```python
import os
import glob
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import re
from PIL import Image
from tqdm.notebook import tqdm

import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms
from torchvision.models import resnet18

torch.random.manual_seed(42)
np.random.seed(42)

#Dataset Preparation

class EuropenaDataset(Dataset):
    def __init__(self, image_path, file_path, file_list):
        self.image_path= image_path
        self.file_path= file_path
        self.images_dict= self.image_process()
        self.labels_dict= self.text_process()
        self.file_list= file_list

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

    def __getitem__(self, index):
        filename= self.file_list[index]
        return self.images_dict[filename], self.labels_dict[filename]

    def image_process(self):
        transform= transforms.Compose(
            [
                transforms.Resize((50, 200)),
                transforms.ToTensor(),
                transforms.Normalize(mean=(0.485, 0.456, 0.406),
std=(0.229, 0.224, 0.225))
            ]
        )
        images=
{val:transform(Image.open(os.path.join(self.image_path,
val)).convert("RGB"))
                 for val in os.listdir(self.image_path)}
```

```
        return images

    def text_process(self):
        with open(self.file_path) as f:
            text= f.read().split("\n")

        labels_dict={}
        for i in range(len(text)):
            ind= text[i].find("=")
            filename= text[i][:ind].strip()
            cont= text[i][ind+1:].strip()

            cont_cleaned = re.sub(r'[^a-zA-Z0-9 ]+', '', cont)
            labels_dict[filename]= cont_cleaned
        return labels_dict

with open("./data_words.txt") as f:
    text= f.read().split("\n")

file_list=[]
for i in range(len(text)):
    try:
        ind= text[i].index("=")
        filename= text[i][:ind].strip()
        file_list.append(filename)
    except:
        continue
train_size= int(len(file_list)*0.8)
train_file_inds= np.random.choice(len(file_list), size=(train_size, ),
replace=False)
train_file_names= [file_list[i] for i in train_file_inds]
test_file_names= [val for val in file_list if val not in
train_file_names]

train_set= EuropenaDataset("./cropped_words", "./data_words.txt",
train_file_names)
test_set= EuropenaDataset("./cropped_words", "./data_words.txt",
test_file_names)
train_loader= DataLoader(train_set, 16)
test_loader= DataLoader(test_set, 16)

#Utility Functions
criterion = nn.CTCLoss(blank=0)
alphabet= [val for val in "-
0123456789ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz"]
encoder_map= {ind:val for val, ind in enumerate(alphabet)}
decoder_map= {val:ind for val, ind in enumerate(alphabet)}

def encode_text(text_batch):
    text_lengths=[]
```

```python
    for text in text_batch:
        text_lengths.append(len(text))
    strv= "".join(text_batch)
    encoding=[encoder_map[char] for char in strv]
    text_lengths= torch.IntTensor(text_lengths)
    encoding= torch.IntTensor(encoding)
    return encoding, text_lengths

def calculate_CTCLoss(output_logits, text_labels, device):
    log_probs= nn.functional.log_softmax(output_logits, 2)
    input_lengths= torch.full(size=(log_probs.size(1),),
fill_value=log_probs.size(0), dtype=torch.int32).to(device)
    targets, target_lengths= encode_text(text_labels)
    return criterion(log_probs, targets, input_lengths,
target_lengths)

def decode_predictions(text_batch_logits):
    text_batch_tokens = F.softmax(text_batch_logits, 2).argmax(2) #
[T, batch_size]
    text_batch_tokens = text_batch_tokens.numpy().T # [batch_size, T]

    text_batch_tokens_new = []
    for text_tokens in text_batch_tokens:
        text = [decoder_map[idx] for idx in text_tokens]
        text = "".join(text)
        text_batch_tokens_new.append(text)

    return text_batch_tokens_new

def remove_duplicates(text):
    if len(text) > 1:
        letters = [text[0]] + [letter for idx, letter in
enumerate(text[1:], start=1) if text[idx] != text[idx-1]]
    elif len(text) == 1:
        letters = [text[0]]
    else:
        return ""
    return "".join(letters)

def correct_prediction(word):
    parts = word.split("-")
    parts = [remove_duplicates(part) for part in parts]
    corrected_word = "".join(parts)
    return corrected_word

batch_size = 16
num_chars = len(encoder_map)
rnn_hidden_size = 256
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(device)
```

```
cuda
```

```
resnet = resnet18(pretrained=True)
```

```
c:\Users\deban\AppData\Local\Programs\Python\Python312\Lib\site-
packages\torchvision\models\_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the
future, please use 'weights' instead.
