LAB 2

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github : https://github.com/wesalawida/Handwritten-Roman-numerals-lab-2

In [13]:
```
import tarfile
import imgaug as ia
from imgaug import augmenters as iaa
import os
from glob import glob
import shutil
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from PIL import Image, ImageOps
import random
import torchvision
from torchvision import models, transforms, datasets
import torch
```

Our first experience :

Our 'go-to' was to filter mislabled training images based by training some classifiers and use their predictions (noise elimination). In other words. Mark every instance in the training set as mislabeled (1) or not (0). Then, we tried 3 methods:

1. Filter by majority vote label (the one which most of the claafiers predicted). If this label differs from the 'real' given label we omit this sample.
2. Filter by consensus label. Instance is marked as mislabeled if all of the learnes (algorithms) tagged it as mislabeled. We tried 6 algorithms and changed them a bit during our analysis. There is an easy tutorial here: https://longjp.github.io/statcomp/projects/mislabeled.pdf Note: we didn't use the third method (where filtering is done by one algorithm) because it's doesn't seem accurate and we need some prior bound on the % of "label-errors" and more data to train and being able to generalize, let alone this noisy and complex data. This topic also delas with some formulated errors which we couldn't calculate in our case (depends on prior info on the noise or similar assumptions).

Unfotunately, all the methods failed because the predictions were bad (almost 1950 were wrong). The main reason is our shallow learning on the complicated data (with small sample comlexity) which led to underfitting. We tried to train a simple fully connected netowrk which led to overfitting as expected. Again, the given dataset is too small for this. It works amazing on MNIST when we added noise (changed random labels) and we even could calculate the errors but not here in our case. Surely because MNIST is easy and big enough. So eventually we did it by hand. It sounds bad but not at all since the dataset is small (now it's an advantage) and the images were clear (at least for us). Sometimes the simpler the better.

The script (code) doesn't seem to be relevant so there are some of it in a seperate notebook (first_attempt.ipynb), not important to go on.

preprocessing :

In [ ]:
```
my_tar = tarfile.open('lab 2\data.tar')
my_tar.extractall('./my_folder') # specify which folder to extract to
my_tar.close()
```

In [ ]:
```
RAW_DATA_FOLDER = '/lab 2/cleaned'
TRAIN_DATA = f'{RAW_DATA_FOLDER}/train'
VALID_DATA = f'{RAW_DATA_FOLDER}/val'
print(f'Validation data folder: {os.listdir(VALID_DATA)}')
```

In [ ]:
```
# Create new directory to store cleaned images (copy raw data)
CLEAN_DATA_FOLDER = 'cleaned'
TRAIN_DATA = f'{CLEAN_DATA_FOLDER}/train'
VALID_DATA = f'{CLEAN_DATA_FOLDER}/val'

try:
    shutil.copytree('data', CLEAN_DATA_FOLDER, dirs_exist_ok=False)
    print('Created new folder')
except:
    print('Folder already exists')
```

In [ ]:
```
# change the names of the images :

data_types = [TRAIN_DATA, VALID_DATA]

for data_type in data_types:
    for folder in os.listdir(data_type):
            for index, file in enumerate(os.listdir(data_type + '/' + folder)):
                data_type_name = data_type.split('/')[-1]
                os.rename(os.path.join(data_type, folder, file), os.path.join(data_
```

after changing the names, we delete the images that show just drawings that not related to the our labels

In [44]:
```
# Paths to your train and val directories
deleted_dir = os.path.join("cleaned","deleted")


images = []
for image in os.listdir(deleted_dir):
    images.append(os.path.join(deleted_dir ,image))
```

```
random_index = random.choice(range(len(images)))
random_img = images[random_index]
img_original = Image.open(random_img)
img_original = ImageOps.grayscale(img_original)
# Display images side by side
fig = plt.figure(figsize=(6, 3))

# show original image

fig.add_subplot(222)
plt.title('deleted  Image')
plt.axis('off')
plt.imshow(img_original , cmap=plt.get_cmap('gray'))

plt.show();
```

deleted Image

image augmentation:

After deleting the irrelevant pictures and arranging the rest of the pictures so that each folder now contains the correct pictures of the Roman numeral

- We will use image augmentation to increase our dataset to contain 10000 samples, 8000 in the training dataset and 2000 data validation dataset (1,000 images for each of the 10 Roman numeral labels).
- We have transferred all the data to the training folder, 1899 sapmles, the amount of pictures of the Roman numeral in each file :

