Skincancer HAM-dataset using Pytorch

Standardimporter

[1]

```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, Dataset
from torchvision import datasets, transforms, models
from torchvision.utils import make_grid
from torch.utils.data import WeightedRandomSampler

import os
from PIL import Image
# from skimage import io, transform

import numpy as np
import pandas as pd

from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix,
classification_report
from sklearn.model_selection import train_test_split

import matplotlib.pyplot as plt
%matplotlib inline
```

[2]

```
# Nedan används om man t.ex. vill ha tusentalsavgränsare:
import locale
locale.setlocale(locale.LC_ALL, '')
```

```
'LC_CTYPE=en_US.UTF-8;LC_NUMERIC=sv_SE.UTF-8;LC_TIME=sv_SE.UTF-
8;LC_COLLATE=en_US.UTF-8;LC_MONETARY=sv_SE.UTF-8;LC_MESSAGES=en_US.UTF-
8;LC_PAPER=sv_SE.UTF-8;LC_NAME=sv_SE.UTF-8;LC_ADDRESS=sv_SE.UTF-
8;LC_TELEPHONE=sv_SE.UTF-8;LC_MEASUREMENT=sv_SE.UTF-
8;LC_IDENTIFICATION=sv_SE.UTF-8'
```

Hjälpfunktioner

[3]
```
def create_filename(filename):
    global file_name
    file_name = filename + "_e" + str(epochs) + "_bsz" + 
str(batchsz) + \
                "_lr" + str(f'{learning_rate:.0e}')
    return file_name
```

[4]
```
# https://pytorch.org/docs/master/notes/serialization.html

def save_trained_model(modelname):
    model_folder = "trained_models"
    model_file_suffix = ".pt"
    create_filename(modelname) # spottar ur sig ett filnamn i 
variabeln "file_name"

    full_model_filename = model_folder + "/" + file_name + 
model_file_suffix

    torch.save(mult_model.state_dict(), full_model_filename)
```

[5]
```
def load_trained_model(modelname):
    model_folder = "trained_models"
    model_file_suffix = ".pt"
    create_filename(modelname) # spottar ur sig ett filnamn i 
variabeln "file_name"

    full_model_filename = model_folder + "/" + file_name + 
model_file_suffix

    if torch.cuda.is_available():
        model.load_state_dict(torch.load(full_model_filename))
    else:
        model.load_state_dict(torch.load(full_model_filename, 
map_location=torch.device('cpu')))
```

[6]
```
# Följande återställer modellens vikter
# mellan körningar:

# usage: model.apply(weights_init)

def weights_init(m):
    if isinstance(m, nn.Conv2d):
        torch.nn.init.xavier_uniform_(m.weight.data)
```

Importera data och definiera sökvägar

[7]
```
imageFolder = "../../../ml/Datasets/skin-cancer-mnist-
ham10000/images_in_one"

metadataSkincancerFilename =  "../../../ml/Datasets/skin-cancer-
mnist-ham10000/csv/HAM10000_metadata.csv"
```

[8]
```
# Importera metadatan i en Pandas DataFrame:

skincancer_df = pd.read_csv(metadataSkincancerFilename)
```

Utforska och bearbeta vårt data

[9]
```
# Kolla om vi har några noll-värden i vår Dataframe:

skincancer_df.isnull().sum()
```

```
lesion_id        0
image_id         0
dx               0
dx_type          0
age             57
sex              0
localization     0
dtype: int64
```

[10]
```
# Enligt ovan är det bara i "age"-kolumnen som vi har noll-
värden.
# Dessa fyller vi ut genom att beräkna medevärdet:

skincancer_df['age'].fillna((skincancer_df['age'].mean()),
inplace=True)
```

[11]
```
# Definiera var vi har våra labels:

labels = skincancer_df['dx']
```

```
num_classes = len(labels.unique()) # --> 7
```

[12]

```
# Innan vi fortsätter måste vi göra om
# text-datan till numeriska features.

# 1. Flytta labels sist i df
# 2. Flytta age till efter image_id
# 3. Alla categorical features emellan.

skincancer_df = skincancer_df[['lesion_id', 'image_id', 'age',
'dx_type', 'sex', 'localization', 'dx']]
```

[13]

```
dxtype_feat_df = skincancer_df.iloc[:, 3]
dxtype_feat_df.value_counts()
```

```
histo        5340
follow_up    3704
consensus     902
confocal       69
Name: dx_type, dtype: int64
```

[14]

```
sex_feat_df = skincancer_df.iloc[:, 4]
sex_feat_df.value_counts()
```

```
male       5406
female     4552
unknown      57
Name: sex, dtype: int64
```