  warnings.warn(
c:\Users\deban\AppData\Local\Programs\Python\Python312\Lib\site-
packages\torchvision\models\_utils.py:223: UserWarning: Arguments
other than a weight enum or `None` for 'weights' are deprecated since
0.13 and may be removed in the future. The current behavior is
equivalent to passing `weights=ResNet18_Weights.IMAGENET1K_V1`. You
can also use `weights=ResNet18_Weights.DEFAULT` to get the most up-to-
date weights.
  warnings.warn(msg)
```

```
class CRNN(nn.Module):

    def __init__(self, num_chars, rnn_hidden_size=256):

        super(CRNN, self).__init__()
        self.num_chars = num_chars
        self.rnn_hidden_size = rnn_hidden_size

        self.seq = nn.Sequential(*list(resnet.children())
[:7]).to("cpu")

        self.linear1 = nn.Sequential(nn.Linear(1024, 512),
                                     nn.Dropout(0.2),
                                     nn.ReLU(),
                                     nn.Linear(512, 256))

        self.rnn1 = nn.LSTM(input_size=rnn_hidden_size,
                            hidden_size=rnn_hidden_size,
                            bidirectional=True,
                            batch_first=True,
                            num_layers=2,
                            dropout=0.2)

        self.linear2 = nn.Linear(self.rnn_hidden_size*2, num_chars)


    def forward(self, X):
        X= self.seq(X)
        X= X.permute(0,3,1,2)
        b, t, _, _ = X.shape
        X= X.view(b, t, -1)
        X= self.linear1(X)
        X, _ = self.rnn1(X)
```

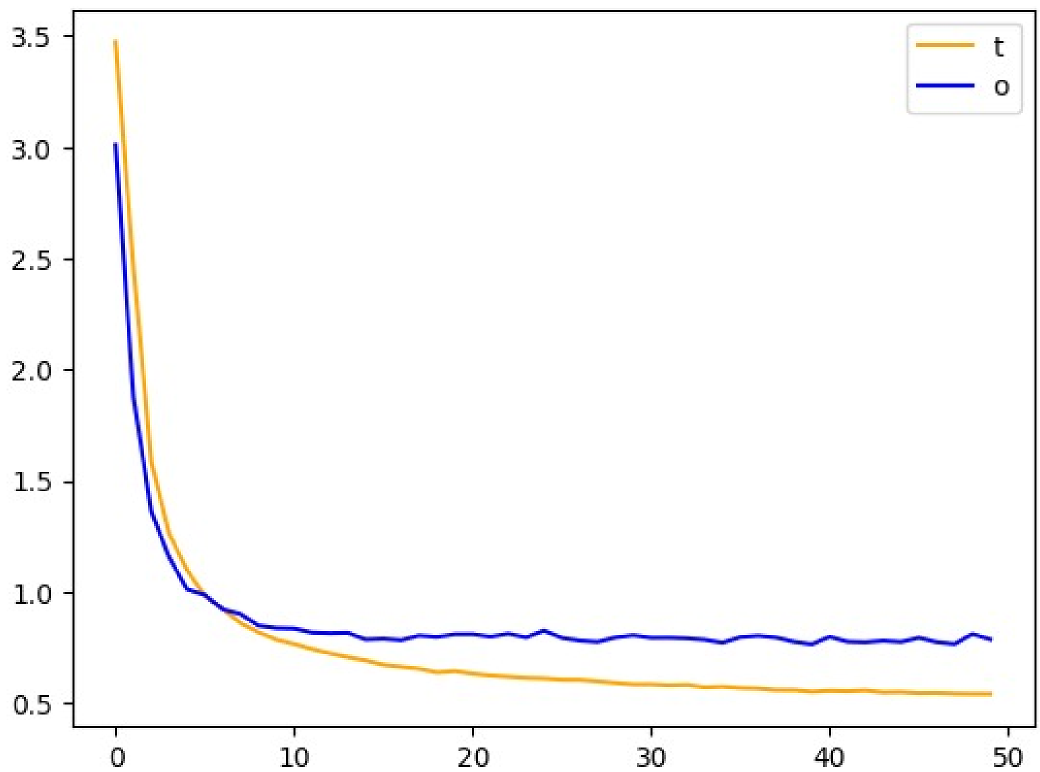
```
        X = self.linear2(X)
        X = X.permute(1, 0, 2)
        return X

def weights_init(m):
    classname = m.__class__.__name__
    if type(m) in [nn.Linear, nn.Conv2d, nn.Conv1d]:
        torch.nn.init.xavier_uniform_(m.weight)
        if m.bias is not None:
            m.bias.data.fill_(0.01)
    elif classname.find('BatchNorm') != -1:
        m.weight.data.normal_(1.0, 0.02)
        m.bias.data.fill_(0)

num_epochs = 50
lr = 0.001
weight_decay = 1e-3
clip_norm = 5

crnn = CRNN(num_chars, rnn_hidden_size=rnn_hidden_size)
crnn.apply(weights_init)
crnn = crnn.to(device)

optimizer = optim.Adam(crnn.parameters(), lr=lr,
weight_decay=weight_decay)
lr_scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer,
patience=5)

epoch_losses = []
test_epoch_losses = []

for epoch in range(1, num_epochs+1):
    crnn.train()
    epoch_loss_list = []
    for image_batch, text_batch in train_loader:
        optimizer.zero_grad()
        text_batch_logits = crnn(image_batch.to(device))
        loss = calculate_CTCLoss(text_batch_logits, text_batch,
device)
        iteration_loss = loss.item()

        if np.isnan(iteration_loss) or np.isinf(iteration_loss):