In [9]:
```
train_dir = os.path.join("cleaned", "train")
val_dir = os.path.join("cleaned", "val")
```

In [10]:
```
# all the labeles
numerals =os.listdir(train_dir)
```

In [11]:
```
train_data = [os.path.join(dirpath, filename) for dirpath, _, filenames in os.walk(
len(train_data)
```

Out[11]:
```
1899
```

In [12]:
```
for i in numerals:
    print(f'The amount of data in the folder {i} : ' + str(len(os.listdir(f'{train_
```

```
The amount of data in the folder i : 243
The amount of data in the folder iii : 156
The amount of data in the folder vi : 169
The amount of data in the folder v : 177
The amount of data in the folder vii : 174
The amount of data in the folder iv : 262
The amount of data in the folder ii : 158
The amount of data in the folder viii : 172
The amount of data in the folder x : 175
The amount of data in the folder ix : 213
```

We used imgaug imgaug library, it's a library for image augmentation in machine learning experiments. It supports a wide range of augmentation techniques, allows to easily combine these and to execute them in random order or on multiple CPU cores, has a simple yet powerful stochastic interface and can not only augment images, but also keypoints/landmarks, bounding boxes, heatmaps and segmentation maps

We applied a set of generic augmentation steps for all images with the help of the imgaug library:

1. AdditiveGaussianNoise : Add noise sampled from gaussian distributions elementwise to images.
2. Resize :- Augmenter that resizes images to specified heights and widths.(The maximum horizontal and vertical length is selected between all images)
3. GaussianBlur : Augmenter to blur images using gaussian kernels.
4. AdditiveLaplaceNois : Add noise sampled from laplace distributions elementwise to images.
5. Multiply : Multiply all pixels in an image with a specific value, thereby making the image darker or brighter
6. JpegCompression : Degrade the quality of images by JPEG-compressing them.

There are certain labels where flippin makes sense, and others where flippin does not

Divide numbers into four groups and explain which groups need horizontal or vertical inversion or both or without none :

1. Groub of = iv , vi , vii , viii :

- flipping them horizontally or vertically will result in numbers that do not resemble the original digits, And so we will not flip them into any side.

2. Groub of = v :

- doing a horizontal flip will still allow us to get another variation of the same digit, And so we will flip them into random horizontal flipping .

3. Groub of = ix :

- doing a vertical flip will still allow us to get another variation of the same digit, And so we will flip them into random vertical flipping .

4. Groub of = i, ii, iii, x :

- both horizontal and vertical flipping yield new variations of the image that still resemble the original digits, And so we will flip them into both random vertical flipping and horizontal flipping.

In [6]:
```
#iv, vi, vii, viii
aug_Noflip = iaa.Sequential([
    iaa.AdditiveGaussianNoise(scale=0.1*255),
    iaa.Resize({"height": 390, "width":275}),
    iaa.Sometimes(0.5, iaa.GaussianBlur(sigma=2.0)),
    iaa.AdditiveLaplaceNoise(scale=(0, 0.2*255)),
    iaa.Multiply((0.5, 1.5)),
    iaa.JpegCompression(compression=(70, 99)),
], random_order=False)

# v
aug_Hflip = iaa.Sequential([
    iaa.Fliplr(0.5),
    iaa.AdditiveGaussianNoise(scale=0.1*255),
    iaa.Resize({"height": 390, "width":275}),
    iaa.Sometimes(0.5, iaa.GaussianBlur(sigma=2.0)),
    iaa.AdditiveLaplaceNoise(scale=(0, 0.2*255)),
    iaa.Multiply((0.5, 1.5)),
    iaa.JpegCompression(compression=(70, 99)),
], random_order=False)

#  ix
aug_Vflip = iaa.Sequential([
    iaa.Flipud(0.5),
    iaa.AdditiveGaussianNoise(scale=0.1*255),
    iaa.Resize({"height": 390, "width":275}),
    iaa.Sometimes(0.5, iaa.GaussianBlur(sigma=2.0)),
    iaa.AdditiveLaplaceNoise(scale=(0, 0.2*255)),
    iaa.Multiply((0.5, 1.5)),
    iaa.JpegCompression(compression=(70, 99)),
], random_order=False)

# i, ii, iii, x
aug_HVflip = iaa.Sequential([
    iaa.Flipud(0.5),
    iaa.Fliplr(0.5),
    iaa.AdditiveGaussianNoise(scale=0.1*255),
    iaa.Resize({"height": 390, "width":275}),
    iaa.Sometimes(0.5, iaa.GaussianBlur(sigma=2.0)),
    iaa.AdditiveLaplaceNoise(scale=(0, 0.2*255)),
    iaa.Multiply((0.5, 1.5)),
    iaa.JpegCompression(compression=(70, 99)),
], random_order=False)
```

