MachineLearning-FinalProject

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1 Celebrity Attribute Categorization with Machine Learning

This project's goal is to create a machine learning model that categorizes photos of celebrities based on 40 different attributes corresponding to facial features, facial expression, accessories, hair, and gender. The attributes are: - 5 o-Clock Shadow - Arched Eyebrows - Attractive - Bags Under Eyes - Bald - Bangs - Big Lips - Big Nose - Black Hair - Blond Hair - Blurry - Brown Hair - Bushy Eyebrows - Chubby - Double Chin - Eyeglasses - Goatee - Gray Hair - Heavy Makeup - High Cheekbones - Male - Mouth Slightly Open - Mustache - Narrow Eyes - No Beard - Oval Face - Pale Skin - Pointy Nose - Receding Hairline - Rosy Cheeks - Sideburns - Smiling - Straight Hair - Wavy Hair - Wearing Earrings - Wearing Hat - Wearing Lipstick - Wearing Necklace - Wearing Necktie - Young

2 Dataset

2.1 Mounting to Google Drive to access the data

[ ]:
```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

[ ]:
```
import tensorflow as tf

gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
  tf.config.experimental.set_memory_growth(gpu, True)
```

[ ]:
```
gpus
```

[ ]:
```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```

Loading all images to all_images

[ ]:
```
import os
from torchvision import transforms
from torch.utils.data import Dataset, DataLoader
```

```python
from PIL import Image
import torch

# path to the images
images_path = '/content/drive/MyDrive/MachineLearningFinalProject/CelebA-001/
 ↪CelebA/Img/img_align_celeb'

# custom dataset class
class CustomImagesDataset(Dataset):
    def __init__(self, root_dir, transform=None):
        self.root_dir = root_dir
        self.transform = transform
        self.image_paths = sorted(os.listdir(root_dir))  # Sort the image paths

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

    def __getitem__(self, idx):
        img_name = os.path.join(self.root_dir, self.image_paths[idx])
        image = Image.open(img_name).convert('RGB')

        if self.transform:
            image = self.transform(image)

        return image

# transformation to preprocess the data (image size is 128x128)
transform = transforms.Compose([
    transforms.Resize((128, 128)),
    transforms.ToTensor(),
])

# instance of CustomImageDataset
custom_img_dataset = CustomImagesDataset(root_dir=images_path,␣
 ↪transform=transform)

# DataLoader for the dataset
batch_size = 32
data_loader = DataLoader(custom_img_dataset, batch_size=batch_size,␣
 ↪shuffle=False)

# loading all images into a pytorch tensor.
# all_images[0] corresponds to 000001.jpg and so on
all_images = torch.cat([batch.squeeze() for batch in data_loader])
```

[ ]:
```python
all_images[0]
```

[ ]:
```
tensor([[[0.9922, 0.9922, 0.9922,  …, 0.9922, 0.9804, 0.9961],
         [0.9922, 0.9922, 0.9922,  …, 0.9961, 0.9882, 1.0000],
         [0.9922, 0.9922, 0.9922,  …, 0.9804, 0.9922, 0.9961],
         …,
         [0.6980, 0.6549, 0.5608,  …, 0.3961, 0.3804, 0.3765],
         [0.5451, 0.5333, 0.6157,  …, 0.4627, 0.4627, 0.4549],
         [0.6235, 0.7569, 0.8549,  …, 0.4627, 0.4667, 0.4706]],

        [[0.9059, 0.9059, 0.9059,  …, 0.9216, 0.9098, 0.9333],
         [0.9059, 0.9059, 0.9059,  …, 0.9294, 0.9216, 0.9373],
         [0.9059, 0.9059, 0.9059,  …, 0.9176, 0.9294, 0.9333],
         …,
         [0.4392, 0.3922, 0.2980,  …, 0.1451, 0.1333, 0.1294],
         [0.2824, 0.2706, 0.3412,  …, 0.1961, 0.1961, 0.1961],
         [0.3569, 0.4902, 0.5804,  …, 0.1922, 0.1922, 0.2000]],

        [[0.7608, 0.7608, 0.7608,  …, 0.8353, 0.8588, 0.8706],
         [0.7608, 0.7608, 0.7608,  …, 0.8431, 0.8706, 0.8745],
         [0.7608, 0.7608, 0.7608,  …, 0.8353, 0.8745, 0.8706],
         …,
         [0.2471, 0.2118, 0.1294,  …, 0.0471, 0.0353, 0.0314],
         [0.0980, 0.0902, 0.1765,  …, 0.0902, 0.0941, 0.0941],
         [0.1725, 0.3098, 0.4157,  …, 0.0784, 0.0863, 0.0941]]])
```

2.2 Loading in the attributes to all_attributes

[ ]:
```python
import os
from torch.utils.data import Dataset, DataLoader
from PIL import Image
import torch

# attributes file path
attributes_file = '/content/drive/MyDrive/MachineLearningFinalProject/
 ↪CelebA-001/CelebA/Anno/list_attr_celeba.txt'

# custom attribute dataset class
class CustomAttrDataset(Dataset):
    def __init__(self, root_dir, attributes_file, transform=None):
        self.root_dir = root_dir
        self.transform = transform

        # loading attributes from the attribute file
        with open(attributes_file, 'r') as file:
            lines = file.readlines()
            attribute_labels = lines[1].split()[1:]

            # skipping the first 2 lines since the first line is the number of
```

```
            # images, and the second line is the attribute names/labels
            lines = lines[2:]
            self.attributes = {line.split()[0]: list(map(int, line.split()[1:
↪])) for line in lines}

        # loading and sorting image paths
        self.image_paths = sorted(os.listdir(root_dir))

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

    def __getitem__(self, idx):
        img_name = os.path.join(self.root_dir, self.image_paths[idx])
        image = Image.open(img_name).convert('RGB')

        if self.transform:
            image = self.transform(image)

        # get the attributes for the current image (-1 or 1)
        attributes = torch.tensor(self.attributes[self.image_paths[idx]])

        return image, attributes


# instance of the custom attribute dataset
custom_attr_dataset = CustomAttrDataset(
    root_dir=images_path, attributes_file=attributes_file, transform=transform)

# create a dataloader for the attribute dataset
batch_size = 32
data_loader = DataLoader(custom_attr_dataset, batch_size=batch_size,␣
↪shuffle=False)

# iterate through the dataloader to load attributes into a list
all_attributes_list = [batch[1] for batch in data_loader]

# and now concatenate the attribute tensors into one single tensor
all_attributes = torch.cat(all_attributes_list)
```

