

The data consists of 48x48 pixel grayscale images of faces. The faces have been automatically registered so that the face is more or less centered and occupies about the same amount of space in each image. The task is to categorize each face based on the emotion shown in the facial expression in to one of seven categories (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral).

The dataset consists of 35,887 examples. This dataset was prepared by Pierre-Luc Carrier and Aaron Courville, as part of an ongoing research project.

We will be using Pytorch package to create the Convolutional Neural Network model to classify the images and various metrics like Confusion matrix and plots will be eused to evaluate the performance of the model and at the end we will be testing the model by few images taken from google

Ref: https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data (https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data (https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data (https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data (https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data (https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data (<a href="https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenges-in-representation-learning-facial-expression-recognition-challenges-in-representation-learning-facial-expression-recognition-challenges-in-representation-learning-facial-expression-recognition-challenges-in-representation-recognition-challenges-in-representation-learning-facial-expression-recognition-challenges-in-representation-learning-facial-expression-recognition-challenges-in-representation-recognition-challenges-in-representation-recognition-challenges-in-representation-challenges-in-representation-recognition-challenges-in-repres

Importing the Necessary Libraries

In [218]:

import torch
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import torch.nn as nn
import torch.nn.functional as F
from torchvision import datasets, transforms
from torch.utils.data import TensorDataset, DataLoader

```
In [2]:
                                                                                                     H
df = pd.read_csv(r'C:\FER\fer2013\fer2013.csv')
In [3]:
                                                                                                     H
df.head()
Out[3]:
   emotion
                                                pixels
                                                        Usage
              70 80 82 72 58 58 60 63 54 58 60 48 89 115 121... Training
0
         0
            151 150 147 155 148 133 111 140 170 174 182 15... Training
1
2
         2 231 212 156 164 174 138 161 173 182 200 106 38... Training
3
         4
              24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1... Training
                4 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84... Training
         6
In [4]:
                                                                                                     H
df.shape
Out[4]:
(35887, 3)
                                                                                                     M
In [5]:
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35887 entries, 0 to 35886
Data columns (total 3 columns):
            35887 non-null int64
emotion
pixels
            35887 non-null object
            35887 non-null object
Usage
dtypes: int64(1), object(2)
memory usage: 841.2+ KB
In [6]:
#converting the string values of pixels into array
def arr_conv (strg):
    b=[]
    a=strg.split(" ")
    for elements in a:
         b.append(int (elements))
    return np.array(b)
In [7]:
                                                                                                     H
df["pixels_arr"] = df['pixels'].apply(arr_conv)
```

```
In [8]:
min(df["pixels_arr"][100])
Out[8]:
62
In [9]:
                                                                                                               M
max(df["pixels_arr"][0])
Out[9]:
210
In [10]:
                                                                                                               H
image,label = df["pixels_arr"][0],df["emotion"][0]
print('Shape:', image.shape, '\nLabel:', label)
Shape: (2304,)
Label: 0
                                                                                                               H
In [11]:
plt.imshow(df["pixels_arr"][106].reshape(48,48),cmap='gray');
  0
 10
 20
                  20
                          30
           10
```

```
In [12]:
len(df['pixels_arr'][0])
```

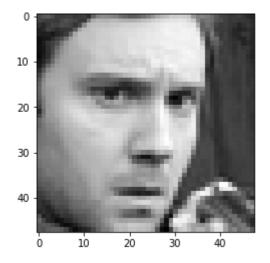
Out[12]:

2304

```
In [13]:
                                                                                           H
type(df['pixels_arr'][0])
Out[13]:
numpy.ndarray
In [14]:
                                                                                           M
train_data_fer= torch.Tensor(df['pixels_arr']) ##important step
In [15]:
train_data_fer[0]
Out[15]:
tensor([ 70., 80., 82., ..., 106., 109., 82.])
In [16]:
                                                                                           M
train_data_fer.shape
Out[16]:
torch.Size([35887, 2304])
In [17]:
                                                                                           M
train_data_fer= train_data_fer.reshape(35887,1,48,48) #reshaping to 1 color channel and 48%
In [18]:
                                                                                           H
train_data_fer.shape
Out[18]:
torch.Size([35887, 1, 48, 48])
In [19]:
                                                                                           H
train data fer[0].shape # 1st image as a tensor
Out[19]:
torch.Size([1, 48, 48])
In [21]:
                                                                                           H
train_data_fer[0:5].shape #first 5 images
Out[21]:
torch.Size([5, 1, 48, 48])
```