In [7]:
```
# dictionary and function that help as wditting the right augmentation
augment_dect={
```

```
            1: aug_Noflip ,
            2 : aug_Hflip,
            3 : aug_Vflip,
            4 : aug_HVflip}

def num_aug(num):
    if num =='v' :
        return augment_dect[2]
    elif num == 'ix' :
        return augment_dect[3]
    elif num == 'i' or num == 'ii' or num== 'iii' or num ==  'x':
        return augment_dect[4]
    else : return augment_dect[1]
```

In [22]:
```
# creat a folder to copy all the data to it and work in it in this folder  :

directory = "all_data"

all_path = os.path.join(directory)

os.mkdir(all_path)
```

Visualization of Augmentation

In [75]:
```
# function that help us to visualizes the augmentation :

def show_single_transform(num):
    images, filenames = [], []
    for image in os.listdir(f'{train_dir}/{num}'):
        images.append(os.path.join(train_dir,num, image))
        filenames.append(f'{image}')

    random_index = random.choice(range(len(images)))
    random_filename = filenames[random_index]
    random_img = images[random_index]

    img_original = Image.open(random_img)
    img_original = ImageOps.grayscale(img_original)

    aug_seq = num_aug(num)

    try:
        img_transformed = aug_seq(img_original)
    except:
        img_transformed = aug_seq(images=np.asarray(img_original))
    print(f'Successful image Augmentation')

    # Display images side by side
    fig = plt.figure(figsize=(14, 8))

    # show original image
    fig.add_subplot(221)
    plt.title('Original Image')
    plt.axis('off')
    plt.imshow(img_original, cmap=plt.get_cmap('gray'))
```

```
    fig.add_subplot(222)
    plt.title('Transformed Image')
    plt.axis('off')
    plt.imshow(img_transformed, cmap=plt.get_cmap('gray'))

    plt.show();
```

In [62]:
```
# Augmentation of the Groub of = v :

show_single_transform('v')
```

```
Successful image Augmentation
```

In [70]:
```
# Augmentation of the Groub of = i :

show_single_transform('i')
```

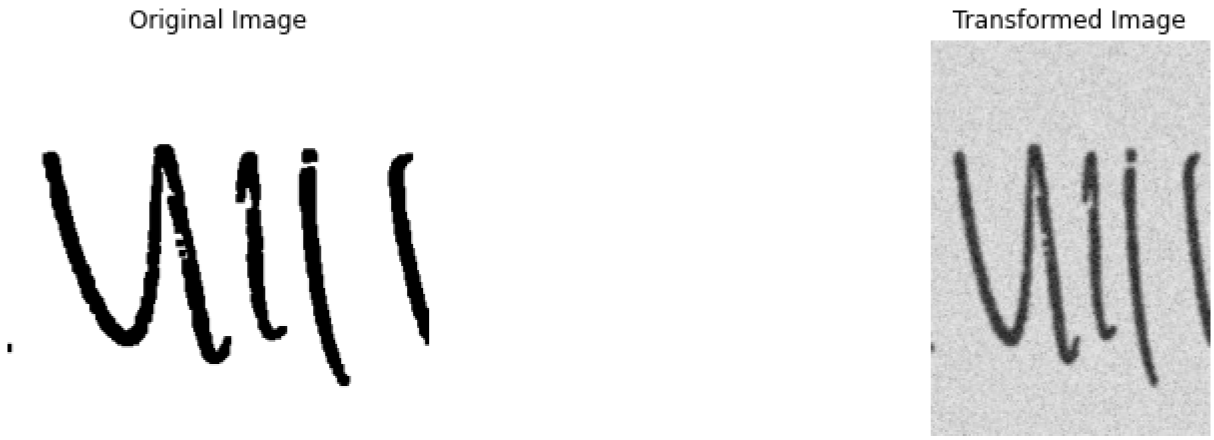
```
Successful image Augmentation
```

In [71]:
```
# Augmentation of the Groub of = ix :

show_single_transform('ix')
```

```
Successful image Augmentation
```


```
In [73]: # Augmentation of the Groub of = viii :

         show_single_transform('viii')
```

```
Successful image Augmentation
```



