))

    return(float(correct / total))


current_accuracy = test(test_dataloader, classifier_model, loss_fn)
```

```
Testing:   0%|          | 0/2 [00:00<?, ?it/s]

Test Loss: 0.000764

Test Accuracy : 100% (110/110)
```

As we can see we got a test Accuracy of 100%

4 Save the Final Classifier

[25]:
```
chk_path = 'models/AvengersClassifier.pth'

def save_model(model, chk_path, idx_to_class, current_accuracy=1.0):
    '''Saves the model only if model doesnt exist or
       if the previous model accuracy was better'''
    try:
        checkpoint = torch.load(chk_path)
        if(current_accuracy < checkpoint['accuracy']):
            print("Not Saving, Previous model was better")
            return

    except FileNotFoundError:
        print("Previous model not found")

    torch.save({
        'model_state_dict' : model.state_dict(),
        'accuracy' : current_accuracy,
        'idx_to_class': idx_to_class
    }, chk_path)

    print("Model Saved : %s" % chk_path)

save_model(classifier_model, chk_path, idx_to_class, current_accuracy)
```

```
Model Saved : models/AvengersClassifier.pth
```

[26]:
```
# Load the model
chk_path = 'models/AvengersClassifier.pth'

def load_model(model, chk_path):
    '''Returns model and idx_to_class dictionary'''
    try:
        checkpoint = torch.load(chk_path)
        model.load_state_dict(checkpoint['model_state_dict'])
        print("Model Loaded from %s" % chk_path)
        return model, checkpoint['idx_to_class']
    except FileNotFoundError:
        print("Model checkpoint not found %s" % chk_path)
        return None

classifier_model, idx_to_class = load_model(classifier_model, chk_path)
```

```
Model Loaded from models/AvengersClassifier.pth
```

5 Using the Classifer for doing Predictions

[27]:
```
from torch.nn import Softmax
from facenet_pytorch import MTCNN
from PIL import Image
from torchvision import transforms

mtcnn = MTCNN(
    image_size=160, margin=0, min_face_size=20,
    thresholds=[0.6, 0.7, 0.7], factor=0.709, post_process=False,
    device=device
)

face_transform = transforms.Compose([transforms.Resize(96),
                                    transforms.ToTensor()])

classifier_model = classifier_model.to(device)
classifier_model.eval()

softmax = Softmax(dim=1)
```

[29]:
```
def predict_and_display(img_path, prob_theshold = 0.9):
    img = Image.open(img_path)

    # Plt the image
    fig = plt.figure()
    ## Plt original image
    ax1 = fig.add_subplot(1, 2, 1, xticks=[], yticks=[])
    plt.imshow(img)
    ax1.set_title("Original Image")

    # Crop, Align and standardize the Image
    mtcnn_img = mtcnn(img.convert('RGB'))

    if mtcnn_img is None:
        plt.show()
        print("ERROR, Could not detect a face in image")
        return

    # convert to PIL image
    mtcnn_img = Image.fromarray(np.array(mtcnn_img.permute(1, 2, 0).numpy(),␣
 ↪dtype=np.uint8))

    ## Plt MTCNN image
    ax1 = fig.add_subplot(1, 2, 2, xticks=[], yticks=[])
    plt.imshow(mtcnn_img)
    ax1.set_title("MTCNN Image")
```

```
    fig.tight_layout()
    plt.show()


    # Do the Prediction
    mtcnn_img = face_transform(mtcnn_img).unsqueeze(0)
    mtcnn_img = mtcnn_img.to(device)

    with torch.no_grad():
        label = classifier_model(mtcnn_img)
        label = softmax(label) # To Convert the logit to probabilities

    prob, pred = label.data.max(1, keepdim=True)
    prob, pred = float(prob), int(pred)

    if prob < prob_theshold:
        print("UNKNOWN FACE, but similar to %s with %0.2f%% probability" %
                 (idx_to_class[pred], 100 * prob))
    else:
        print("%s with %0.2f%% probability" %
                 (idx_to_class[pred], 100 * prob))
```

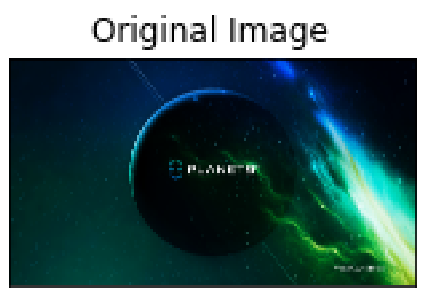
[30]:
```
import os

img_dir = './sample'
for file in os.listdir(img_dir):
    img_path = os.path.join(img_dir, file)
    predict_and_display(img_path)
```

chris_evans with 98.71% probability

chris_hemsworth with 99.09% probability

UNKNOWN FACE, but similar to mark_ruffalo with 49.56% probability

mark_ruffalo with 95.88% probability



ERROR, Could not detect a face in image


```
robert_downey_jr with 99.05% probability
```


```
scarlett_johansson with 94.83% probability
```