2.3 Change the -1 values to 0

[ ]:
```
all_attributes[all_attributes == -1] = 0
```

2.4 Moving the all_images and all_attributes tensors to use GPU

[ ]:
```python
import torch

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# moving the 2 tensors to the GPU
all_images = all_images.to(device)
all_attributes = all_attributes.to(device)
```

2.5 Combining all_images and all_attributes together

[ ]:
```python
from torch.utils.data import TensorDataset

all_data = TensorDataset(all_images, all_attributes)
```

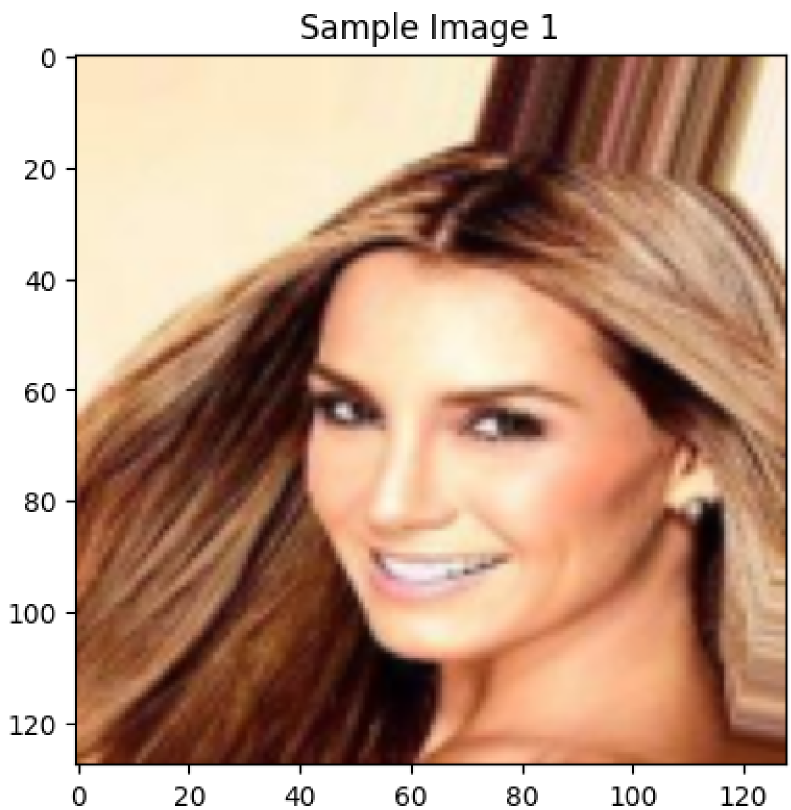
[ ]:
```python
all_data[0]
```

[ ]:
```
(tensor([[[0.9922, 0.9922, 0.9922,  …, 0.9922, 0.9804, 0.9961],
          [0.9922, 0.9922, 0.9922,  …, 0.9961, 0.9882, 1.0000],
          [0.9922, 0.9922, 0.9922,  …, 0.9804, 0.9922, 0.9961],
          …,
          [0.6980, 0.6549, 0.5608,  …, 0.3961, 0.3804, 0.3765],
          [0.5451, 0.5333, 0.6157,  …, 0.4627, 0.4627, 0.4549],
          [0.6235, 0.7569, 0.8549,  …, 0.4627, 0.4667, 0.4706]],

         [[0.9059, 0.9059, 0.9059,  …, 0.9216, 0.9098, 0.9333],
          [0.9059, 0.9059, 0.9059,  …, 0.9294, 0.9216, 0.9373],
          [0.9059, 0.9059, 0.9059,  …, 0.9176, 0.9294, 0.9333],
          …,
          [0.4392, 0.3922, 0.2980,  …, 0.1451, 0.1333, 0.1294],
          [0.2824, 0.2706, 0.3412,  …, 0.1961, 0.1961, 0.1961],
          [0.3569, 0.4902, 0.5804,  …, 0.1922, 0.1922, 0.2000]],

         [[0.7608, 0.7608, 0.7608,  …, 0.8353, 0.8588, 0.8706],
          [0.7608, 0.7608, 0.7608,  …, 0.8431, 0.8706, 0.8745],
          [0.7608, 0.7608, 0.7608,  …, 0.8353, 0.8745, 0.8706],
          …,
          [0.2471, 0.2118, 0.1294,  …, 0.0471, 0.0353, 0.0314],
          [0.0980, 0.0902, 0.1765,  …, 0.0902, 0.0941, 0.0941],
          [0.1725, 0.3098, 0.4157,  …, 0.0784, 0.0863, 0.0941]]],
        device='cuda:0'),
 tensor([0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0,
         1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1], device='cuda:0'))
```

Understanding The Dataset

2.6 Displaying The First Image

[ ]:
```
import matplotlib.pyplot as plt

# converting the tensor to a numpy array and transposing the channels
# .cpu() is used since matplotlib.pyplot uses CPU and not GPU
image_np = all_images[0].cpu().permute(1, 2, 0).numpy()

# and then displaying the image with matplotlib.pyplot
plt.imshow(image_np)
plt.title("Sample Image 1")
plt.show()
```



2.7 The Attributes of this Image

[ ]:
```
all_attributes[0]
```

[ ]:
```
tensor([0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0,
        1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1], device='cuda:0')
```

Function to display the attribute information in a way that's easier to understand

```
[ ]: attribute_names = ["5 o-Clock Shadow", "Arched Eyebrows", "Attractive", "Bags␣
     ↪Under Eyes", "Bald", "Bangs", "Big Lips", "Big Nose", "Black Hair", "Blond␣
     ↪Hair", "Blurry", "Brown Hair", "Bushy Eyebrows", "Chubby", "Double Chin",␣
     ↪"Eyeglasses", "Goatee", "Gray Hair", "Heavy Makeup", "High Cheekbones",␣
     ↪"Male", "Mouth Slightly Open", "Mustache", "Narrow Eyes", "No Beard", "Oval␣
     ↪Face", "Pale Skin", "Pointy Nose", "Receding Hairline", "Rosy Cheeks",␣
     ↪"Sideburns", "Smiling", "Straight Hair", "Wavy Hair", "Wearing Earrings",␣
     ↪"Wearing Hat", "Wearing Lipstick", "Wearing Necklace", "Wearing Necktie",␣
     ↪"Young"]

     def display_attributes(attribute_tensor):

         # for each attribute
         for name, value in zip(attribute_names, attribute_tensor):
             # 1 -> "Yes", 0 -> "No"
             attribute_status = "Yes" if value.item() == 1 else "No"

             # displaying the attribute information
             # (the underscores are replaced with a space)
             print(f"{name.replace('_', ' ')}: {attribute_status}")
```