            continue

        epoch_loss_list.append(iteration_loss)
        loss.backward()
        nn.utils.clip_grad_norm_(crnn.parameters(), clip_norm)
        optimizer.step()
    epoch_loss = np.mean(epoch_loss_list)
    epoch_losses.append(epoch_loss)
```

```
    lr_scheduler.step(epoch_loss)

    crnn.eval()
    test_epoch_loss_list = []
    with torch.inference_mode():
        for image_batch, text_batch in test_loader:
            text_batch_logits = crnn(image_batch.to(device))
            loss = calculate_CTCLoss(text_batch_logits, text_batch,
device)
            iteration_loss = loss.item()
            if np.isnan(iteration_loss) or np.isinf(iteration_loss):
                continue
            test_epoch_loss_list.append(iteration_loss)
    test_epoch_loss = np.mean(test_epoch_loss_list)
    test_epoch_losses.append(test_epoch_loss)

    print("Epoch:{}  Train Loss:{}  Test Loss: {}".format(epoch,
epoch_loss, test_epoch_loss))
```

```
Epoch:1  Train Loss:3.4731808347565134  Test Loss: 3.0107797839926937
Epoch:2  Train Loss:2.458435390098243  Test Loss: 1.8751136368305987
Epoch:3  Train Loss:1.5842683704846214  Test Loss: 1.3607881101402077
Epoch:4  Train Loss:1.2606917689861863  Test Loss: 1.1550536779363183
Epoch:5  Train Loss:1.0982734324259051  Test Loss: 1.0114679811774074
Epoch:6  Train Loss:0.9824755316430872  Test Loss: 0.9863931872957462
Epoch:7  Train Loss:0.9242007535111391  Test Loss: 0.9218032123614462
Epoch:8  Train Loss:0.859545601719019  Test Loss: 0.900417598863366
Epoch:9  Train Loss:0.8191549528158453  Test Loss: 0.8487451852058352
Epoch:10  Train Loss:0.7852462433456804  Test Loss: 0.8374804900419758
Epoch:11  Train Loss:0.7655119483835959  Test Loss: 0.8355328032034934
Epoch:12  Train Loss:0.7431564062334705  Test Loss: 0.8175519360481082
Epoch:13  Train Loss:0.7242213743297677  Test Loss: 0.814755421721567
Epoch:14  Train Loss:0.7066529675819087  Test Loss: 0.816472921218421
Epoch:15  Train Loss:0.6918471796375713  Test Loss: 0.7859431503764911
Epoch:16  Train Loss:0.6724498062612908  Test Loss: 0.789270181208849
Epoch:17  Train Loss:0.6634302640217914  Test Loss: 0.7826848493522198
Epoch:18  Train Loss:0.6546809032202908  Test Loss: 0.8038327762332087
Epoch:19  Train Loss:0.6378656679292044  Test Loss: 0.7971760447219762
Epoch:20  Train Loss:0.6437949247266117  Test Loss: 0.8094912817176705
Epoch:21  Train Loss:0.6322848795561129  Test Loss: 0.8097754651716547
Epoch:22  Train Loss:0.6239831251818597  Test Loss: 0.7985463232578688
Epoch:23  Train Loss:0.6188764363883785  Test Loss: 0.8120800104409341
Epoch:24  Train Loss:0.6134428479526032  Test Loss: 0.7951186394757631
Epoch:25  Train Loss:0.6111450459683341  Test Loss: 0.8266358675298543
Epoch:26  Train Loss:0.605249994850615  Test Loss: 0.792989252394058
Epoch:27  Train Loss:0.6049732050328164  Test Loss: 0.7809182388355603
Epoch:28  Train Loss:0.5983000218511768  Test Loss: 0.7750753135956162
Epoch:29  Train Loss:0.5909290796903331  Test Loss: 0.7950089076195904
Epoch:30  Train Loss:0.5846650014867623  Test Loss: 0.8050797673150839
Epoch:31  Train Loss:0.5842842684051637  Test Loss: 0.7936258008523798
```

```
Epoch:32  Train Loss:0.5800906461641264  Test Loss: 0.7940571243410866
Epoch:33  Train Loss:0.5823490197364793  Test Loss: 0.7913100133761476
Epoch:34  Train Loss:0.5711916005176505  Test Loss: 0.7848888492089441
Epoch:35  Train Loss:0.5742328241538773  Test Loss: 0.7712164230529636
Epoch:36  Train Loss:0.5682428265088483  Test Loss: 0.7966168045163384
Epoch:37  Train Loss:0.5661663965103729  Test Loss: 0.802892906504996
Epoch:38  Train Loss:0.5584302660701663  Test Loss: 0.7946912133670682
Epoch:39  Train Loss:0.5587257727980613  Test Loss: 0.7757290671201976
Epoch:40  Train Loss:0.551216513617187  Test Loss: 0.7642784455942141
Epoch:41  Train Loss:0.555831287516076  Test Loss: 0.7980399131343402
Epoch:42  Train Loss:0.5535261519360201  Test Loss: 0.7760960974201963
Epoch:43  Train Loss:0.5572962617831367  Test Loss: 0.7732255493999103
Epoch:44  Train Loss:0.5482994141725547  Test Loss: 0.7805390681452963
Epoch:45  Train Loss:0.5496758268245955  Test Loss: 0.7748767138246634
Epoch:46  Train Loss:0.5449914050444461  Test Loss: 0.7937413368906293
Epoch:47  Train Loss:0.5455981116082395  Test Loss: 0.7741713747094496
Epoch:48  Train Loss:0.5426202269618591  Test Loss: 0.7653982825577259
Epoch:49  Train Loss:0.5415597493033946  Test Loss: 0.810625221939851
Epoch:50  Train Loss:0.5413240872822594  Test Loss: 0.7864760395973691
```

```
plt.plot(range(len(epoch_losses)), epoch_losses, c="orange",
label="train loss")
plt.plot(range(len(test_epoch_losses)), test_epoch_losses, c="blue",
label="test loss")
plt.legend("top right")
plt.show()
```




```
results_final = pd.DataFrame(columns=['actual', 'prediction', 'dset'])

with torch.no_grad():
    for image_batch, text_batch in tqdm(train_loader, leave=True):
        text_batch_logits = crnn(image_batch.to(device)) # [T,
batch_size, num_classes==num_features]
        text_batch_pred = decode_predictions(text_batch_logits.cpu())
        #print(text_batch, text_batch_pred)
        df = pd.DataFrame(columns=['actual', 'prediction'])
        df['actual'] = text_batch
        df['prediction'] = text_batch_pred
        df['dset'] = "train"
        results_final = pd.concat([results_final, df])
results_final = results_final.reset_index(drop=True)
```


{"model_id":"8849fefe095d404b88ae84db56cdc0f4","version_major":2,"vers
ion_minor":0}


```