In [23]:

```
plt.imshow(train_data_fer[0].reshape(48,48),cmap='gray');
```



In [24]: ▶

class_names= ['Angry', 'Disgust','Fear', 'Happy', 'Sad', 'Surprise', 'Neutral']

In [25]: ▶

labels= list(df['emotion'][0:5])
labels

Out[25]:

[0, 0, 2, 4, 6]

```
In [265]:
np.set_printoptions(formatter=dict(int=lambda x: f'{x:5}')) # to widen the printed array
from torchvision.utils import make_grid
labels =list(df['emotion'][0:5])
print('Label:', np.array(labels))
print('Class: ', *np.array([class_names[i] for i in labels]))
images= train_data_fer[0:5]
im = make_grid(images, nrow=5)
plt.figure(figsize=(12,4))
plt.imshow(np.transpose(im, (1, 2, 0)));
Label: [
                0
                        2
                               4
           0
Class: Angry Angry Fear Sad Neutral
 0
10
 20
 30
 40
 50
                                100
                                               150
In [29]:
                                                                                            M
Y=torch.Tensor(df['emotion'])# target variable values
In [30]:
Υ
Out[30]:
tensor([0., 0., 2., ..., 0., 3., 2.])
                                                                                            H
In [31]:
Y. shape
Out[31]:
torch.Size([35887])
In [32]:
Y = Y.type(torch.LongTensor)
In [33]:
                                                                                            H
Y.type()
Out[33]:
'torch.LongTensor'
```

```
H
In [34]:
Out[34]:
tensor([0, 0, 2, ..., 0, 3, 2])
In [35]:
                                                                                           M
len(Y)
Out[35]:
35887
  Data Paritioning
In [36]:
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test=train_test_split(train_data_fer, Y,test_size=0.20, random_
In [37]:
                                                                                            H
x_train[0].shape
Out[37]:
torch.Size([1, 48, 48])
In [38]:
                                                                                            H
x_train.shape
Out[38]:
torch.Size([28709, 1, 48, 48])
In [39]:
                                                                                            H
y_train.shape
Out[39]:
torch.Size([28709])
```

```
In [40]:
                                                                                          H
y_train
Out[40]:
tensor([2, 6, 4, ..., 0, 2, 4])
In [41]:
                                                                                          H
train_dataset = TensorDataset(x_train, y_train) #imp step
In [42]:
test_dataset = TensorDataset(x_test, y_test) #imp step
In [43]:
                                                                                          M
train_dataset[0]
Out[43]:
(tensor([[[147., 147., 148., ..., 132., 133., 135.],
          [146., 146., 149., ..., 133., 134., 136.],
          [149., 151., 155.,
                             ..., 135., 136., 137.],
          . . . ,
          [ 49., 42., 36., ..., 157., 159., 158.],
          [ 42., 32., 38., ..., 155., 157., 158.],
          [ 37., 35., 35., ..., 155., 156., 156.]]]), tensor(2))
In [44]:
                                                                                          M
train_dataset[0][0].shape
Out[44]:
torch.Size([1, 48, 48])
In [45]:
                                                                                          H
test dataset[0]
Out[45]:
(tensor([[[239., 239., 239., ..., 255., 254., 255.],
          [239., 239., 239., ..., 255., 254., 255.],
          [239., 239., 239.,
                             ..., 255., 255., 255.],
          [ 46., 80., 117., ..., 138., 207., 255.],
          [ 95., 112., 141., ..., 133., 217., 255.],
          [107., 108., 148., ..., 179., 221., 255.]]]), tensor(0))
```

```
In [46]:
                                                                                               H
test_dataset[0][0].shape
Out[46]:
torch.Size([1, 48, 48])
In [47]:
                                                                                               H
type(train_dataset)
Out[47]:
torch.utils.data.dataset.TensorDataset
In [48]:
                                                                                               H
train_dataset
Out[48]:
<torch.utils.data.dataset.TensorDataset at 0x1f9f3783cf8>
In [49]:
                                                                                               H
from torch.utils.data import TensorDataset, DataLoader
Initializing train/test dataloader object which splits the training dataset into small bate
and this can be used later in the CNN model
torch.manual_seed(101)
bat_sz=50
train_loader = DataLoader(train_dataset,batch_size=bat_sz,shuffle=True)
test_loader = DataLoader(test_dataset,batch_size=bat_sz,shuffle=False)
In [50]:
                                                                                               H
len(train dataset)
Out[50]:
28709
In [51]:
                                                                                               H
len(test dataset)
Out[51]:
7178
Then we have 7 emotions that we are predicting namely (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad,
5=Surprise, 6=Neutral), so we have 7 labels. We will be processing our inputs with a batch size of 50
```