[15]

```
loc_feat_df = skincancer_df.iloc[:, 5]
loc_feat_df.value_counts()
```

```
back               2192
lower extremity    2077
trunk              1404
upper extremity    1118
abdomen            1022
face                745
chest               407
foot                319
unknown             234
neck                168
scalp               128
hand                 90
ear                  56
```

```
genital               48
acral                  7
Name: localization, dtype: int64
```

[16]

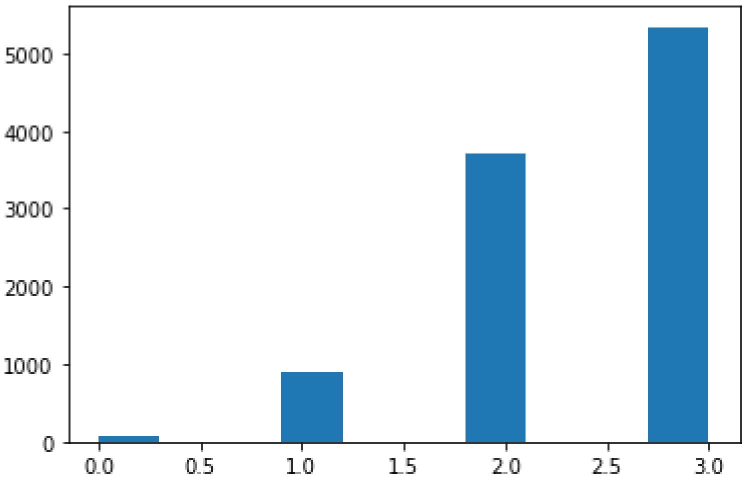
```python
label_df = skincancer_df.iloc[:, 6]
label_df.value_counts()
```

```
nv       6705
mel      1113
bkl      1099
bcc       514
akiec     327
vasc      142
df        115
Name: dx, dtype: int64
```

[17]

```python
le = LabelEncoder()
dxtype_feat = le.fit_transform(dxtype_feat_df)
plt.hist(dxtype_feat)
```

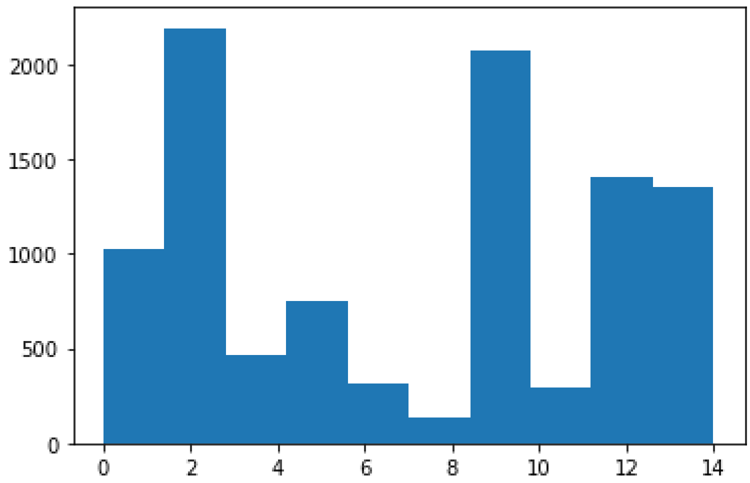
```
(array([  69.,    0.,    0.,  902.,    0.,    0., 3704.,    0.,    0.,
        5340.]),
 array([0. , 0.3, 0.6, 0.9, 1.2, 1.5, 1.8, 2.1, 2.4, 2.7, 3. ]),
 <a list of 10 Patch objects>)
```



[18]

```python
loc_feat = le.fit_transform(loc_feat_df)
plt.hist(loc_feat)
```

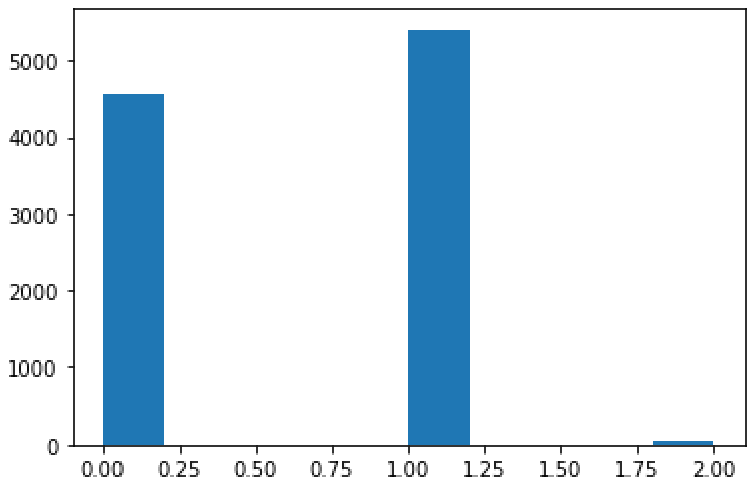
```
(array([1029., 2192.,  463.,  745.,  319.,  138., 2077.,  296., 1404.,
        1352.]),
 array([ 0. ,  1.4,  2.8,  4.2,  5.6,  7. ,  8.4,  9.8, 11.2, 12.6, 14.
]),
 <a list of 10 Patch objects>)
```