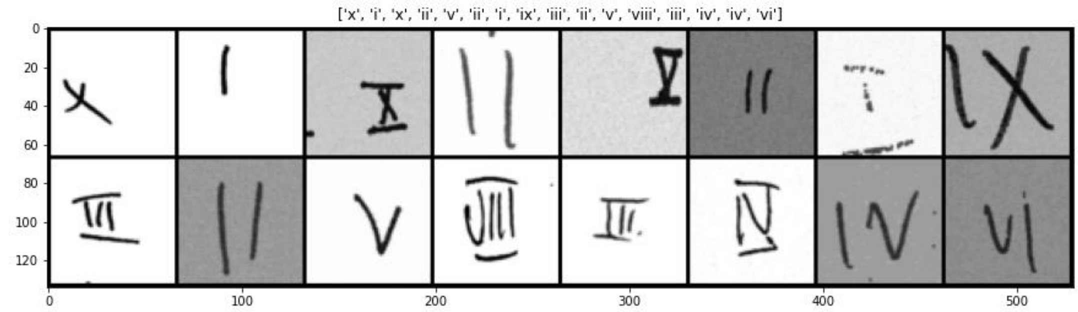
The augmentation over all the data :

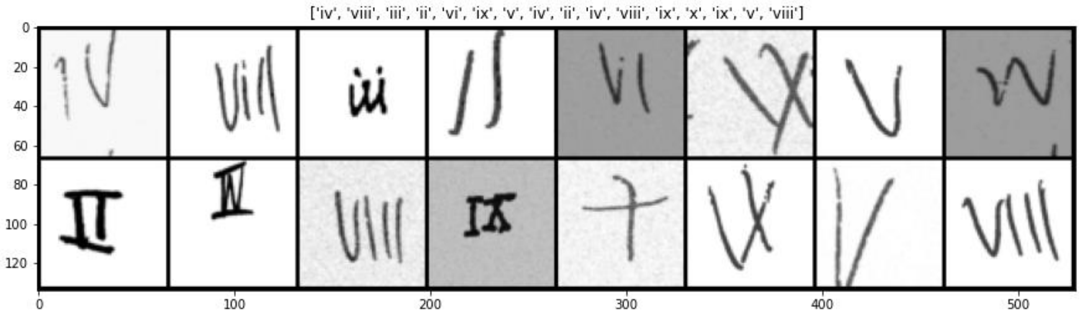
```
In [ ]: # Go through all the numerals and do the augmentation :

        for num in numerals:
            # creat folder to save the org imgs:
            all_data_num =  f'{all_path}/{num}'

            # final path of the num data:
            org_path =  f'{train_dir}/{num}'
            print(all_data_num)

            # copy all the data to new folder :
            shutil.copytree(org_path, all_data_num)

            # ceate new folders for the num to but the The final result of the 1000 images
            data_train = f'{all_path}/train/{num}'
            data_val = f'{all_path}/val/{num}'
            Path(data_train).mkdir(parents=True, exist_ok=True)
            Path(data_val).mkdir(parents=True, exist_ok=True)

            img_files = glob(os.path.join(all_data_num, "*.png"))
```

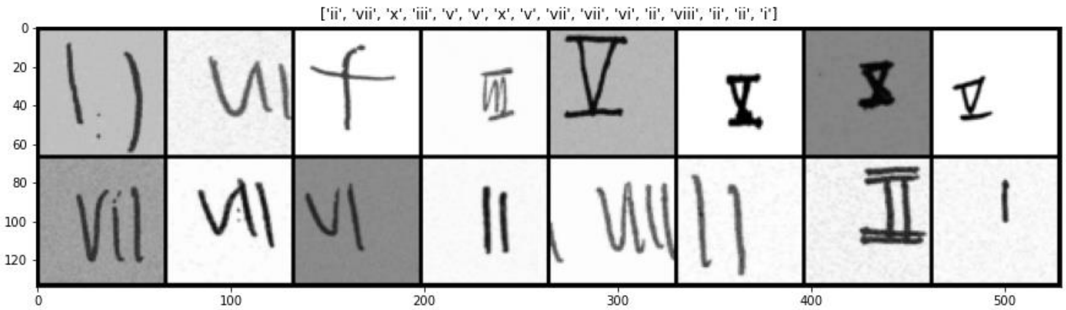
```python
    g = len(img_files)

    # Find the complementary number to 1000 :
    count = 1000 - g
    print(len(img_files))

    aug_seq = num_aug(num)
    n = 0
    # Go through (the complementary number to 1000) times and create new images
    # according to the corresponding augmentation for the num :
    for i in range(count):
        n += 1

        random_index = random.choice(range(len(img_files)-1))
        random_file = img_files[random_index]
        img_random = Image.open(random_file)
        img_random = ImageOps.grayscale(img_random)

        # This is where the augmentation is done :
        try:
            transformed_img_random = aug_seq(img_random)
        except:
            transformed_img_random = aug_seq(images=np.asarray(img_random))



        # Convert back to PIL to save
        transformed_img_random = Image.fromarray(transformed_img_random)
        transformed_img_random.save(f'{all_data_num}/{num}_random_{i}.png', 'PNG')

    # Distribute the 1000 samples for training and validation datasets :

    imgs = glob(os.path.join(all_data_num, "*.png"))
    train_imgs = random.sample(imgs,800)
    val_imgs = [x for x in imgs if x not in train_imgs]
    for file in train_imgs:
        shutil.copy(file, data_train)
    for file in val_imgs:
        shutil.copy(file, data_val)
    #
    shutil.rmtree(all_data_num, ignore_errors=True)
```

Visualization for part of the new dataset (10000 samples) from the run_train_eval.py :

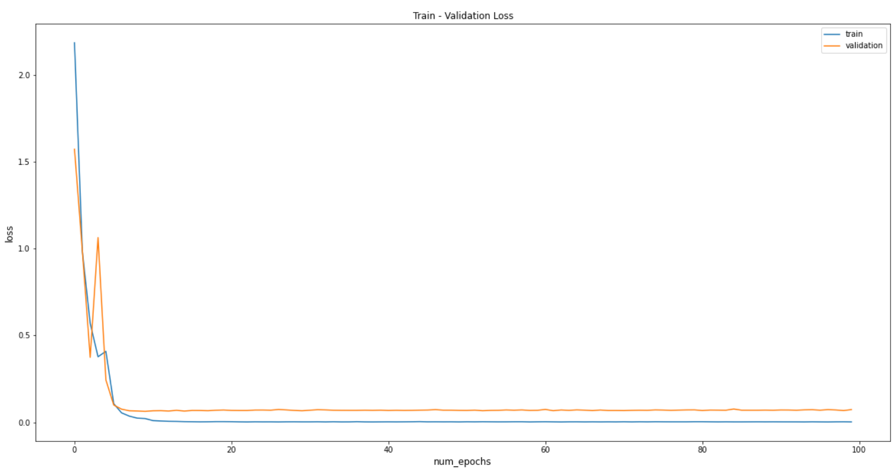
```
The classes are:  ['i', 'ii', 'iii', 'iv', 'ix', 'v', 'vi', 'vii', 'viii', 'x']
```

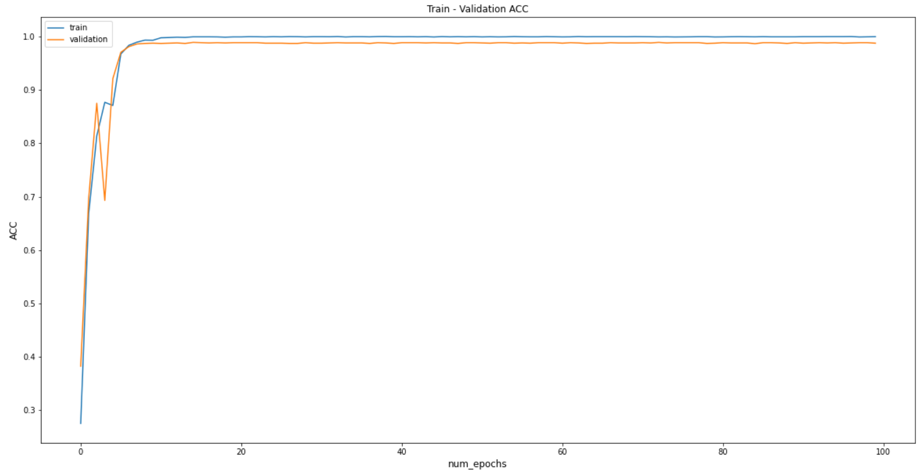






The Rustles:





1- The training loss and the validation loss seem to reduce and stay at a constant value. This means that the model is well trained and is equally good on the training data as well as the hidden data.

2- From the plot of accuracy we can see that the model be trained good as the trend for accuracy on both datasets is rising and stable with the epochs increasing.