localhost:8888/notebooks/Face Expression Recognition CNN -Pytorch.ipynb#

Creating a Class from the nn.Module of Pytorch

```
In [52]:
class CONVNN(nn.Module):
   def __init__(self):
       super().__init__()
       self.conv1 = nn.Conv2d(1, 300 , kernel_size =5, stride=1,padding=2)#1 color channe
       self.norm1 = nn.BatchNorm2d(300)
       \#self.drop1 = nn.Dropout2d(p=0.2)
       self.conv2 = nn.Conv2d(300, 150, 5, 1,padding=2)
       self.norm2 = nn.BatchNorm2d(150)
       self.conv3 = nn.Conv2d(150, 75, 5 , 1,padding=2)
       self.norm3 = nn.BatchNorm2d(75)
       \#self.drop2 = nn.Dropout2d(p=0.2)
       self.layer1 = nn.Linear(6*6*75,180) # we need to calculate the resulting number of
       self.drop3 = nn.Dropout2d(p=0.1)
       self.layer2 = nn.Linear(180,84)
       self.layer3 = nn.Linear(84,7) #only 7 classes of Dogs and Cats
   def forward(self,x):
                        #self.drop1
                                    ( F.relu( self.norm1(self.conv1(x)) )
       x= F.max_pool2d(
                                                                                   ,2,2)
       x= F.max pool2d(
                                    (F.relu(
                                              self.norm2(self.conv2(x)) )
                                                                                   ,2,2)
       x= F.max_pool2d(
                                    (F.relu(
                                               self.norm3(self.conv3(x)) )
                                                                                   ,2,2)
       x= self.drop3(F.relu(
                                 self.layer1( x.view(-1,6*6*75) )))
                                                                            #flattening
       x= F.relu(self.layer2(x))
       x= F.log_softmax( self.layer3(x), dim=1) #multi class classification
       return x
```

```
In [53]:
                                                                                           M
torch.manual_seed(101)
model = CONVNN()#to instansiate the model as cuda use "model = CONVNN().to(device) " or
                                                                                         "mc
model
                                                                                           Þ
Out[53]:
CONVNN(
  (conv1): Conv2d(1, 300, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
  (norm1): BatchNorm2d(300, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
  (conv2): Conv2d(300, 150, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2))
  (norm2): BatchNorm2d(150, eps=1e-05, momentum=0.1, affine=True, track_runn
ing stats=True)
  (conv3): Conv2d(150, 75, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2))
  (norm3): BatchNorm2d(75, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)
  (layer1): Linear(in_features=2700, out_features=180, bias=True)
  (drop3): Dropout2d(p=0.1, inplace=False)
  (layer2): Linear(in_features=180, out_features=84, bias=True)
  (layer3): Linear(in_features=84, out_features=7, bias=True)
In [54]:
                                                                                           H
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

Data Modelling & Training