[19]

```
sex_feat = le.fit_transform(sex_feat_df)
plt.hist(sex_feat)
```

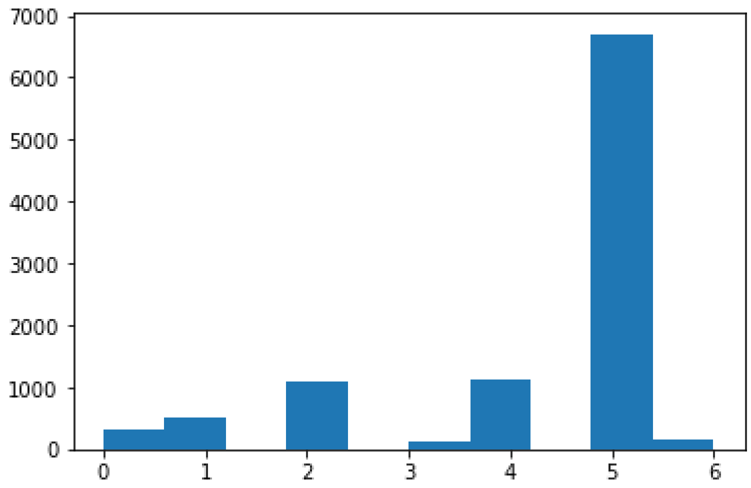
```
(array([4552.,    0.,    0.,    0.,    0., 5406.,    0.,    0.,    0.,
          57.]),
 array([0. , 0.2, 0.4, 0.6, 0.8, 1. , 1.2, 1.4, 1.6, 1.8, 2. ]),
 <a list of 10 Patch objects>)
```



[20]

```
labels = le.fit_transform(label_df)
plt.hist(labels)
```

```
(array([ 327.,  514.,    0., 1099.,    0.,  115., 1113.,    0., 6705.,
         142.]),
 array([0. , 0.6, 1.2, 1.8, 2.4, 3. , 3.6, 4.2, 4.8, 5.4, 6. ]),
 <a list of 10 Patch objects>)
```




```
[21]  le_skincancer_df = skincancer_df.copy()
      del skincancer_df
```

```
[22]  le_skincancer_df['dxtype'] = dxtype_feat
      le_skincancer_df['sex'] = sex_feat
      le_skincancer_df['loc'] = loc_feat
      le_skincancer_df['label'] = labels
      le_skincancer_df.drop(columns=['localization', 'dx_type', 'dx'],
      inplace = True)
      le_skincancer_df.head()
```

	lesion_id	image_id	age	sex	dxtype	loc	label
0	HAM_0000118	ISIC_0027419	80.0	1	3	11	2
1	HAM_0000118	ISIC_0025030	80.0	1	3	11	2
2	HAM_0002730	ISIC_0026769	80.0	1	3	11	2
3	HAM_0002730	ISIC_0025661	80.0	1	3	11	2
4	HAM_0001466	ISIC_0031633	75.0	1	3	4	2

```
[23]  # Vi normaliserar metadata-features
      # innan vi skickar in det till Pytorch
      # för träning:

      from sklearn.preprocessing import MinMaxScaler

      scaler = MinMaxScaler()
```

```
[24]  le_skincancer_df[['age', 'dxtype', 'loc']] =
      scaler.fit_transform(le_skincancer_df[['age', 'dxtype', 'loc']])
```

```
[25]    le_skincancer_df.drop(columns='lesion_id', axis = 1,
        inplace=True)
```

```
[26]    le_skincancer_df.head(n = 5)
```

	image_id	age	sex	dxtype	loc	label
0	ISIC_0027419	0.941176	1	1.0	0.785714	2
1	ISIC_0025030	0.941176	1	1.0	0.785714	2
2	ISIC_0026769	0.941176	1	1.0	0.785714	2
3	ISIC_0025661	0.941176	1	1.0	0.785714	2
4	ISIC_0031633	0.882353	1	1.0	0.285714	2

```
[27]    features_df = le_skincancer_df.iloc[:, :5]
```

```
[28]    labels_df = le_skincancer_df.iloc[:, 5:]
```

Bygg en egen dataloader-klass för bilder och Pandas-dataframe

```
[29]    class SkinCancerHamDF(Dataset):

            def __init__(self, features_df, labels_df, root_dir,
        transform = None):

                self.features_df = features_df
                self.labels_df = labels_df
                self.root_dir = root_dir
                self.transform = transform

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

            def __getitem__(self, idx):
                if torch.is_tensor(idx):
                    idx = idx.tolist()
```

```python
        img_name = self.features_df.iloc[idx, 0]
        #print(type(img_name))
        img_name = str(img_name)
        #print(type(img_name))

        full_img_name_woext = os.path.join(self.root_dir, \
                                        img_name)

        full_img_name = full_img_name_woext + ".jpg"

        # pillow:
        image = Image.open(full_img_name)

        # labels:
        label = self.labels_df.iloc[idx]
        label_np = np.array([label], dtype = int)

        # features:
        metadata = self.features_df.iloc[idx, 1:5]
        metadata_np = np.array([metadata], dtype = float)

        # Skapar en batch utan transforms:
        sample = {'image': image, \
                  'metadata': metadata_np, \
                  'label': label_np}

        # Skapar en batch med transforms:
        if self.transform:
            sample = {'image': self.transform(image), \
                      'metadata': metadata_np, \
                      'label': label_np.flatten()}

        return sample
```

```python
[30] # Definiera en batch-storlek:
batchsz = 2**5

# Definiera vilken augmentation som ska göras:
train_data_transform = transforms.Compose([

transforms.Resize([224, 224]),\
                                           transforms.ToTensor(),

transforms.Normalize(mean = [0.485, 0.456, 0.406],

 std = [0.229, 0.224, 0.225])
                                           ])

val_data_transform = transforms.Compose([
```

```
        transforms.Resize([224, 224]),\
                                            transforms.ToTensor(),
\

transforms.Normalize(mean = [0.485, 0.456, 0.406],

 std = [0.229, 0.224, 0.225])
                                            ])
```

Dela upp i tränings- och valideringsdata

```
[31]  features_train, features_val, labels_train, labels_val =
      train_test_split(features_df, \

              labels_df, \

              test_size = 0.1, \

              shuffle = True)
```

```
[32]  ham10k_train = SkinCancerHamDF(features_df = features_train, \
                                     labels_df = labels_train, \
                                     root_dir = imageFolder, \
                                     transform = train_data_transform)
```

```
[33]  ham10k_val = SkinCancerHamDF(features_df = features_val, \
                                   labels_df = labels_val, \
                                   root_dir = imageFolder, \
                                   transform = val_data_transform)
```

```
[34]  ham10k_train_dl = DataLoader(ham10k_train, \
                                   batch_size = batchsz, \
                                   num_workers = 4, \
                                   pin_memory = True, \
                                   )
```

```
[35]  ham10k_val_dl = DataLoader(ham10k_val, \
                                 batch_size = batchsz, \
                                 pin_memory = True, \
                                 num_workers = 4, \
                                  )
```

```
[36]  # Flytta till grafikkortet:

      use_cuda = torch.cuda.is_available() # True/False
      device = torch.device("cuda:0" if use_cuda else "cpu")
      print(device)

      # Override:
      # device = "cpu"
```

```
cuda:0
```

Importera en Alexnet-modell

```
[37]  # W_out = (W_in - Kernel_Filtersz + 2*padding) / stride + 1
      # Avrundas neråt.

      metadata_input_dim = features_df.shape[1] -1 # första kolumnen är
      bildnamnet...
```

```
[38]  model = models.AlexNet(num_classes = num_classes)
```

```
[39]  print(model)
```

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2,
2))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=
```

```
(1, 1))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=7, bias=True)
  )
)
```

[40]

```
# Hämta en batch för att skicka igenom
# ett nätverk:

for x in ham10k_train_dl:
    x = x['image']
    print("Ursprunglig storlek: ", x.shape)
    break
```

```
Ursprunglig storlek:  torch.Size([32, 3, 224, 224])
```

[41]

```
x_0 = x
```

[42]

```
x_1 = model.features(x_0)
```

[43]

```
x_2 = model.avgpool(x_1)
```

[44]

```
x_2.shape
```

```
torch.Size([32, 256, 6, 6])
```

[45]

```
model = models.AlexNet(7)
```

[46]

```
model.modules
```

```
<bound method Module.modules of AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2,
2))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=7, bias=True)
  )
)>
```

[47]

```
class MultInput(nn.Module):
    def __init__(self):
        super(MultInput, self).__init__()

        #model = models.AlexNet(num_classes = 7)

        self.alexnet = models.AlexNet(num_classes = 7)
        #self.