2.8 The attributes which accurately describe the image

```
[ ]: display_attributes(all_attributes[0])
```

```
5 o-Clock Shadow: No
Arched Eyebrows: Yes
Attractive: Yes
Bags Under Eyes: No
Bald: No
Bangs: No
Big Lips: No
Big Nose: No
Black Hair: No
Blond Hair: No
Blurry: No
Brown Hair: Yes
Bushy Eyebrows: No
Chubby: No
Double Chin: No
Eyeglasses: No
Goatee: No
Gray Hair: No
Heavy Makeup: Yes
High Cheekbones: Yes
Male: No
Mouth Slightly Open: Yes
```

```
Mustache: No
Narrow Eyes: No
No Beard: Yes
Oval Face: No
Pale Skin: No
Pointy Nose: Yes
Receding Hairline: No
Rosy Cheeks: No
Sideburns: No
Smiling: Yes
Straight Hair: Yes
Wavy Hair: No
Wearing Earrings: Yes
Wearing Hat: No
Wearing Lipstick: Yes
Wearing Necklace: No
Wearing Necktie: No
Young: Yes
```

Splitting the Data for training, validation, and testing

[ ]:
```
from sklearn.model_selection import train_test_split

# the splits.  80% train, 10% validation, 10% test
train_size = 0.8
val_size = 0.1
test_size = 0.1

train_data, remaining_data = train_test_split(
    all_data, train_size=train_size, random_state=42)

val_data, test_data = train_test_split(
    remaining_data, test_size=test_size/(test_size + val_size), random_state=42)

# displaying the sizes of all these
print(f"Total dataset size: {len(all_data)}")
print(f"Training set size: {len(train_data)}")
print(f"Validation set size: {len(val_data)}")
print(f"Test set size: {len(test_data)}")
```

```
Total dataset size: 3000
Training set size: 2400
Validation set size: 300
Test set size: 300
```

[ ]:
```
batch_size = 32

train_loader = DataLoader(train_data, batch_size=batch_size, shuffle=True)
```

```
val_loader = DataLoader(val_data, batch_size=batch_size, shuffle=False)
test_loader = DataLoader(test_data, batch_size=batch_size, shuffle=False)
```

Creating the model - Convolutional Neural Network (CNN)

[ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F

# Convolutional Neural Network class
class SimpleCNN(nn.Module):
    def __init__(self, num_attributes):
        super(SimpleCNN, self).__init__()

        # layers:
        # first convolutional layer
        # (applying 64 kernels, each of 3x3 size, to the input which is 3)
        self.conv1 = nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1)

        # second convolutional layer
        # (applying 128 kernels, each of 3x3 size, to the input which is 64)
        self.conv2 = nn.Conv2d(64, 128, kernel_size=3, stride=1, padding=1)

        # max-pooling layer, to reduce computational complexity
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

        # first fully connected dense layer
        # (takes the flattened output prior, and connects it to 512 neurons)
        self.fc1 = nn.Linear(128 * 32 * 32, 512)

        # second fully connected dense layer
        # (takes the output prior, and connects it to num_attributes amount of␣
 ↪neurons)
        self.fc2 = nn.Linear(512, num_attributes)

    # forward pass function
    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 128 * 32 * 32)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x


# the model
```

```
model = SimpleCNN(num_attributes = len(attribute_names))

# binary cross-entropy loss since each attribute is binary (0 or 1)
criterion = nn.BCEWithLogitsLoss()

# adam optimizer
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

Moving the model to the GPU

[ ]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)
```

[ ]:
```
SimpleCNN(
  (conv1): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (fc1): Linear(in_features=131072, out_features=512, bias=True)
  (fc2): Linear(in_features=512, out_features=40, bias=True)
)
```

2.9 Validation Functions

[ ]:
```
def find_optimal_threshold(outputs, targets, num_thresholds=100):

    # generating 100 (num_thresholds) thresholds with values from 0 to 1
    thresholds = np.linspace(0, 1, num_thresholds)

    f1_scores = []

    # loop for each threshold
    for threshold in thresholds:

        # converting model outputs to binary predictions using the current
        # threshold
        predictions = torch.sigmoid(outputs) > threshold

        # calculating f1 score between the actual attribute values and the
        # predictions.  And appending the result to the list
        f1 = f1_score(targets.cpu().numpy(), predictions.cpu().numpy(),␣
 ↪average="micro")
        f1_scores.append(f1)

    # returning the optimal threshold, which is the largest f1 score
    optimal_threshold = thresholds[np.argmax(f1_scores)]
    return optimal_threshold
```

[ ]:
```python
def validation_step(model):
    # set the model to evaluation mode
    model.eval()

    total_correct = 0
    total_instances = 0
    all_predictions = []
    all_correct_vals = []

    # temporarily disable gradient computation (since this is not for training)
    with torch.no_grad():
        # loop for the batches of data in val_loader
        for images, attributes in val_loader:
            # moving images and attributes to use the GPU device
            images, attributes = images.to(device), attributes.to(device)

            # outputs_model used to make predictions based on the input images
            outputs_model = model(images)

            # finding an optimal threshold using validation set
            threshold = find_optimal_threshold(outputs_model, attributes)

            # appending the attributes and prediction results
            predictions = torch.sigmoid(outputs_model) > threshold
            total_correct += torch.sum(torch.eq(predictions, attributes)).item()
            total_instances += attributes.numel()
            all_correct_vals.append(attributes.cpu().numpy())
            all_predictions.append(predictions.cpu().numpy())

    all_correct_vals = np.concatenate(all_correct_vals)
    all_predictions = np.concatenate(all_predictions)

    # Calculate and display validation accuracy
    accuracy = total_correct / total_instances
    print(f'Validation Accuracy: {accuracy * 100:.2f}%')

    # Calculate and display validation F1 score (micro-average)
    f1 = f1_score(all_correct_vals, all_predictions, average="micro")
    print(f'Validation F1 Score: {f1 * 100:.2f}%')
    return f1*100, accuracy*100
```

2.10 Training Loop

[ ]:
```python
import numpy as np
import torch.nn.functional as F
from sklearn.metrics import f1_score
```

```python
def training_loop(model, num_epochs):

  val_accs = []
  val_f1s = []
  train_accs = []
  train_f1s = []

  # loop for num_epochs amount of times
  for epoch in range(num_epochs):
      total_correct = 0
      total_samples = 0
      total_loss = 0.0
      all_predictions = []
      all_correct_vals = []

      # for each batch of data in train_loader
      for images, attributes in train_loader:

          # moving images and attributes to use the GPU device
          images, attributes = images.to(device), attributes.to(device)

          # clearing/initializing the gradients to zero
          optimizer.zero_grad()

          # outputs_model used to make predictions based on the input images
          outputs_model = model(images)

          # calculate the loss for binary classification
          loss = criterion(outputs_model, attributes.float())

          # backpropagation used to compute the gradients of the loss
          loss.backward()

          # taking a step to update the model parameters based on the gradients␣
↪computed
          optimizer.step()

          # calculate training accuracy
          predicted = torch.sigmoid(outputs_model) > 0.5
          # predicted = (torch.sigmoid(outputs_model) > 0.5).float()  # Convert␣
↪logits to binary predictions
          total_correct += (predicted == attributes).sum().item()
          total_samples += attributes.numel()

          # accumulate total loss
          total_loss += loss.item() * images.size(0)
          all_correct_vals.append(attributes.cpu().numpy())
```

```
            all_predictions.append(predicted.cpu().numpy())

        # calculate training accuracy after each epoch
        all_correct_vals = np.concatenate(all_correct_vals)
        all_predictions = np.concatenate(all_predictions)
        accuracy = 100 * total_correct / total_samples
        train_f1 = 100 * f1_score(all_correct_vals, all_predictions,␣
↪average="micro")
        average_loss = total_loss / len(train_loader.dataset)
        print(f"Epoch [{epoch + 1}/{num_epochs}], Training F1 Score: {train_f1:.
↪2f}%, Training Accuracy: {accuracy:.2f}%, Average Loss: {average_loss:.4f}")

        # validation after each epoch
        val_f1, val_acc = validation_step(model)
        val_accs.append(val_acc)
        val_f1s.append(val_f1)
        train_accs.append(accuracy)
        train_f1s.append(train_f1)
        print("")
    return train_accs, train_f1s, val_accs, val_f1s
```

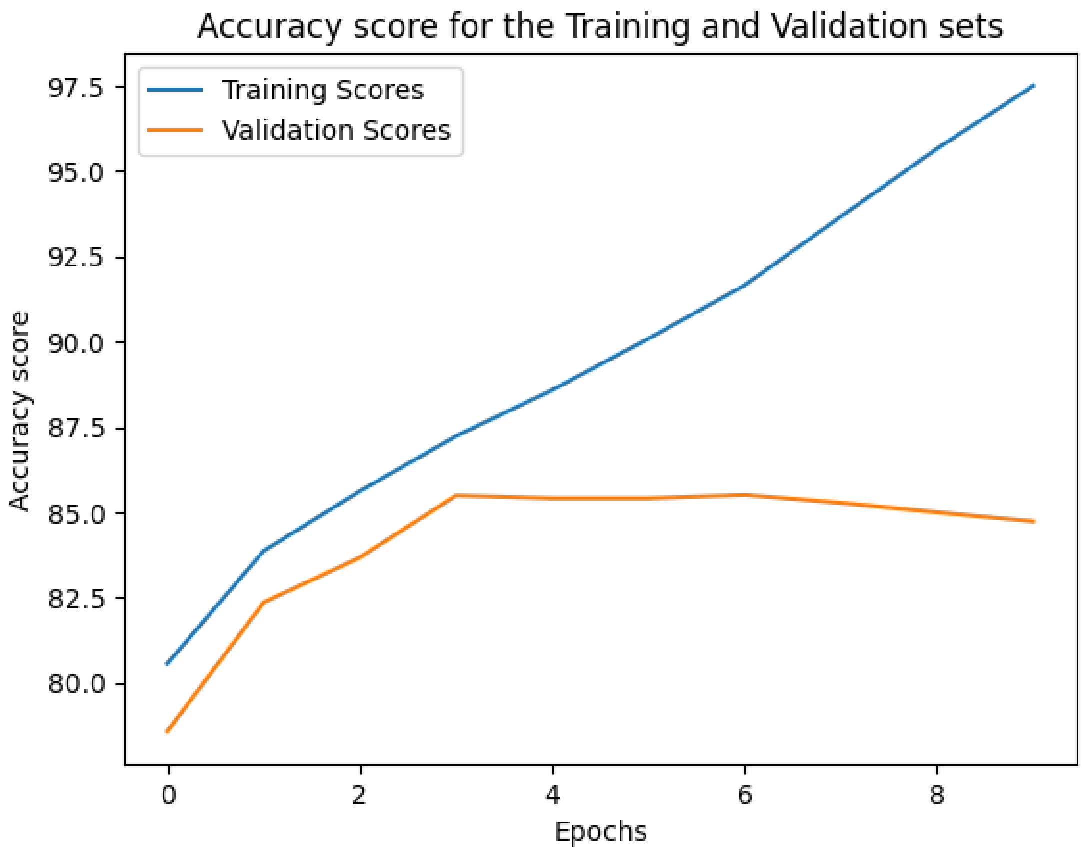
[ ]:
```
train_accs, train_f1s, val_accs, val_f1s = training_loop(model, 10)
```

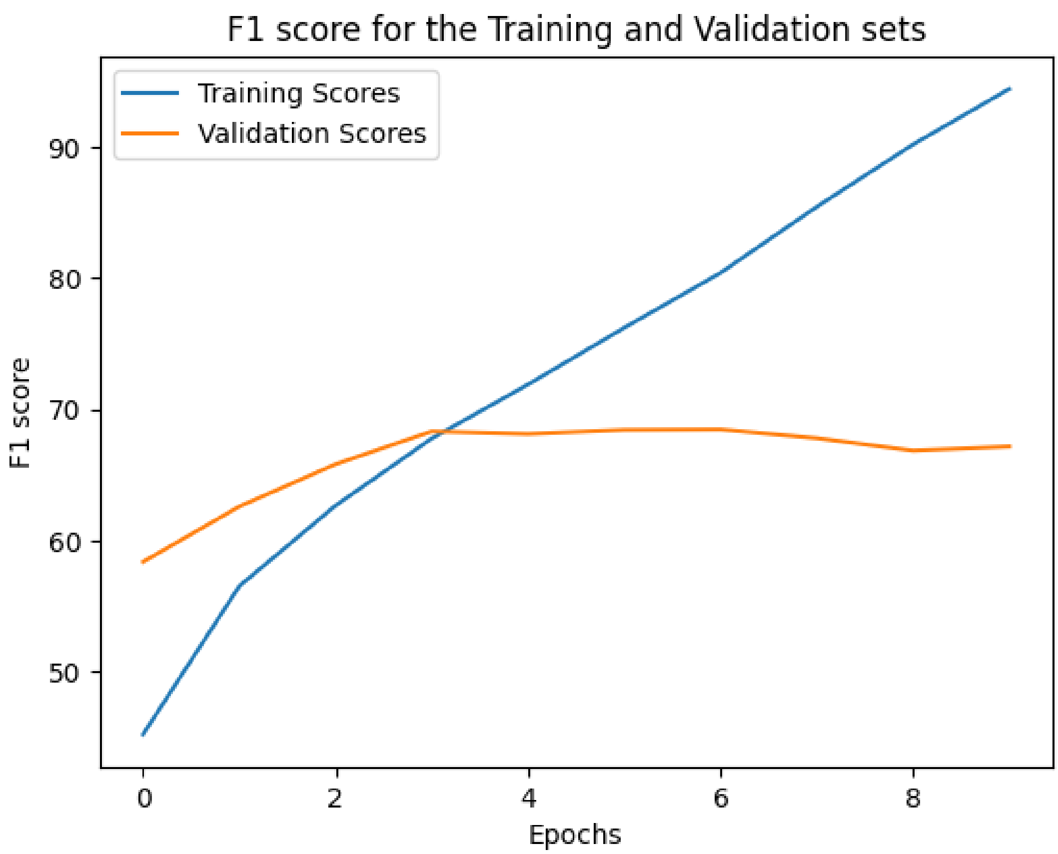
```
Epoch [1/10], Training F1 Score: 45.22%, Training Accuracy: 80.57%, Average
Loss: 0.4466
Validation Accuracy: 78.58%
Validation F1 Score: 58.37%

Epoch [2/10], Training F1 Score: 56.52%, Training Accuracy: 83.87%, Average
Loss: 0.3710
Validation Accuracy: 82.36%
Validation F1 Score: 62.59%

Epoch [3/10], Training F1 Score: 62.66%, Training Accuracy: 85.62%, Average
Loss: 0.3312
Validation Accuracy: 83.67%
Validation F1 Score: 65.82%

Epoch [4/10], Training F1 Score: 67.78%, Training Accuracy: 87.23%, Average
Loss: 0.2944
Validation Accuracy: 85.49%
Validation F1 Score: 68.32%

Epoch [5/10], Training F1 Score: 71.89%, Training Accuracy: 88.59%, Average
Loss: 0.2622
Validation Accuracy: 85.41%
Validation F1 Score: 68.12%
```

```
Epoch [6/10], Training F1 Score: 76.22%, Training Accuracy: 90.09%, Average
Loss: 0.2299
Validation Accuracy: 85.41%
Validation F1 Score: 68.43%

Epoch [7/10], Training F1 Score: 80.40%, Training Accuracy: 91.65%, Average
Loss: 0.1957
Validation Accuracy: 85.51%
Validation F1 Score: 68.47%

Epoch [8/10], Training F1 Score: 85.43%, Training Accuracy: 93.67%, Average
Loss: 0.1548
Validation Accuracy: 85.28%
Validation F1 Score: 67.80%

Epoch [9/10], Training F1 Score: 90.18%, Training Accuracy: 95.66%, Average
Loss: 0.1103
Validation Accuracy: 85.00%
Validation F1 Score: 66.85%

Epoch [10/10], Training F1 Score: 94.42%, Training Accuracy: 97.50%, Average
Loss: 0.0703
Validation Accuracy: 84.73%
Validation F1 Score: 67.16%
```

[171]:
```python
# function used to plot an accuracy graph and f1 score graph from the train and
# validation.
def plot_train_and_validation_metrics(train_accs, train_f1s, val_accs, val_f1s):
    # Accuracy scores
    plt.plot(train_accs)
    plt.plot(val_accs)
    plt.title("Accuracy score for the Training and Validation sets")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy score")
    plt.legend(["Training Scores", "Validation Scores"])
    plt.show()

    # F1 Scores
    plt.plot(train_f1s)
    plt.plot(val_f1s)
    plt.title("F1 score for the Training and Validation sets")
    plt.xlabel("Epochs")
    plt.ylabel("F1 score")
    plt.legend(["Training Scores", "Validation Scores"])
    plt.show()
```

[172]:
```
plot_train_and_validation_metrics(train_accs, train_f1s, val_accs, val_f1s)
```





2.11 Testing

[173]:
```
import numpy as np
from sklearn.metrics import f1_score

def test_step(model):
    # set the model to evaluation mode
    model.eval()

    # temporarily disable gradient computation
    with torch.no_grad():
        all_correct_vals = []
        all_predictions = []

        # loop for the batches of data in the test_loader
        for images, attributes in test_loader:
            # moving images and attributes to use the GPU device
            images, attributes = images.to(device), attributes.to(device)
```

```
            # make predictions on the test data
            outputs_model = model(images)
            predictions = torch.sigmoid(outputs_model) > 0.5

            # append the ground truth and prediction values
            all_correct_vals.append(attributes.cpu().numpy())
            all_predictions.append(predictions.cpu().numpy())

    # concatenate the results for the entire test dataset
    all_correct_vals = np.concatenate(all_correct_vals)
    all_predictions = np.concatenate(all_predictions)

    # calculate and display test accuracy
    test_accuracy = np.sum(all_correct_vals == all_predictions) /␣
↪all_correct_vals.size
    print(f'Test Accuracy: {test_accuracy * 100:.2f}%')

