Model

This model is build to work with data from multiple datasets that have been processed to 112x112 size.

Imports and information

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from typing import Sequence
from functools import partial
from random import randint

import torch
from torch.utils.data import Dataset, DataLoader
from torch import nn
import torchmetrics

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
```

In [2]:
```
## WWMR data paths
mlfw_X_fp = r'D:\data\face_mask\MLFW\MLFW_X.npy'
mlfw_y_fp = r'D:\data\face_mask\MLFW\MLFW_y.npy'
```

Build data loader

In [3]:
```
class maskDataset(Dataset):
    def __init__(
        self,
        X_data,
        y_data,
        norm_0_1: bool = True,
        print_stats: bool = True,
    ):
        self.X_data = X_data

        # Norm
        if norm_0_1:
            self.X = self.X_data / 255
        else:
            self.X = self.X_data

        self.y = y_data

        self.length = len(self.y)

        # Print Stats
        if print_stats:
            print('# examples:    {}'.format(self.length))
            ratio = sum(self.y) / self.length
            print('class balence: {:.2f}'.format(ratio))

        # reshape?? see comment in __getitem__() ?????
        self.X = self.X.reshape((self.length, 3, 112, 112))

    def __len__(self):
        return self.length


    def __getitem__(self, index):
        image = self.X[index]

        # the input to a conv2d must be in [N, C, W, H] format
        #  n = number of examples, c is channels, w is width, and h is height
        #  This means we do not in fact need to transpose the data. it should
        #  be in the shape (3, 112, 112)
        #image = np.transpose(image)
        #image = np.rot90(image, k=3)

        return image.astype(np.float32), torch.tensor(self.y[index]).long()
```

In [4]:
```
# function to concat the various data sets and split into train val test

def merge_split(
    X_data_lists: list,
    y_data_lists: list,
    train=0.7,
    val=0.15,
    test=0.15
):
    if (train + val + test) != 1:
        print('splits must add to 1, added to {}'.format(train + val + test))
        return None
    if train < 0 or val < 0 or test < 0:
        print('splits must be positive')
        return None

    # Concat
    X = np.concatenate(X_data_lists)
    y = np.concatenate(y_data_lists)

    # split off test
    X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=test, random_state=42)

    # split off val
    val_percent_tv = val / (val + train)  # 15 percent of total data is equal to this
    X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val, test_size=val_percent_tv, random_state=42)

    return [(X_train, y_train), (X_val, y_val), (X_test, y_test)]
```

Test data loader

In [5]:
```
# data file paths
X_fp_list = [mlfw_X_fp]
y_fp_list = [mlfw_y_fp]

X_data_list = [np.load(fp) for fp in X_fp_list]
y_data_list = [np.load(fp) for fp in y_fp_list]
```

In [6]:

```python
# merge data and split into train val and test
(X_train, y_train), (X_val, y_val), (X_test, y_test) = merge_split(X_data_list, y_data_list)
```

In [7]:

```python
ds = maskDataset(
    X_data=X_train,
    y_data=y_train,
    norm_0_1=True,
    print_stats=True,
)
```

```
# examples:    8399
class balence: 0.75
```

In [8]:

```python
ds.X.shape
```

Out[8]:

```
(8399, 3, 112, 112)
```

In [9]:

```python
ds[2][0].shape
```

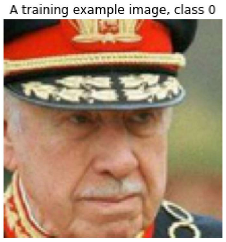
Out[9]:

```
(3, 112, 112)
```

In [10]:

```python
img_idx = randint(0, 8399)

image, label = ds[img_idx]

# un-normalize
image = (image * 255).astype(np.uint8)

# show image
plt.imshow(image.reshape(112, 112, 3))
plt.title('A training example image, class {}'.format(label) )
plt.axis('off')
plt.show()
```

A training example image, class 0



Model

The following model is implemented in pytorch. It uses several convotutional layers followed by several linear layers.

In [11]:

```python
class CNN(nn.Module):
    def __init__(
        self,
        input_size: Sequence[int] = (3, 112, 112),
        num_classes: int = 2,
        channels: Sequence[int] = (8, 16, 32),
        kernel_sizes: Sequence[int] = (10, 10, 10, 10),
        linear_units: Sequence[int] = (100, 10),
    ):
        super(CNN, self).__init__()

        self.input_size = input_size
        self.num_classes = num_classes
        self.channels = input_size[0:1] + channels
        self.kernel_sizes = kernel_sizes
        self.linear_units = linear_units

        self.flatten = nn.Flatten()
        self.pool = partial(nn.MaxPool2d, kernel_size=2, stride=2)  # first 2 is for 2x2 kernel, second is stride length
        self.dropout = nn.Dropout
        self.activation = nn.ReLU
        self.accuracy = torchmetrics.functional.accuracy
        self.conf_matrix = torchmetrics.functional.confusion_matrix

        # optional, define batch norm here

        # build the convolutional layers
        conv_layers = list()
        for in_channels, out_channels, kernel_size in zip(
            self.channels[:-2], self.channels[1:-1], self.kernel_sizes[:-1]
        ):
            conv_layers.append(
                nn.Conv2d(
                    in_channels=in_channels,
                    out_channels=out_channels,
                    kernel_size=kernel_size,
                    #stride=2,
                    #padding='same',
                )
            )
            conv_layers.append(self.activation())
            conv_layers.append(self.pool())
        # add final layer to convolutions
        conv_layers.append(
            nn.Conv2d(
                in_channels=self.channels[-2],
                out_channels=self.channels[-1],
                kernel_size=self.kernel_sizes[-1],
                stride=2,
                #padding='same',
            )
        )
        conv_layers.append(self.activation())
        conv_layers.append(self.pool())


        # turn list into layers
        self.conv_net = nn.Sequential(*conv_layers)

        # linear layers
        linear_layers = list()
        prev_linear_size = self.channels[-1] * 9  # const scale it correctly
        for dense_layer_size in self.linear_units:
```

```
            linear_layers.append(
                nn.Linear(
                    in_features=prev_linear_size,
                    out_features=dense_layer_size,
                )
            )
            linear_layers.append(self.activation())
            prev_linear_size=dense_layer_size

        self.penultimate_dense = nn.Sequential(*linear_layers)
        self.ultimate_dense = nn.Linear(
            in_features=self.linear_units[-1],
            out_features=self.num_classes
        )


    def forward(self, x: torch.Tensor) -> torch.Tensor:
        x = self.conv_net(x)
        x = self.flatten(x)
        # may need to expand dense entry since flatten
        x = self.penultimate_dense(x)
        x = self.ultimate_dense(x)
        return x


def train(dataloader, model, loss_fn, optimizer, verbose=False):
    #model = model.float()  # sometime fixes random obscure type error
    model.train()  # configures for training, grad on, dropout if there is dropout
    size = len(dataloader.dataset)

    for batch, (X, y) in enumerate(dataloader):
        optimizer.zero_grad()

        # compute prediction loss
        preds = model(X)
        loss = loss_fn(preds, y)

        # backprop
        loss.backward()
        optimizer.step()

        if batch % 5 == 0 and verbose:
            loss, current = loss.item(), batch * len(X)
            print(f"loss: {loss:>7f}  [{current:>5d}/{size:>5d}]")
    return loss

# for evaluating on validation data too
def test(dataloader, model, loss_fn, verbose=False):
    model.eval()
    test_loss, correct = 0, 0
    size = len(dataloader.dataset)
    num_batches = len(dataloader)

    with torch.no_grad():
        for X, y in dataloader:

            pred = model(X.float())
            test_loss += loss_fn(pred, y).item()
            correct += (pred.argmax(1) == y).type(torch.float).sum().item()

    test_loss /= num_batches
    correct /= size
    if verbose:
        print(f"Results: \n Accuracy: {(100*correct):>0.1f}%, Avg loss: {test_loss:>8f} \n")
    return correct, test_loss
```

The below 2 blocks show the structure of the model with the default parameters for the convolution sizes, convolution kernel sizes, and linear layer sizes.

In [12]:
```
net = CNN()
```

In [13]:
```
net
```

Out[13]:
```
CNN(
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (conv_net): Sequential(
    (0): Conv2d(3, 8, kernel_size=(10, 10), stride=(1, 1))
    (1): ReLU()
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(8, 16, kernel_size=(10, 10), stride=(1, 1))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(16, 32, kernel_size=(10, 10), stride=(2, 2))
    (7): ReLU()
    (8): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (penultimate_dense): Sequential(
    (0): Linear(in_features=288, out_features=100, bias=True)
    (1): ReLU()
    (2): Linear(in_features=100, out_features=10, bias=True)
    (3): ReLU()
  )
  (ultimate_dense): Linear(in_features=10, out_features=2, bias=True)
)
```

Running the model

Running the pytorch model involves several steps. First, the pytorch datasets must be set up. They take in the X and y data at construction to become an object that can serve up the data on command. Next, the pytorch data loaders are created. These data loaders are another pytorch object which takes in the dataset, whether to shuffle or not, and the batch size.

The model, loss function, and optimizer are created next. The training loop follows. This loop runs the training loop defined above with the model and then evaluates on the validation data.

In [16]:
```
# Create datasets
train_dataset = maskDataset(
    X_data=X_train,
    y_data=y_train,
    norm_0_1=True,
    print_stats=False,
)

val_dataset = maskDataset(
    X_data=X_val,
    y_data=y_val,
    norm_0_1=True,
    print_stats=False,
)
```

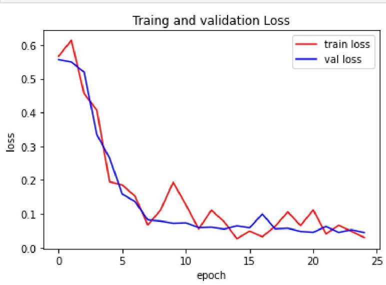
```python
test_dataset = maskDataset(
    X_data=X_test,
    y_data=y_test,
    norm_0_1=True,
    print_stats=False,
)
```

In [17]:
```python
# Create the dataloaders
batch_size = 128

train_dataloader = DataLoader(
    train_dataset,
    batch_size=batch_size,
    shuffle=True
)

val_dataloader = DataLoader(
    val_dataset,
    batch_size=batch_size,
    shuffle=False
)

test_dataloader = DataLoader(
    test_dataset,
    batch_size=batch_size,
    shuffle=False
)

device = "cuda" if torch.cuda.is_available() else "cpu"
print(f"Using {device} device")

# Create CNN
model = CNN()

# use cross entropy loss
loss_fn = nn.CrossEntropyLoss()

# SGD optimizer
optimizer = torch.optim.SGD(
    model.parameters(),
    lr=0.003,
    momentum=0.9,
    #nesterov =True
    weight_decay =.0001
)
#optimizer = torch.optim.Adam(model.parameters(), lr=0.003, betas=(0.9, 0.999), eps=1e-08, weight_decay=0, amsgrad=False)


# record results
train_loss = []
val_loss = []
val_accur = []

epochs = 25
for t in range(epochs):
    #print(f"Epoch {t+1}\n-------------------------------")

    train_l = train(train_dataloader, model, loss_fn, optimizer, verbose=False)
    train_loss.append(train_l)

    val_a, val_l = test(val_dataloader, model, loss_fn, verbose=True)
    val_loss.append(val_l)
    val_accur.append(val_a)
```

```
Using cpu device
Results:
 Accuracy: 75.7%, Avg loss: 0.556957

Results:
 Accuracy: 75.7%, Avg loss: 0.549833

Results:
 Accuracy: 75.7%, Avg loss: 0.519702

Results:
 Accuracy: 75.7%, Avg loss: 0.334983

Results:
 Accuracy: 88.7%, Avg loss: 0.264947

Results:
 Accuracy: 93.7%, Avg loss: 0.158517

Results:
 Accuracy: 94.2%, Avg loss: 0.136182

Results:
 Accuracy: 96.7%, Avg loss: 0.082187

Results:
 Accuracy: 96.9%, Avg loss: 0.078342

Results:
 Accuracy: 96.6%, Avg loss: 0.071900

Results:
 Accuracy: 97.4%, Avg loss: 0.073186

Results:
 Accuracy: 97.5%, Avg loss: 0.059025

Results:
 Accuracy: 97.3%, Avg loss: 0.060188

Results:
 Accuracy: 97.7%, Avg loss: 0.054623

Results:
 Accuracy: 96.6%, Avg loss: 0.064278

Results:
 Accuracy: 97.4%, Avg loss: 0.058505

Results:
 Accuracy: 95.7%, Avg loss: 0.099461

Results:
 Accuracy: 97.3%, Avg loss: 0.055437

Results:
 Accuracy: 97.7%, Avg loss: 0.057198

Results:
 Accuracy: 98.0%, Avg loss: 0.047593

Results:
 Accuracy: 98.4%, Avg loss: 0.045007

Results:
 Accuracy: 97.1%, Avg loss: 0.062430

Results:
 Accuracy: 98.5%, Avg loss: 0.044701

Results:
 Accuracy: 97.9%, Avg loss: 0.052582

Results:
 Accuracy: 97.9%, Avg loss: 0.044387
```

In [20]:

```python
# plot training loss and validation loss
plt.plot(np.arange(len(train_loss)), [i.item() for i in train_loss], 'r', label='train loss') # train in red
plt.plot(np.arange(len(val_loss)), val_loss, 'b', label='val loss')# val in blue
plt.xlabel('epoch')
plt.ylabel('loss')
plt.legend()
plt.title('Traing and validation Loss')
plt.show()
```



In [21]:

```python
# get val predictions and true labels for a classification report
preds = []
y_true = []

model.eval()
with torch.no_grad():
    for X, y in val_dataloader:
        pred = model(X.float())
        preds.append(pred)
        y_true.append(y)

y_pred = np.concatenate(preds).argmax(1)
y_true = np.concatenate(y_true)

report = classification_report(y_true=y_true, y_pred=y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.99      0.92      0.95       437
           1       0.97      1.00      0.99      1364

    accuracy                           0.98      1801
   macro avg       0.98      0.96      0.97      1801
weighted avg       0.98      0.98      0.98      1801
```

With the current parameters, we get an accuracy of 99% on the validation data and an f1 score of 0.99.

Optimizer param sweep

Given the high performance, A parameter sweep isn't nessisary.

Saving the model weights

To reuse the model, we will save the weights. Pytorch offers a very easy way to save model weights. The model itself will be placed into a python file so it can be imported.

In [22]:
```
weights_fp = './results/torch_model_weights_mlfw_only'
torch.save(model.state_dict(), weights_fp)
```

In [ ]:
```

```