        self.fcc = nn.Sequential(
            nn.Linear(6*6*256 + metadata_input_dim, 512),
            nn.Linear(512, 256),
            nn.Linear(256, 64),
            nn.Dropout(p = 0.3),
            nn.Linear(64, num_classes),
```

```
            )

    def forward(self, x1, x2):
        x1 = self.alexnet.features(x1)
        x1 = self.alexnet.avgpool(x1)

        x1 = x1.view(x1.size(0), -1)
        x2 = x2.view(x2.size(0), -1)

        x = torch.cat((x1, x2), dim = 1)
        x = self.fcc(x)

        return x
```

```
[48] # Definiera en instans av CNN():
     mult_model = MultInput()

     # Flytta till rätt device för träning:
     mult_model.to(device)
```

```
MultInput(
  (alexnet): AlexNet(
    (features): Sequential(
      (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=
(2, 2))
      (1): ReLU(inplace=True)
      (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
      (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=
(2, 2))
      (4): ReLU(inplace=True)
      (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
      (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
      (7): ReLU(inplace=True)
      (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
      (9): ReLU(inplace=True)
      (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
      (11): ReLU(inplace=True)
      (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    )
    (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
    (classifier): Sequential(
      (0): Dropout(p=0.5, inplace=False)
      (1): Linear(in_features=9216, out_features=4096, bias=True)
      (2): ReLU(inplace=True)
      (3): Dropout(p=0.5, inplace=False)
      (4): Linear(in_features=4096, out_features=4096, bias=True)
      (5): ReLU(inplace=True)
```

```
      (6): Linear(in_features=4096, out_features=7, bias=True)
    )
  )
  (fcc): Sequential(
    (0): Linear(in_features=9220, out_features=512, bias=True)
    (1): Linear(in_features=512, out_features=256, bias=True)
    (2): Linear(in_features=256, out_features=64, bias=True)
    (3): Dropout(p=0.3, inplace=False)
    (4): Linear(in_features=64, out_features=7, bias=True)
  )
)
```

[49]

```
# Dubbelkolla att modellen flyttats till
# grafikkortet eller ej (True/False):

next(mult_model.parameters()).is_cuda
```

```
True
```

[50]

```
# Hur många parametrar har modellen
# att träna?

trainableparameters = []
for param in mult_model.parameters():
    # trainableparameters = param.numel()
    trainableparameters.append(param.numel())

tot_params = np.sum(trainableparameters)

print(f'Antalet träningsbara parametrar är {tot_params:n} st')
```

```
Antalet träningsbara parametrar är 61 901 902 st
```

Återställ nätets vikter

[51]

```
mult_model.apply(weights_init)
```

```
MultInput(
  (alexnet): AlexNet(
    (features): Sequential(
      (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=
(2, 2))
      (1): ReLU(inplace=True)
      (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
```

```
ceil_mode=False)
      (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=
(2, 2))
      (4): ReLU(inplace=True)
      (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
      (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
      (7): ReLU(inplace=True)
      (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
      (9): ReLU(inplace=True)
      (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1))
      (11): ReLU(inplace=True)
      (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    )
    (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
    (classifier): Sequential(
      (0): Dropout(p=0.5, inplace=False)
      (1): Linear(in_features=9216, out_features=4096, bias=True)
      (2): ReLU(inplace=True)
      (3): Dropout(p=0.5, inplace=False)
      (4): Linear(in_features=4096, out_features=4096, bias=True)
      (5): ReLU(inplace=True)
      (6): Linear(in_features=4096, out_features=7, bias=True)
    )
  )
  (fcc): Sequential(
    (0): Linear(in_features=9220, out_features=512, bias=True)
    (1): Linear(in_features=512, out_features=256, bias=True)
    (2): Linear(in_features=256, out_features=64, bias=True)
    (3): Dropout(p=0.3, inplace=False)
    (4): Linear(in_features=64, out_features=7, bias=True)
  )
)
```

Loss och optimiser

[52]

```
# Definiera loss-function och vilken optimerare som ska användas:

epochs = 10 # verkar räcka med tanke på overfitting.

learning_rate = 1e-4

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(mult_model.parameters(), lr =
learning_rate)
```

```
[53]  modelname = create_filename("multi_model_cnn")
      print(modelname)
```

```
multi_model_cnn_e20_bsz32_lr1e-04
```

Trainingloop:

```
[54]  mult_model.apply(weights_init)

      do_validation = 1

      import time
      start_training_time = time.time()

      num_training_images = len(ham10k_train_dl.dataset)
      num_val_images = len(ham10k_val_dl.dataset)

      accuracy_train = []
      losses_train = []
      accuracy_val = []
      losses_val = []

      for epoch in range(epochs):
          start_epoch_time = time.time()

          num_correct_per_epoch_train = 0
          tot_loss_per_epoch_train = 0.0

          for idx_train, inputs_train in enumerate(ham10k_train_dl):
              images_train = inputs_train['image'].float().to(device)
              metadata_train =
      inputs_train['metadata'].float().to(device)
              labels_train = inputs_train['label'].flatten().to(device)

              mult_model.train()
              # Låt modellen göra förutsägelser:
              predictions_train = mult_model.forward(images_train,
      metadata_train)

              # Beräkna statistik från träningen på träningsmängden:
              _, predicted_train = torch.max(predictions_train.data, 1)
              num_correct_per_batch_train =
      torch.sum(predicted_train.detach() == labels_train.detach())
              num_correct_per_epoch_train +=
      num_correct_per_batch_train
```

```
        # Beräkna loss:
        loss_per_batch_train = criterion(predictions_train,
labels_train)
        tot_loss_per_epoch_train += loss_per_batch_train.item() *
batchsz

        # Nolla ackadumulerade gradienter, göra
        # backprop. & uppdatera vår optimeringsfunktion:
        optimizer.zero_grad()
        loss_per_batch_train.backward()
        optimizer.step()

    # Validation
    if do_validation == True:
        start_eval_time = time.time()
        mult_model.eval()

        num_correct_per_epoch_val = 0
        tot_loss_per_epoch_val = 0.0

        for idx_val, inputs_val in enumerate(ham10k_val_dl):
            images_val = inputs_val['image'].float().to(device)
            metadata_val =
inputs_val['metadata'].float().to(device)
            labels_val = inputs_val['label'].flatten().to(device)

            with torch.no_grad():

                predictions_val = mult_model.forward(images_val,
metadata_val)
                _, predicted_val = torch.max(predictions_val, 1)
                # Behöver ej använda .detach med torch.no_grad()
                num_correct_per_batch_val =
torch.sum(predicted_val == labels_val)
                #num_correct_per_batch_val =
torch.sum(predicted_val.detach() == labels_val.detach())
                num_correct_per_epoch_val +=
num_correct_per_batch_val

                loss_per_batch_val = criterion(predictions_val,
labels_val)
                tot_loss_per_epoch_val +=
loss_per_batch_val.item() * batchsz

        end_eval_time = time.time()
    else:
        pass

    # Beräkna statistik från epoken:
    # Use torch.Tensor.item() to get a Python number
    # from a tensor containing a single value:
```

```python
    # acc, train:
    accuracy_per_epoch_train = num_correct_per_epoch_train.item()
/ num_training_images
    accuracy_train.append(accuracy_per_epoch_train)

    # loss, train:
    loss_per_epoch_train = tot_loss_per_epoch_train /
num_training_images
    losses_train.append(loss_per_epoch_train)

    if do_validation == True:
        # acc, val:
        accuracy_per_epoch_val = num_correct_per_epoch_val.item()
/ num_val_images
        accuracy_val.append(accuracy_per_epoch_val)

        # loss, val:
        loss_per_epoch_val = tot_loss_per_epoch_val /
num_val_images
        losses_val.append(loss_per_epoch_val)
    else:
        pass

    end_epoch_time = time.time()
    epoch_time = end_epoch_time - start_epoch_time

    # epoch startar på 0, därav "+1" nedan:
    if do_validation == True:
        print(f"Epok {epoch+1:03}, {epoch_time:4.1f} sek. ---
train acc = {accuracy_per_epoch_train:4.3f} --- val acc =
{accuracy_per_epoch_val:4.3f} --- train loss =
{loss_per_epoch_train:4.5f} --- val loss =
{loss_per_epoch_val:4.5f}")
    else:
        print(f"Epok {epoch+1:03}, {epoch_time:4.1f} sek. ---
train acc = {accuracy_per_epoch_train:4.3f} --- train loss =
{loss_per_epoch_train:4.5f}")

end_training_time = time.time()

delta = end_training_time - start_training_time

print(f'\nTraining took {delta/60:.2f} minutes.')
```

```
Epok 001, 38.7 sek. --- train acc = 0.672 --- val acc = 0.680 --- train
loss = 0.95033 --- val loss = 0.91445
Epok 002, 37.4 sek. --- train acc = 0.693 --- val acc = 0.703 --- train
loss = 0.84901 --- val loss = 0.85084
Epok 003, 38.5 sek. --- train acc = 0.710 --- val acc = 0.714 --- train
loss = 0.79567 --- val loss = 0.81534
Epok 004, 38.3 sek. --- train acc = 0.731 --- val acc = 0.728 --- train
```

```
loss = 0.74376 --- val loss = 0.76473
Epok 005, 39.1 sek. --- train acc = 0.750 --- val acc = 0.752 --- train
loss = 0.69561 --- val loss = 0.71512
Epok 006, 38.2 sek. --- train acc = 0.764 --- val acc = 0.754 --- train
loss = 0.65553 --- val loss = 0.69711
Epok 007, 38.1 sek. --- train acc = 0.775 --- val acc = 0.756 --- train
loss = 0.61099 --- val loss = 0.70397
Epok 008, 39.0 sek. --- train acc = 0.793 --- val acc = 0.763 --- train
loss = 0.57082 --- val loss = 0.71992
Epok 009, 36.8 sek. --- train acc = 0.812 --- val acc = 0.750 --- train
loss = 0.51579 --- val loss = 0.77799
Epok 010, 36.5 sek. --- train acc = 0.830 --- val acc = 0.746 --- train
loss = 0.46456 --- val loss = 0.82143
Epok 011, 37.8 sek. --- train acc = 0.848 --- val acc = 0.749 --- train
loss = 0.41798 --- val loss = 0.78295
Epok 012, 36.6 sek. --- train acc = 0.864 --- val acc = 0.745 --- train
loss = 0.37439 --- val loss = 0.89099
Epok 013, 37.4 sek. --- train acc = 0.881 --- val acc = 0.754 --- train
loss = 0.34085 --- val loss = 0.88456
Epok 014, 36.3 sek. --- train acc = 0.887 --- val acc = 0.745 --- train
loss = 0.32284 --- val loss = 1.00964
Epok 015, 37.2 sek. --- train acc = 0.908 --- val acc = 0.749 --- train
loss = 0.25535 --- val loss = 1.11338
Epok 016, 36.6 sek. --- train acc = 0.917 --- val acc = 0.742 --- train
loss = 0.23726 --- val loss = 1.01239
Epok 017, 37.9 sek. --- train acc = 0.930 --- val acc = 0.723 --- train
loss = 0.19908 --- val loss = 1.10928
Epok 018, 36.8 sek. --- train acc = 0.935 --- val acc = 0.741 --- train
loss = 0.18606 --- val loss = 1.11537
Epok 019, 36.8 sek. --- train acc = 0.937 --- val acc = 0.735 --- train
loss = 0.17785 --- val loss = 1.38238
Epok 020, 38.2 sek. --- train acc = 0.946 --- val acc = 0.729 --- train
loss = 0.15765 --- val loss = 1.19798

Training took 12.54 minutes.
```

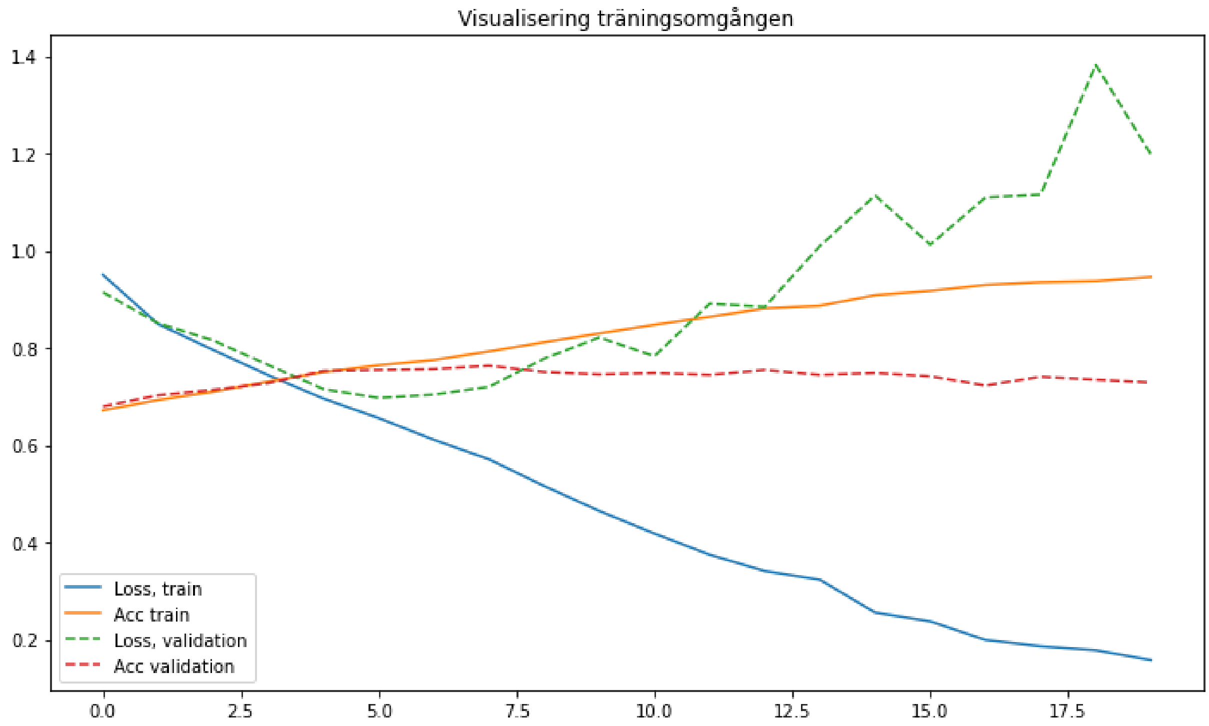
[55]
```python
save_trained_model(modelname)
```

Visualisering av träningsomgången

[56]
```python
if do_validation == False:

    plt.figure(figsize = (12, 7))
    plt.title("Visualisering träningsomgången")
    plt.plot(losses_train, label = "Loss")
```

```
        plt.plot(accuracy_train, label = "Andel korrekta")
        plt.legend()
        plt.show()
    else:
        plt.figure(figsize = (12, 7))
        plt.title("Visualisering träningsomgången")
        plt.plot(losses_train, label = "Loss, train")
        plt.plot(accuracy_train, label = "Acc train")
        plt.plot(losses_val, label = "Loss, validation",
linestyle='dashed')
        plt.plot(accuracy_val, label = "Acc validation",
linestyle='dashed')
        plt.legend(loc = 'lower left')
        plt.show()
```



Utvärdering

[57]

```
def evaluate_model(num_eval_images, data_generator, model):

    model.eval()

    start_eval_test_time = time.time()

    global labels_val_true_np, predicted_val_np

    labels_ground_truth = []
    predicted_classes_val = []
```

```
    with torch.no_grad():
        correct_val = 0
        # Antal iterationer = num_images / batchsz = x st.
        for inputs in data_generator:
            images = inputs['image'].float().to(device)
            metadata = inputs['metadata'].float().to(device)
            labels = inputs['label'].flatten().to(device)

            # Spara för mer utvärdering utanför denna funktion:
            labels_ground_truth.append(labels.cpu().numpy())

            # Låt modellen göra förutsägelser:
            predictions_val = mult_model.forward(images,
metadata)
            _, predicted_val = torch.max(input = predictions_val,
dim = 1)

 predicted_classes_val.append(predicted_val.cpu().numpy())

            correct_val += (predicted_val == labels).sum()

        # Platta till listorna...
        labels_ground_truth = [item for sublist in
labels_ground_truth for item in sublist]
        predicted_classes_val = [item for sublist in
predicted_classes_val for item in sublist]

        #flat_list = []
        #for sublist in predicted_classes_val:
        #    for item in sublist:
        #        flat_list.append(item)

        labels_val_true_np = np.array(labels_ground_truth)
        predicted_val_np = np.array(predicted_classes_val)


        end_eval_test_time = time.time()
        eval_test_time = end_eval_test_time -
start_eval_test_time

    print(f'Test accuracy: {correct_val.item()}/{num_eval_images}
= {100*correct_val.item()/(num_eval_images):5.2f} %')
    print(f"\nEvaluation took {eval_test_time:.2f} seconds.")
```

[58]

```
evaluate_model(len(ham10k_val_dl.dataset), ham10k_val_dl,
mult_model)
```

```
Test accuracy: 730/1002 = 72.85 %

Evaluation took 4.15 seconds.
```

[59]
```
cm_pytorch = confusion_matrix(labels_val_true_np,
predicted_val_np)
```

[60]
```
print(cm_pytorch)
```

```
[[  9   2  15   0   0   5   0]
 [ 10  20  16   3   2   9   0]
 [  8   2  66   1  14  21   0]
 [  1   0   6   4   2   2   0]
 [  4   5  20   0  66  29   0]
 [  1   2  49   1  35 556   0]
 [  0   2   0   0   2   3   9]]
```

[61]
```
print(classification_report(labels_val_true_np,
predicted_val_np))
```

```
              precision    recall  f1-score   support

           0       0.27      0.29      0.28        31
           1       0.61      0.33      0.43        60
           2       0.38      0.59      0.46       112
           3       0.44      0.27      0.33        15
           4       0.55      0.53      0.54       124
           5       0.89      0.86      0.88       644
           6       1.00      0.56      0.72        16

    accuracy                           0.73      1002
   macro avg       0.59      0.49      0.52      1002
weighted avg       0.75      0.73      0.73      1002
```

[ ]

[ ]