```
In [55]:
```

```
epochs = 8
train_loss= []
test_loss= []
train acc=[]
test_acc = []
print(f'\nConvolutional Neural Network Model Metrics:\n')
print(f'\t This CNN model configuration has {epochs} epochs with each batch size of {bat_sz
for i in range(epochs):
    train_crt_pred = 0
    test_crt_pred = 0
    conf_mat= torch.FloatTensor([])
    for b,(x_train,y_train) in enumerate (train_loader):
        b += 1
        y_pred = model.forward(x_train)
        loss= criterion(y_pred,y_train.long() )
        buffer = torch.max(y_pred.data, 1) [1]
        batch_acc = (buffer == y_train).sum()
        train_crt_pred += batch_acc
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        if b% int((len(train dataset)/bat sz)/3 ) == 0:
            print(f'Epoch{i+1:2} Batch {b:4} loss: {loss.item():5.2f} Train Accuracy: {trai
    train_loss.append(loss) #loss after 1 epoch
    train_acc.append(train_crt_pred) # crt predictions after 1 epoch
   with torch.no_grad(): #testing after 1 complete epoch
        for b,(x_test,y_test) in enumerate (test_loader):
            b += 1
            y_{eval} = model(x_{test})
            loss= criterion(y eval,y test.long())
            buffer1 = torch.max(y eval.data, 1) [1]
            conf_mat = torch.cat((conf_mat.float(),buffer1.float()),0)
            batch_acc = (buffer1 == y_test).sum()
            test_crt_pred += batch_acc
    test loss.append(loss) #test loss after the last completed epoch
    test acc.append(test crt pred) # crt predictions using the last completed epoch
    print(f'After {i+1} Epoch(s) the Train Accuracy is {(train crt pred.item()/len(train da
```

Convolutional Neural Network Model Metrics:

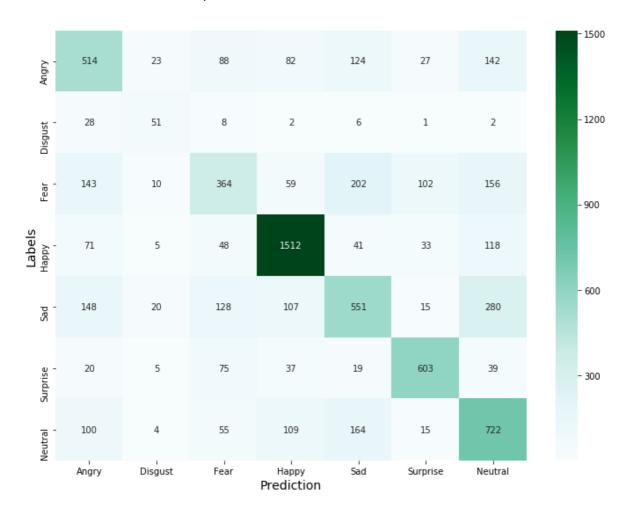
This CNN model configuration has 8 epochs with each batch size of 5 0 images:

```
Epoch 1 Batch 191 loss: 1.54 Train Accuracy: 28.911%
Epoch 1 Batch 382 loss: 1.30 Train Accuracy: 34.607%
Epoch 1 Batch 573 loss: 1.37 Train Accuracy: 38.300%
After 1 Epoch(s) the Train Accuracy is 38.316% and Test Accuracy is 45.639%
Epoch 2 Batch 191 loss: 1.29 Train Accuracy: 48.555%
Epoch 2 Batch 382 loss: 1.28 Train Accuracy: 49.665%
Epoch 2 Batch 573 loss: 1.24 Train Accuracy: 50.265%
After 2 Epoch(s) the Train Accuracy is 50.270% and Test Accuracy is 53.469%
Epoch 3 Batch 191 loss: 1.28 Train Accuracy: 55.414%
Epoch 3 Batch 382 loss: 1.29 Train Accuracy: 54.817%
Epoch 3 Batch 573 loss: 1.13 Train Accuracy: 55.145%
After 3 Epoch(s) the Train Accuracy is 55.143% and Test Accuracy is 55.726%
Epoch 4 Batch 191 loss: 1.07 Train Accuracy: 59.267%
Epoch 4 Batch 382 loss: 1.17 Train Accuracy: 58.864%
Epoch 4 Batch 573 loss: 1.16 Train Accuracy: 58.970%
After 4 Epoch(s) the Train Accuracy is 58.978% and Test Accuracy is 56.534%
Epoch 5 Batch 191 loss: 1.11 Train Accuracy: 62.021%
Epoch 5 Batch 382 loss: 1.18 Train Accuracy: 62.120%
Epoch 5 Batch 573 loss: 1.00 Train Accuracy: 61.937%
After 5 Epoch(s) the Train Accuracy is 61.939% and Test Accuracy is 57.788%
Epoch 6 Batch 191 loss: 1.30 Train Accuracy: 65.236%
Epoch 6 Batch 382 loss: 0.66 Train Accuracy: 65.094%
Epoch 6 Batch 573 loss: 0.72 Train Accuracy: 64.852%
After 6 Epoch(s) the Train Accuracy is 64.844% and Test Accuracy is 58.888%
Epoch 7 Batch 191 loss: 0.54 Train Accuracy: 68.628%
Epoch 7 Batch 382 loss: 0.71 Train Accuracy: 68.764%
Epoch 7 Batch 573 loss: 0.96 Train Accuracy: 68.244%
After 7 Epoch(s) the Train Accuracy is 68.223% and Test Accuracy is 57.997%
Epoch 8 Batch 191 loss: 0.71 Train Accuracy: 71.843%
Epoch 8 Batch 382 loss: 0.74 Train Accuracy: 71.770%
Epoch 8 Batch 573 loss: 0.78 Train Accuracy: 71.836%
After 8 Epoch(s) the Train Accuracy is 71.831% and Test Accuracy is 60.142%
```

```
In [101]:
```

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import confusion_matrix,classification_report
import seaborn as sns
print('\nThe Confusion Matrix is plotted below:')
cfmt =pd.DataFrame(confusion_matrix(torch.Tensor([r for q,r in test_dataset]).reshape(-1,1)
plt.figure(figsize=(12,9))
sns.heatmap(cfmt,annot=True,cmap='BuGn',fmt="d")
plt.xlabel("Prediction",fontsize=14)
plt.ylabel("Labels",fontsize=14)
plt.show()
print('\nThe Classification Report is plotted below: \n\n',classification_report(torch.Tens
```

The Confusion Matrix is plotted below:

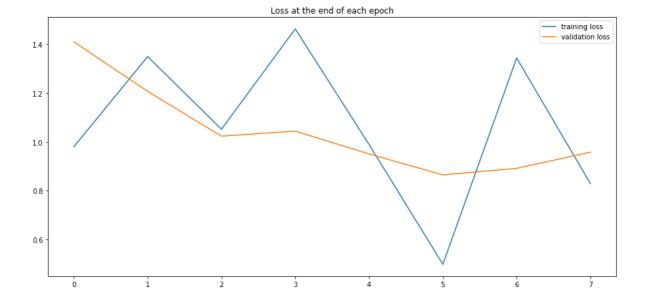


The Classification Report is plotted below:

	precision	recall	f1-score	support
0.0	0.50	0.51	0.51	1000
1.0	0.43	0.52	0.47	98
2.0	0.48	0.35	0.40	1036
3.0	0.79	0.83	0.81	1828
4.0	0.50	0.44	0.47	1249
5.0	0.76	0.76	0.76	798
6.0	0.49	0.62	0.55	1169
accuracy			0.60	7178
macro avg	0.56	0.58	0.57	7178
weighted avg	0.60	0.60	0.60	7178

In [96]: ▶

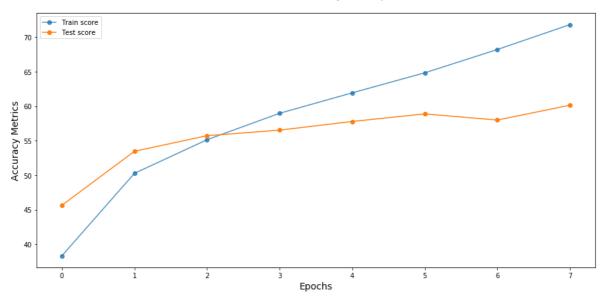
```
plt.figure(figsize=(15,7))
plt.plot(train_loss, label='training loss')
plt.plot(test_loss, label='validation loss')
plt.title('Loss at the end of each epoch')
plt.legend();
```