with torch.no_grad():
    for image_batch, text_batch in tqdm(test_loader, leave=True):
        text_batch_logits = crnn(image_batch.to(device)) # [T,
batch_size, num_classes==num_features]
        text_batch_pred = decode_predictions(text_batch_logits.cpu())
        #print(text_batch, text_batch_pred)
        df = pd.DataFrame(columns=['actual', 'prediction'])
        df['actual'] = text_batch
```

```
        df['prediction'] = text_batch_pred
        df['dset'] = "test"
        results_final = pd.concat([results_final, df])
results_final = results_final.reset_index(drop=True)
```


```
{"model_id":"27b290896ef048b3bd00fe009c570117","version_major":2,"version_minor":0}
```


```
results_final['prediction_corrected'] =
results_final['prediction'].apply(correct_prediction)
results_final
```

```
       actual      prediction   dset prediction_corrected
0      forced  foo-r-c-e-d--  train               forced
1         the  t---h----e---  train                  the
2         den  d----e--n----  train                  den
3         the  t---h----e---  train                  the
4         uit  u------i--t--  train                  uit
...       ...            ...    ...                  ...
23482      de  d------e-----   test                   de
23483   heeft  h---e-e--f-t-   test                heeft
23484      in  i----n-------   test                   in
23485     dat  d----a----t--   test                  dat
23486  ookats  o-o-k--a--l--   test                ookal

[23487 rows x 4 columns]
```

```
import json
from weighted_levenshtein import lev
import numpy as np

with open("./params_weighted_leven.json", "r") as f:
    leven_params = json.load(f)
    for k in leven_params.keys():
        leven_params[k] = np.array(leven_params[k])

results_final["val"] =results_final.apply(lambda row:
lev(row["actual"], row["prediction_corrected"], **leven_params),
axis=1)

results_final
```

```
       actual      prediction   dset prediction_corrected     val
0      forced  foo-r-c-e-d--  train               forced  0.0000
1         the  t---h----e---  train                  the  0.0000
2         den  d----e--n----  train                  den  0.0000
3         the  t---h----e---  train                  the  0.0000
4         uit  u------i--t--  train                  uit  0.0000
...       ...            ...    ...                  ...     ...
23482      de  d------e-----   test                   de  0.0000
23483   heeft  h---e-e--f-t-   test                heeft  0.0000
```

```
23484       in  i----n-------   test                    in  0.0000
23485      dat  d----a----t--   test                   dat  0.0000
23486   ookats  o-o-k--a--l--   test                 ookal  1.7252

[23487 rows x 5 columns]
```