    # calculate and display test F1 score
    test_f1 = f1_score(all_correct_vals, all_predictions, average="micro")
    print(f'Test F1 Score: {test_f1 * 100:.2f}%')
```

[174]:
```
test_step(model)
```

```
Test Accuracy: 85.55%
Test F1 Score: 66.54%
```

Trying with an adjusted Second Model

2.11.1 Adjustments here are:

- Changed learning rate from 0.001 to 0.0001

[177]:
```
# the second model
model_2 = SimpleCNN(num_attributes = len(attribute_names))
model_2 = model_2.to(device)

# binary cross-entropy loss since each attribute is binary (0 or 1)
criterion = nn.BCEWithLogitsLoss()

# adam optimizer
optimizer = optim.Adam(model_2.parameters(), lr=0.0001)
```

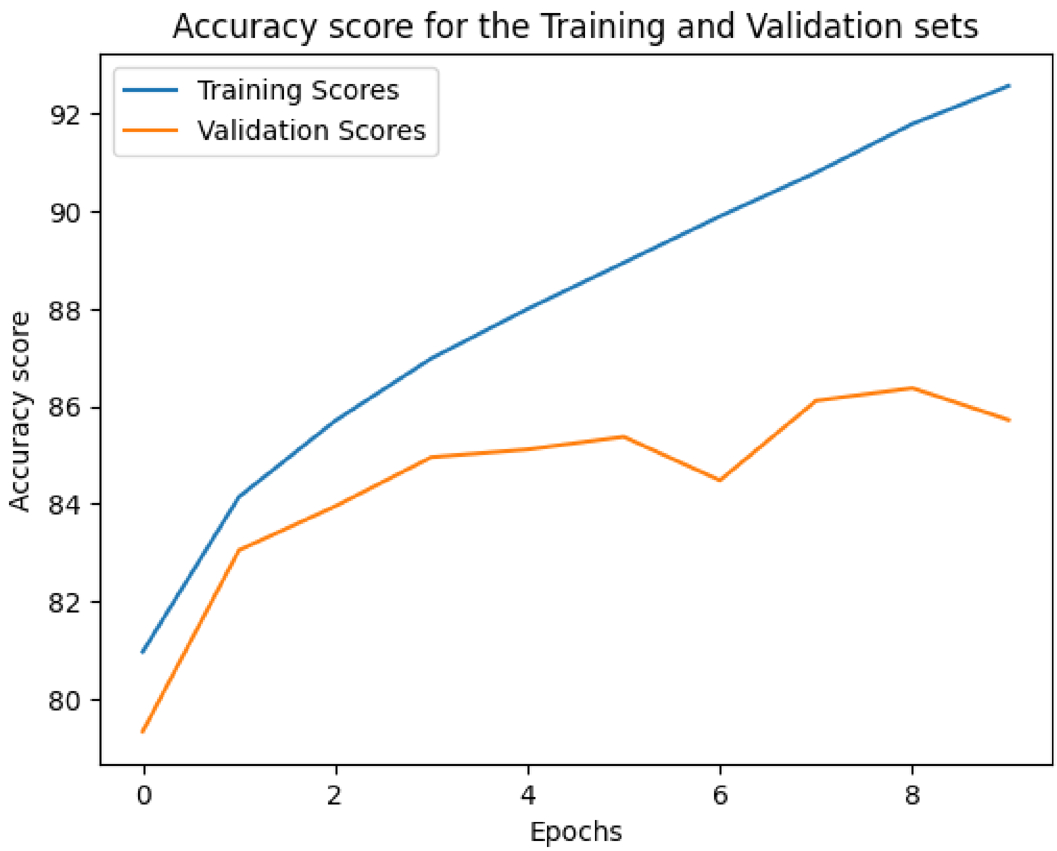
[178]:
```
train_accs, train_f1s, val_accs, val_f1s = training_loop(model_2, 10)
```

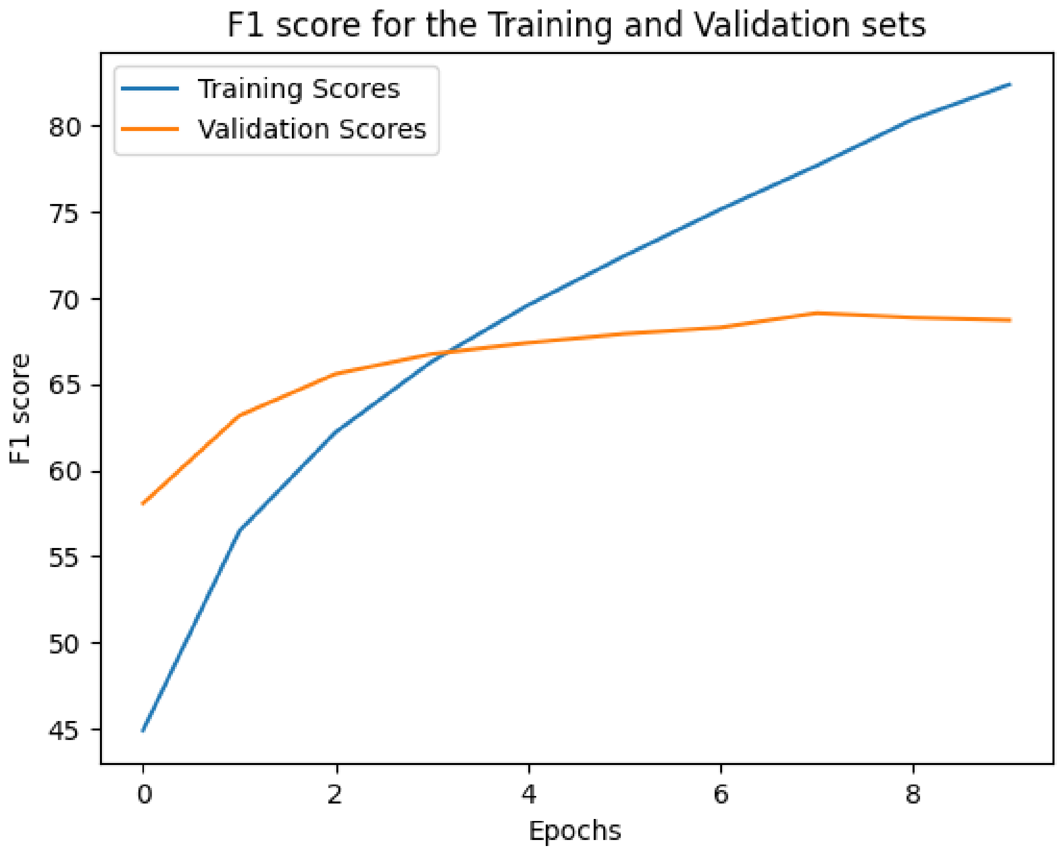
```
Epoch [1/10], Training F1 Score: 44.91%, Training Accuracy: 80.97%, Average
Loss: 0.4305
Validation Accuracy: 79.33%
Validation F1 Score: 58.07%
```

```
Epoch [2/10], Training F1 Score: 56.46%, Training Accuracy: 84.14%, Average
Loss: 0.3707
Validation Accuracy: 83.05%
Validation F1 Score: 63.17%

Epoch [3/10], Training F1 Score: 62.20%, Training Accuracy: 85.71%, Average
Loss: 0.3341
Validation Accuracy: 83.95%
Validation F1 Score: 65.58%

Epoch [4/10], Training F1 Score: 66.30%, Training Accuracy: 86.98%, Average
Loss: 0.3038
Validation Accuracy: 84.96%
Validation F1 Score: 66.74%

Epoch [5/10], Training F1 Score: 69.58%, Training Accuracy: 88.00%, Average
Loss: 0.2799
Validation Accuracy: 85.12%
Validation F1 Score: 67.38%

Epoch [6/10], Training F1 Score: 72.43%, Training Accuracy: 88.95%, Average
Loss: 0.2581
Validation Accuracy: 85.38%
Validation F1 Score: 67.91%

Epoch [7/10], Training F1 Score: 75.13%, Training Accuracy: 89.90%, Average
Loss: 0.2372
Validation Accuracy: 84.48%
Validation F1 Score: 68.28%

Epoch [8/10], Training F1 Score: 77.67%, Training Accuracy: 90.80%, Average
Loss: 0.2187
Validation Accuracy: 86.12%
Validation F1 Score: 69.11%

Epoch [9/10], Training F1 Score: 80.36%, Training Accuracy: 91.79%, Average
Loss: 0.1994
Validation Accuracy: 86.38%
Validation F1 Score: 68.85%

Epoch [10/10], Training F1 Score: 82.37%, Training Accuracy: 92.57%, Average
Loss: 0.1840
Validation Accuracy: 85.72%
Validation F1 Score: 68.70%
```

[179]:

```
plot_train_and_validation_metrics(train_accs, train_f1s, val_accs, val_f1s)
```





[180]:
```
test_step(model_2)
```

```
Test Accuracy: 86.81%
Test F1 Score: 68.54%
```

Trying with an adjusted Third Model

2.11.2 Adjustments here are:

- Added dropout to the model to prevent overfitting

[181]:
```
# Convolutional Neural Network class version 2
# Like SimpleCNN but with dropout added
class SimpleCNNVersionTwo(nn.Module):
    def __init__(self, num_attributes):
        super(SimpleCNNVersionTwo, self).__init__()

        # layers:
        # first convolutional layer
        # (applying 64 kernels, each of 3x3 size, to the input which is 3)
        self.conv1 = nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1)
```

```
        # second convolutional layer
        # (applying 128 kernels, each of 3x3 size, to the input which is 64)
        self.conv2 = nn.Conv2d(64, 128, kernel_size=3, stride=1, padding=1)

        # max-pooling layer, to reduce computational complexity
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

        # first fully connected dense layer
        # (takes the flattened output prior, and connects it to 512 neurons)
        self.fc1 = nn.Linear(128 * 32 * 32, 512)

        # second fully connected dense layer
        # (takes the output prior, and connects it to num_attributes amount of␣
↪neurons)
        self.fc2 = nn.Linear(512, num_attributes)

        # new:  dropout added to help prevent overfitting
        self.dropout = nn.Dropout(0.5)

    # forward pass function
    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 128 * 32 * 32)
        x = F.relu(self.fc1(x))

        # applying the new dropout
        x = self.dropout(x)

        x = self.fc2(x)
        return x
```

[182]:
```
# the third model
model_3 = SimpleCNNVersionTwo(num_attributes = len(attribute_names))
model_3 = model_3.to(device)

# binary cross-entropy loss since each attribute is binary (0 or 1)
criterion = nn.BCEWithLogitsLoss()

# adam optimizer
optimizer = optim.Adam(model_3.parameters(), lr=0.001)
```

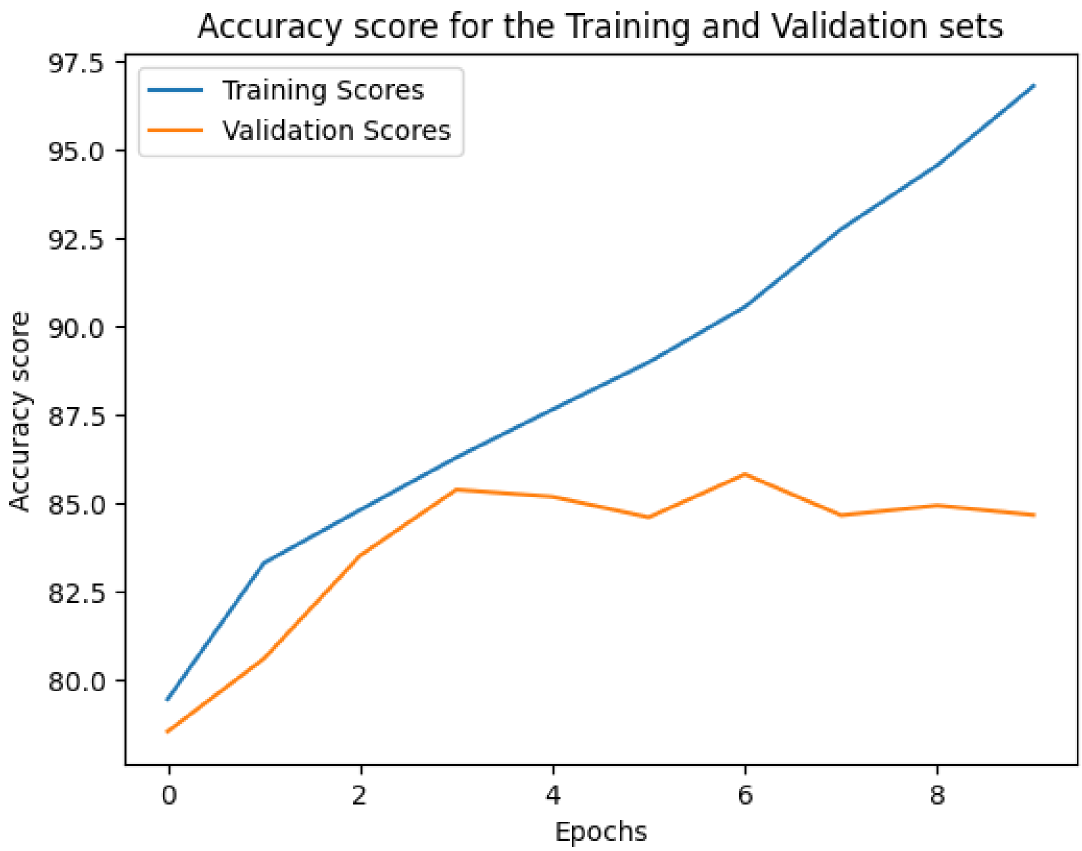
[183]:
```
train_accs, train_f1s, val_accs, val_f1s = training_loop(model_3, 10)
```

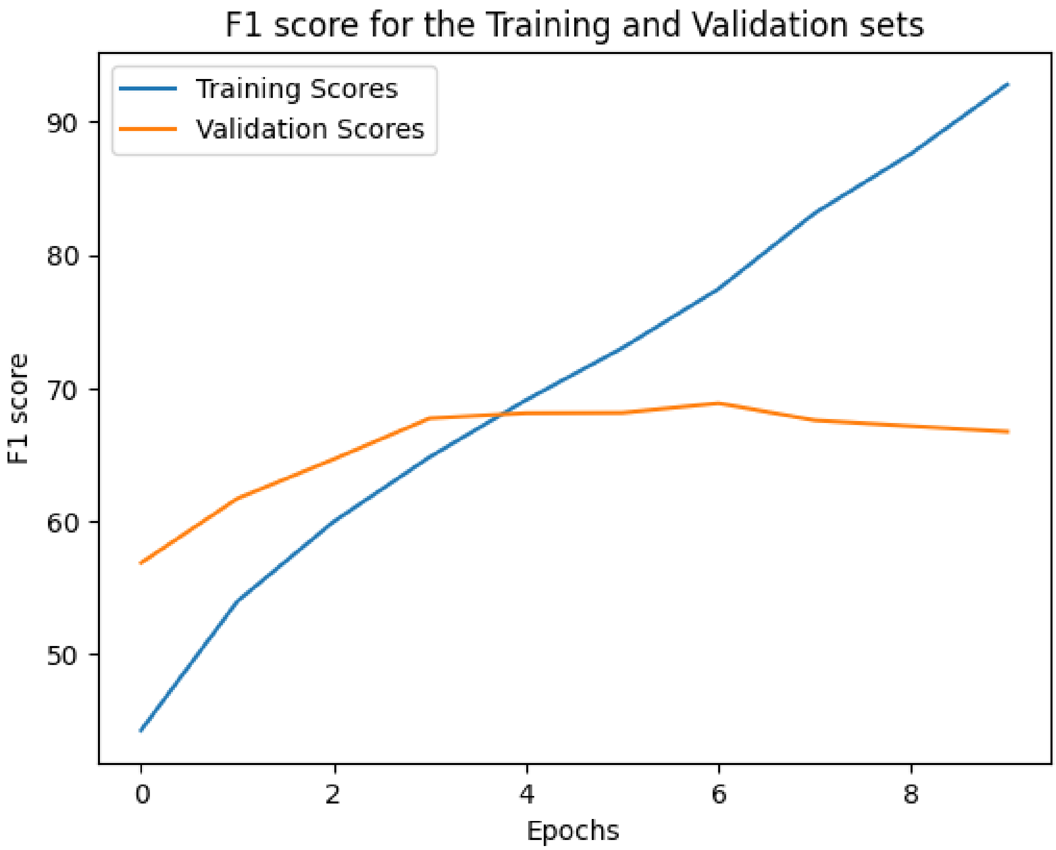
```
Epoch [1/10], Training F1 Score: 44.28%, Training Accuracy: 79.46%, Average
Loss: 0.4674
```

```
Validation Accuracy: 78.54%
Validation F1 Score: 56.86%

Epoch [2/10], Training F1 Score: 53.97%, Training Accuracy: 83.31%, Average
Loss: 0.3820
Validation Accuracy: 80.60%
Validation F1 Score: 61.70%

Epoch [3/10], Training F1 Score: 59.96%, Training Accuracy: 84.81%, Average
Loss: 0.3459
Validation Accuracy: 83.52%
Validation F1 Score: 64.65%

Epoch [4/10], Training F1 Score: 64.83%, Training Accuracy: 86.29%, Average
Loss: 0.3145
Validation Accuracy: 85.38%
Validation F1 Score: 67.73%

Epoch [5/10], Training F1 Score: 69.10%, Training Accuracy: 87.65%, Average
Loss: 0.2821
Validation Accuracy: 85.18%
Validation F1 Score: 68.12%

Epoch [6/10], Training F1 Score: 73.01%, Training Accuracy: 88.99%, Average
Loss: 0.2527
Validation Accuracy: 84.60%
Validation F1 Score: 68.15%

Epoch [7/10], Training F1 Score: 77.45%, Training Accuracy: 90.56%, Average
Loss: 0.2201
Validation Accuracy: 85.82%
Validation F1 Score: 68.86%

Epoch [8/10], Training F1 Score: 83.15%, Training Accuracy: 92.76%, Average
Loss: 0.1755
Validation Accuracy: 84.66%
Validation F1 Score: 67.58%

Epoch [9/10], Training F1 Score: 87.62%, Training Accuracy: 94.56%, Average
Loss: 0.1338
Validation Accuracy: 84.93%
Validation F1 Score: 67.14%

Epoch [10/10], Training F1 Score: 92.82%, Training Accuracy: 96.81%, Average
Loss: 0.0878
Validation Accuracy: 84.67%
Validation F1 Score: 66.73%
```

[184]:

```
plot_train_and_validation_metrics(train_accs, train_f1s, val_accs, val_f1s)
```





[185]:
```
test_step(model_3)
```

```
Test Accuracy: 85.42%
Test F1 Score: 66.36%
```

[ ]:
```

```