In [95]: ▶

```
plt.figure(figsize=(15,7))
plt.plot([(t/(len(train_dataset)/100)) for t in train_acc], label='Train score',marker='o',
plt.plot([(t/(len(test_dataset)/100)) for t in test_acc], label='Test score',marker='o')
plt.title('\nTrain Vs Test Accuracy over Epochs\n',fontsize=16)
# plt.xticks(np.arange(0,20,1));
plt.xlabel('Epochs',fontsize=14)
plt.ylabel('Accuracy Metrics',fontsize=14)
plt.legend();
```

Train Vs Test Accuracy over Epochs



Save the Model

torch.save(model.state_dict(), 'FERCNNModel.pt')

Evaluate the model

```
In [170]:
# Evaluation DATA TRANSFORMATION
eval_transform =transforms.Compose( [
    transforms.Resize((48,48)),
    transforms.Grayscale(num_output_channels=1),# Third transformation -- Resize to 224 as t
    transforms.ToTensor(),
                                                 # Fifth transformation -- to convert it into
])
                                                                                            \triangleright
In [171]:
                                                                                            M
root = r'C:\Univ'
In [202]:
                                                                                            H
import os
from PIL import Image #to operate on pics or images
from IPython.display import display #Only for Jupyter Notebook
import warnings
warnings.filterwarnings('ignore')
eval_data = datasets.ImageFolder(os.path.join(root, 'expr'), transform = eval_transform)
In [203]:
                                                                                            M
eval_data
Out[203]:
Dataset ImageFolder
    Number of datapoints: 2
    Root location: C:\Univ\expr
    StandardTransform
Transform: Compose(
               Resize(size=(48, 48), interpolation=PIL.Image.BILINEAR)
               Grayscale(num_output_channels=1)
               ToTensor()
           )
In [204]:
                                                                                            H
image, label = eval_data[0]
print('Shape:', image.shape, '\nLabel:', label)
Shape: torch.Size([1, 48, 48])
Label: 0
```

In [205]: ▶

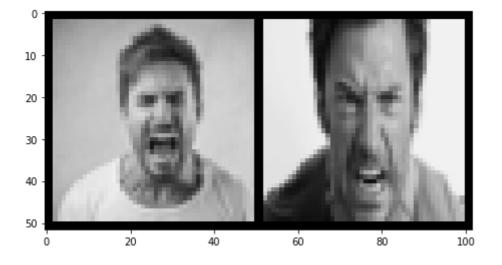
```
np.set_printoptions(formatter=dict(int=lambda x: f'{x:5}')) # to widen the printed array
from torchvision.utils import make_grid
# Grab the first 10 images from the first batch of training data
eval_load_all = DataLoader(eval_data, batch_size=2, shuffle=True)
for images,labels in eval_load_all:
    break

# Print the Labels
print('Label:', labels.numpy())
print('Class: ', *np.array([class_names[i] for i in labels]))

# Print the images
im = make_grid(images, nrow=2) # the default nrow is 8

plt.figure(figsize=(12,4))
plt.imshow(np.transpose(im.numpy(), (1, 2, 0)));
```

Label: [0 0] Class: Angry Angry



In [206]:
<pre>eval_load_all = DataLoader(eval_data, batch_size=2, shuffle=False) model.eval() with torch.no_grad(): correct = 0 for X_test, y_test in eval_load_all: y_val = model(X_test) predicted = torch.max(y_val,1)[1] correct += (predicted == y_test).sum()</pre>
<pre>print(f'Test accuracy: {correct.item()}/{len(eval_data)} = {correct.item()*100/(len(eval_data))}</pre>
Test accuracy: 2/2 = 100.000%
In []:
In []:
In []:
In []: