In [ ]:
```
#import the library
```

In [1]:
```
import torch
import torchvision
import torch.nn as nn
import numpy as np
import torch.nn.functional as F
from torchvision.datasets import EMNIST
from torch.utils.data import DataLoader
import torchvision.transforms as tt
from torch.utils.data import random_split
from torchvision.utils import make_grid
import matplotlib
import matplotlib.pyplot as plt
import pickle
import requests
import zipfile
import os, shutil
from PIL import Image
%matplotlib inline

matplotlib.rcParams['figure.facecolor'] = '#ffffff'
```

In [2]:
```
#load the data from website of matlab format
project_name='emnist-project'
```

In [3]:
```
#load the data. Rotate the image by -90 degree and then flip horizontally
def train_transform(data):
    transform = tt.Compose([lambda img: tt.functional.rotate(img, -90),
                    lambda img: tt.functional.hflip(img),
                    tt.ToTensor()])
    return transform(data)

#seperate the data to train set and data set
dataset = EMNIST(root="data/", split="byclass", train=True, transform=train_t
test_dataset = EMNIST(root="data/", split="byclass", train=False, transform=t

#show the datatype of dataset
print(type(dataset))
```

```
<class 'torchvision.datasets.mnist.EMNIST'>
```

In [4]:
```
#show the number of data in train set and test set
print("Total No of EMNIST dataset:", len(dataset) + len(test_dataset))
print("Training dataset:",len(dataset))
print("Testing dataset:",len(test_dataset))
```

```
Total No of EMNIST dataset: 814255
Training dataset: 697932
Testing dataset: 116323
```

In [5]:
```
#show all classes in EMNIST-ByClass
l = dataset.classes
l.sort()
print("No of classes: ",len(l))
print("List of all classes")
print(l)
```

```
No of classes:  62
List of all classes
['0', '1', '2', '3', '4', '5', '6', '7', '8', '9', 'A', 'B', 'C', 'D', 'E',
'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N', 'O', 'P', 'Q', 'R', 'S', 'T',
'U', 'V', 'W', 'X', 'Y', 'Z', 'a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i',
'j', 'k', 'l', 'm', 'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x',
'y', 'z']
```

In [6]:

```
# Convert the output index [0-61] into the character [0-9],[A-Z],[a-z]
def to_char(num):
    if num<10:
        return str(num)
    elif num < 36:
        return chr(num+55)
    else:
        return chr(num+61)

# Reverse of above function.
# Convert the character [0-9],[A-Z],[a-z] into index [0-61]
def to_index(char):
    if ord(char)<59:
        return ord(char)-48
    elif ord(char)<95:
        return ord(char)-55
    else:
        return ord(char)-61
```

In [ ]:

```
#show the original image in dataset
```

In [7]:

```
def show_example(data):
    img, label = data
    print("Label: ("+to_char(label)+")")
    plt.imshow(img[0], cmap="gray")
```

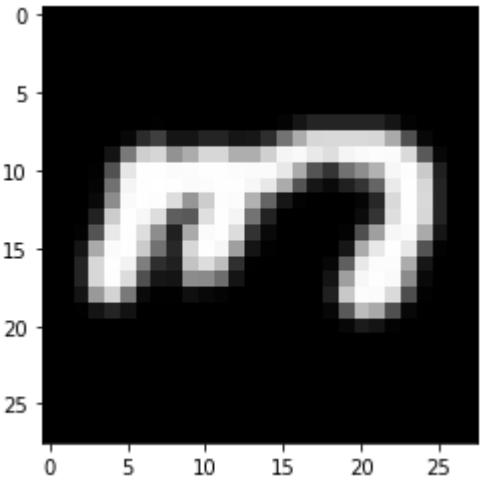
In [ ]:

```
#Uppercase 'm' original image in dataset
```

In [8]:

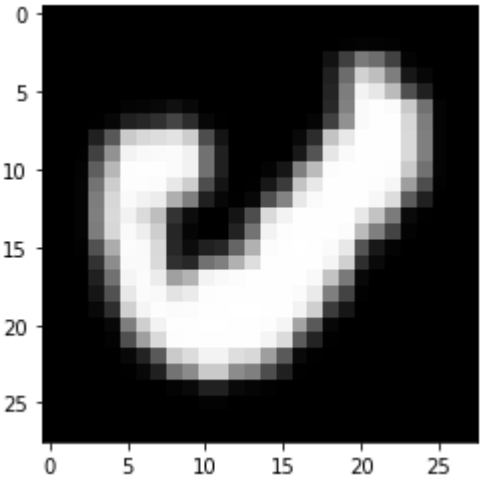
```
count = 0
for (img, label) in test_dataset:
    if label == 22:
        if count == 0:
            show_example((img,label))
            break
        count += 1
```

```
Label: (M)
```



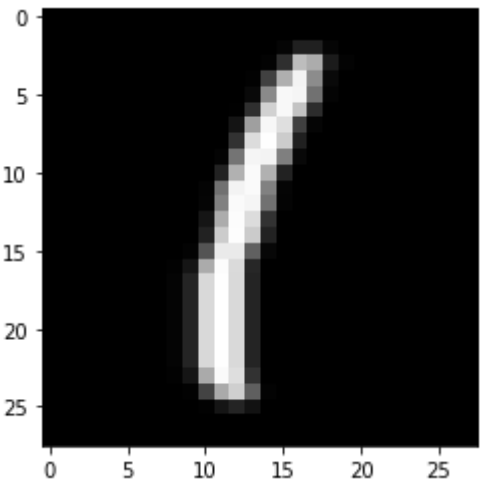
In [9]:
```
#lowercase 'u' original image in dataset
show_example(dataset[2200])
```

```
Label: (u)
```



In [10]:
```
#Arabic numeral 1 original image in dataset
show_example(dataset[30000])
```

```
Label: (1)
```



In [11]:
```
#DataLoader preparation
#Create Training DataLoader for training the model and Validation DataLoader
```

In [12]:
```
random_seed = 50
```

```
torch.manual_seed(random_seed);

val_size = 50000
train_size = len(dataset) - val_size

# Divide the dataset into training dataset and validation dataset
train_ds, val_ds = random_split(dataset, [train_size, val_size])
len(train_ds), len(val_ds)
```

Out[12]: (647932, 50000)

In [13]:
```
#set batch_size to 200
batch_size = 200

train_dl = DataLoader(train_ds, batch_size, shuffle=True, num_workers=0)
val_dl = DataLoader(val_ds, batch_size*2, num_workers=0)
```

In [14]:
```
#show a batch of images in dataset
def show_batch(dl):
    for images, labels in dl:
        fig, ax = plt.subplots(figsize=(12, 12))
        ax.set_xticks([]); ax.set_yticks([])
        ax.imshow(make_grid(images, nrow=20).permute(1, 2, 0))
        break

#show a batch of images in training dataset
for images, labels in train_dl:
    fig, ax = plt.subplots(figsize=(12, 12))
    ax.set_xticks([]); ax.set_yticks([])
    ax.imshow(make_grid(images, nrow=20).permute(1, 2, 0))
    break
show_batch(train_dl)
```

In [15]:
```
#LoadData into prefered Runtime Type
```

In [16]:
```
#GPU if available then pick GPU, else picking CPU
def get_default_device():
    if torch.cuda.is_available():
        return torch.device('cuda')
    else:
        return torch.device('cpu')

#Move tensor(s) to GPU/CPU in this devices
def to_device(data, device):
    if isinstance(data, (list,tuple)):
        return [to_device(x, device) for x in data]
    return data.to(device, non_blocking=True)

#move data to the device
class DeviceDataLoader():
    def __init__(self, dl, device):
        self.dl = dl
        self.device = device

    def __iter__(self):
        for b in self.dl:
            yield to_device(b, self.device)

    def __len__(self):
        return len(self.dl)
```

In [17]:
```
# transfer the training and validation dataloader to CUDA if available
device = get_default_device()
train_dl = DeviceDataLoader(train_dl, device)
val_dl = DeviceDataLoader(val_dl, device)
```

In [ ]:
```
```

In [18]:
```
#Defined the function and training step
```

In [19]:
```
#The accuray function returns the accuracy for a batch
def accuracy(outputs, labels):
    _, preds = torch.max(outputs, dim=1)
    return torch.tensor(torch.sum(preds == labels).item() / len(preds))

#The evaluate function returns the loss and accuracy over the validation or t
@torch.no_grad()
def evaluate(model, val_loader):
    model.eval()
    outputs = [model.validation_step(batch) for batch in val_loader]
    return model.validation_epoch_end(outputs)
```

In [20]:
```
#The training_step function returns the loss of a batch
class CharacterClassificationBase(nn.Module):
    def training_step(self, batch):
        images, labels = batch
        out = self(images)
        loss = F.cross_entropy(out, labels)
        return loss

#The validation_step function returns the loss and accuracy of a batch of val
    def validation_step(self, batch):
        images, labels = batch
        out = self(images)
        loss = F.cross_entropy(out, labels)
        acc = accuracy(out, labels)
        _, preds = torch.max(out, dim=1)
        return {'labels': labels, 'val_pred': preds, 'val_loss': loss.detach(

#The validation_epoch_end function returns combined loss and accuracy of vali
    def validation_epoch_end(self, outputs):
        batch_losses = [x['val_loss'] for x in outputs]
        epoch_loss = torch.stack(batch_losses).mean()
        batch_accs = [x['val_acc'] for x in outputs]
        epoch_acc = torch.stack(batch_accs,).mean()
        batch_preds = [x['val_pred'] for x in outputs]
        epoch_preds = torch.concat(batch_preds,dim=0)
        batch_labels = [x['labels'] for x in outputs]
        epoch_labels = torch.concat(batch_labels,dim=0)
        return {'labels':epoch_labels, 'val_preds':epoch_preds, 'val_loss': e

#The epoch_end function prints the final loss and accuray after an epoch.
    def epoch_end(self, epoch, result):
        print("Epoch [{}], last_lr: {:.5f}, train_loss: {:.4f}, val_loss: {:.
            epoch, result['lrs'][-1], result['train_loss'], result['val_loss'
```

In [ ]:
```
#Perform list of Convolutional Neural Networks ReLUs, MaxPools and Residual b
```

In [21]:
```
def conv_block(in_channels, out_channels, pool=False):
    layers = [nn.Conv2d(in_channels, out_channels, kernel_size=3, padding=1),
              nn.BatchNorm2d(out_channels),
              nn.ReLU(inplace=True)]
    if pool: layers.append(nn.MaxPool2d(2))
    return nn.Sequential(*layers)

#ResNet9 model, inhering the CharacterClassificationBase class
class ResNet9(CharacterClassificationBase):
    def __init__(self, in_channels, num_classes):
        super().__init__()
```

```
        self.conv1 = conv_block(in_channels, 64)
        self.conv2 = conv_block(64, 128, pool=True)
        self.res1 = nn.Sequential(conv_block(128, 128), conv_block(128, 128))

        self.conv3 = conv_block(128, 256)
        self.conv4 = conv_block(256, 512, pool=True)
        self.res2 = nn.Sequential(conv_block(512, 512), conv_block(512, 512))

        self.classifier = nn.Sequential(nn.MaxPool2d(7),
                                        nn.Flatten(),
                                        nn.Dropout(0.2),
                                        nn.Linear(512, num_classes))

    def forward(self, xb):
        out = self.conv1(xb)
        out = self.conv2(out)
        out = self.res1(out) + out
        out = self.conv3(out)
        out = self.conv4(out)
        out = self.res2(out) + out
        out = self.classifier(out)
        return out
```

In [22]:

```
# Creating the model
# Take 1 channel input and return 62 channel output

model = to_device(ResNet9(1, 62), device)
model
```

Out[22]:

```
ResNet9(
  (conv1): Sequential(
    (0): Conv2d(1, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
    (2): ReLU(inplace=True)
  )
  (conv2): Sequential(
    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=F
alse)
  )
  (res1): Sequential(
    (0): Sequential(
      (0): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runnin
g_stats=True)
      (2): ReLU(inplace=True)
    )
    (1): Sequential(
      (0): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runnin
g_stats=True)
      (2): ReLU(inplace=True)
    )
  )
  (conv3): Sequential(
    (0): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
    (2): ReLU(inplace=True)
  )
  (conv4): Sequential(
```

```
    (0): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=F
alse)
  )
  (res2): Sequential(
    (0): Sequential(
      (0): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runnin
g_stats=True)
      (2): ReLU(inplace=True)
    )
    (1): Sequential(
      (0): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runnin
g_stats=True)
      (2): ReLU(inplace=True)
    )
  )
  (classifier): Sequential(
    (0): MaxPool2d(kernel_size=7, stride=7, padding=0, dilation=1, ceil_mode=F
alse)
    (1): Flatten(start_dim=1, end_dim=-1)
    (2): Dropout(p=0.2, inplace=False)
    (3): Linear(in_features=512, out_features=62, bias=True)
  )
)
```

In [69]:

```
def get_lr(optimizer):
    for param_group in optimizer.param_groups:
        return param_group['lr']

#The fit_one_cycle function returns the new features including Learning rate
def fit_one_cycle(epochs, max_lr, model, train_loader, val_loader,
                  weight_decay=0, grad_clip=None, opt_func=torch.optim.SGD):
    torch.cuda.empty_cache()
    history = []
    optimizer = opt_func(model.parameters(), max_lr, weight_decay=weight_deca
    sched = torch.optim.lr_scheduler.StepLR(optimizer, step_size=len(train_lo

    for epoch in range(epochs):
        model.train()
        train_losses = []
        lrs = []
        for batch in train_loader:
            loss = model.training_step(batch)
            train_losses.append(loss)
            loss.backward()

            if grad_clip:
                nn.utils.clip_grad_value_(model.parameters(), grad_clip)

            optimizer.step()
            optimizer.zero_grad()

            lrs.append(get_lr(optimizer))
            sched.step()

        result = evaluate(model, val_loader)
        result['train_loss'] = torch.stack(train_losses).mean().item()
        result['lrs'] = lrs
        model.epoch_end(epoch, result)
        history.append(result)
    return history
```

In [ ]:
```
#Set the training model to true, the model will train from the beginning
```

In [71]:
```
train_model = True
```

In [72]:
```
#Set the parameters. The number of epochs are set to 16
epochs = 16
max_lr = 0.01
grad_clip = 0.1
weight_decay = 1e-4
opt_func = torch.optim.Adam
```

In [73]:
```
import io
class CPU_Unpickler(pickle.Unpickler):
    def find_class(self, module, name):
        if module == 'torch.storage' and name == '_load_from_bytes':
            return lambda b: torch.load(io.BytesIO(b), map_location='cpu')
        else: return super().find_class(module, name)


history = []
if train_model:
    print("Training the model from the begning. Expected time for completion
    history += fit_one_cycle(epochs, max_lr, model, train_dl, val_dl,
                             grad_clip=grad_clip,
                             weight_decay=weight_decay,
                             opt_func=opt_func)
    history_file = open('history_file.pickle', 'wb')
    pickle.dump(history, history_file)
    history_file.close()
    torch.save(model.state_dict(), 'emnist-resnet9.weight')
else:
    print("Using trained pratameters\n")
    print(model.load_state_dict(torch.load('emnist-resnet9.weight', map_locat
    history_file = open('history_file.pickle', 'rb')
    history = CPU_Unpickler(history_file).load()
    history_file.close()
    print()
```

```
Training the model from the begning. Expected time for completion for 8 epochs
is 1 hour


Epoch [0], last_lr: 0.01000, train_loss: 0.4405, val_loss: 0.4628, val_acc: 0.
8303
Epoch [1], last_lr: 0.01000, train_loss: 0.4392, val_loss: 0.4695, val_acc: 0.
8306
Epoch [2], last_lr: 0.01000, train_loss: 0.4415, val_loss: 0.4704, val_acc: 0.
8413
Epoch [3], last_lr: 0.01000, train_loss: 0.4413, val_loss: 0.4867, val_acc: 0.
8324
Epoch [4], last_lr: 0.01000, train_loss: 0.4410, val_loss: 0.4295, val_acc: 0.
8438
Epoch [5], last_lr: 0.01000, train_loss: 0.4423, val_loss: 0.4164, val_acc: 0.
8503
Epoch [6], last_lr: 0.00100, train_loss: 0.3687, val_loss: 0.3529, val_acc: 0.
8668
Epoch [7], last_lr: 0.00100, train_loss: 0.3557, val_loss: 0.3511, val_acc: 0.
8689
Epoch [8], last_lr: 0.00100, train_loss: 0.3521, val_loss: 0.3449, val_acc: 0.
```

```
8702
Epoch [9], last_lr: 0.00100, train_loss: 0.3502, val_loss: 0.3490, val_acc: 0.
8708
Epoch [10], last_lr: 0.00100, train_loss: 0.3483, val_loss: 0.3498, val_acc:
0.8689
Epoch [11], last_lr: 0.00100, train_loss: 0.3470, val_loss: 0.3471, val_acc:
0.8694
Epoch [12], last_lr: 0.00010, train_loss: 0.3295, val_loss: 0.3347, val_acc:
0.8732
Epoch [13], last_lr: 0.00010, train_loss: 0.3253, val_loss: 0.3341, val_acc:
0.8738
Epoch [14], last_lr: 0.00010, train_loss: 0.3232, val_loss: 0.3326, val_acc:
0.8737
Epoch [15], last_lr: 0.00010, train_loss: 0.3222, val_loss: 0.3330, val_acc:
0.8737
```

In [74]:

```
import io
result = evaluate(model, val_dl)
if train_model:
    result_file = open('result.pickle', 'wb')
    pickle.dump(result, result_file)
    result_file.close()
else:
    result_file = open('result.pickle', 'rb')
    result = CPU_Unpickler(result_file).load()
    result_file.close()
print(result)
```

```
{'labels': tensor([46, 29,  3,  ..., 30, 23, 25], device='cuda:0'), 'val_pred
s': tensor([20, 29, 28,  ..., 30, 23, 25], device='cuda:0'), 'val_loss': 0.333
01764726638794, 'val_acc': 0.8736600279808044}
```

In [ ]:

```
#calculate the perfermance metric of CNN model, including precision, recall,
```

In [83]:

```
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
y_true = result['labels'].cpu()
y_pred = result['val_preds'].cpu()
print("f1 score: " + str(f1_score(y_true, y_pred, average='macro')))
print("Recall: " + str(recall_score(y_true, y_pred, average='macro')))
print("Accuracy: " + str(accuracy_score(y_true, y_pred)))
print("Precision: " + str(precision_score(y_true, y_pred, average='macro')))
```

```
f1 score: 0.7572846507249081
Recall: 0.7526667835887991
Accuracy: 0.87366
Precision: 0.8108126852698716
```

In [ ]:

```
#show the confusion_matrix of this CNN model
```

In [76]:

```
from sklearn.metrics import confusion_matrix
matrix = confusion_matrix(y_true, y_pred)
accuracy_list = matrix.diagonal()/matrix.sum(axis=1)
print(sorted(accuracy_list))
print(np.argsort(accuracy_list))
print(matrix[38])
```

```
[0.0, 0.03664921465968586, 0.04265402843601896, 0.07027027027027027, 0.0945945
945945946, 0.12, 0.22506619593998234, 0.30952380952380953, 0.3448275862068966,
```

```
0.45108695652173914, 0.4903954802259887, 0.49193548387096775, 0.52197802197802
2, 0.5494748479823107, 0.5759162303664922, 0.5909090909090909, 0.6047904191616
766, 0.6068376068376068, 0.6875, 0.7129629629629629, 0.7650602409638554, 0.766
3043478260869, 0.7672955974842768, 0.7788944723618091, 0.8125, 0.8189134808853
119, 0.8452722063037249, 0.8870967741935484, 0.8902077151335311, 0.91039426523
2975, 0.9154067674586033, 0.9182389937106918, 0.9348422496570644, 0.9365994236
311239, 0.9403202328966521, 0.9419354838709677, 0.9429241594996091, 0.94539781
59126365, 0.9482976040353089, 0.9502487562189055, 0.9511494252873564, 0.960893
8547486033, 0.9609507640067911, 0.9617224880382775, 0.9648936170212766, 0.9653
739612188366, 0.9782430213464697, 0.9794419970631424, 0.9795221843003413, 0.9
8, 0.98, 0.9806996381182147, 0.9813486370157819, 0.9819494584837545, 0.9834231
247409864, 0.9836512261580381, 0.9849749582637729, 0.9862542955326461, 0.9888,
0.9940119760479041, 0.9968664316490403, 0.9976461357395057]
[50 54 38 48 56 41 47 57 51 44 18 52 60 24 61 35 46 42 45 59 20 33 31 58
 34  0 32 16 37 19  1 13 28 29 36  5 55 15 49 26 21 53 25 43 30 12  6 22
 11 10 17  2 39 23  9 14 40  4  8 27  3  7]
[  0   0   0   0   0   0   0   0   0   0   0   0 197   0   0   0   0   0
   0   0   0   2   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   9   0   1   0   0   0   0   0   0   0   0   0   0   0   0   2
   0   0   0   0   0   0   0   0]
```

In [53]:

```
print(result)
```

```
{'labels': tensor([46, 29,  3,  ..., 30, 23, 25], device='cuda:0'), 'val_pred
s': tensor([20, 29, 28,  ..., 30, 23, 25], device='cuda:0'), 'val_loss': 0.332
0290744304657, 'val_acc': 0.8742799162864685}
```

In [54]:

```
# analysis index 50 image
print(dataset.classes[50])
# confusion matrix for 'o'
print(matrix[50])
print('86 wrong result :' + dataset.classes[0])
print('111 wrong result :' + dataset.classes[24])
```

```
o
[ 95   0   0   0   0   0   0   0   0   0   0   0   0   2   0   0   0   0
   1   0   0   0   0   0 102   0   0   0   0   0   0   0   0   0   0   0
   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0]
86 wrong result :0
111 wrong result :O
```

In [55]:

```
# analysis index 38 image
print(dataset.classes[38])
# confusion matrix for 'c'
print(matrix[38])
print('203 wrong result :' + dataset.classes[12])
```

```
c
[  0   0   0   0   0   0   0   0   0   0   0   0 199   0   0   0   0   0
   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   6   0   1   0   0   0   0   0   0   1   0   0   0   0   0   3
   0   0   0   0   0   0   0   0]
203 wrong result :C
```

In [56]:

```
# analysis index 48 image
print(dataset.classes[48])
# confusion matrix for 'm'
print(matrix[48])
print('181 wrong result :' + dataset.classes[22])
```

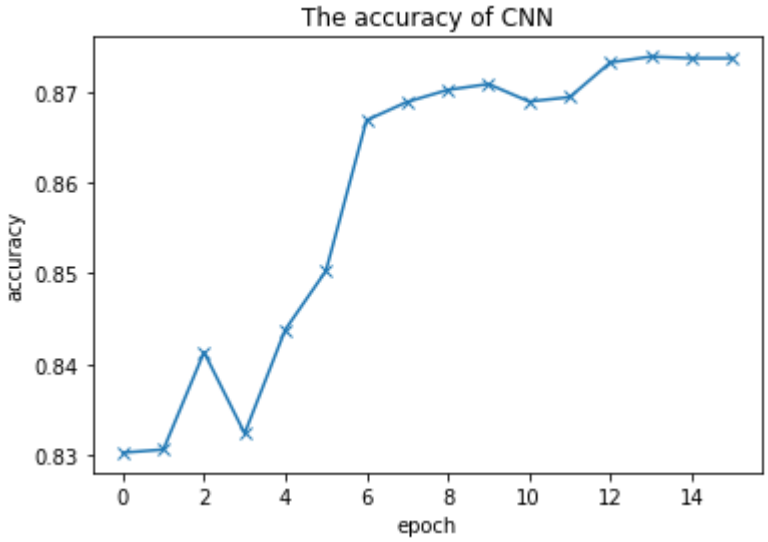
```
m
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0 170   1   0   0   0   0   0   0   0   0   0   0   0   0
```

```
   0   0   0   0   0   0   0   0   0   0   0   0  13   1   0   0   0   0
   0   0   0   0   0   0   0   0]
181 wrong result :M
```

In [57]:
```
#Visualizations for CNN training result
```

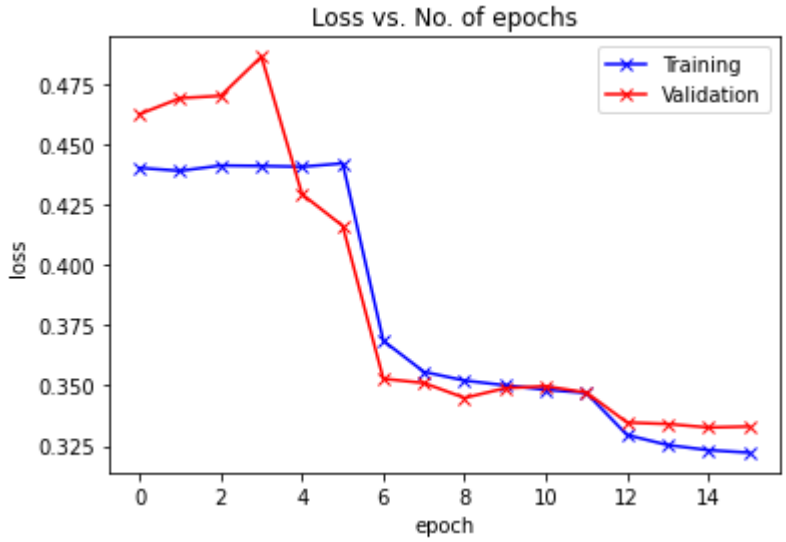
In [77]:
```
#Graph of the accuracy vs. epoch
def plot_accuracies(history):
    accuracies = [x['val_acc'] for x in history]
    plt.plot(accuracies, '-x')
    plt.xlabel('epoch')
    plt.ylabel('accuracy')
    plt.title('The accuracy of CNN');
```

In [78]:
```
plot_accuracies(history)
```



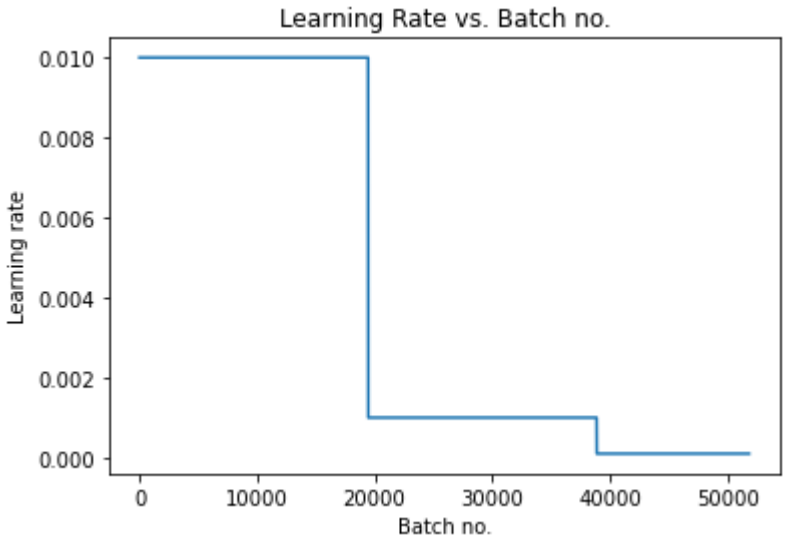
In [79]:
```
#Graph of the loss vs. epoch
def plot_losses(history):
    train_losses = [x.get('train_loss') for x in history]
    val_losses = [x['val_loss'] for x in history]
    plt.plot(train_losses, '-bx')
    plt.plot(val_losses, '-rx')
    plt.xlabel('epoch')
    plt.ylabel('loss')
    plt.legend(['Training', 'Validation'])
    plt.title('Loss vs. No. of epochs');
```

In [80]:
```
plot_losses(history)
```



In [81]:
```
#Graph of the learning rate vs. Batch no.
def plot_lrs(history):
    lrs = np.concatenate([x.get('lrs', []) for x in history])
    plt.plot(lrs)
    plt.xlabel('Batch no.')
    plt.ylabel('Learning rate')
    plt.title('Learning Rate vs. Batch no.');
```

In [82]:
```
plot_lrs(history)
```



In [78]:
```
#Saving the model
```

In [79]:
```
torch.save(model.state_dict(), './EMNIST./zip/matlab/cnn.model')
```

In [ ]:
```
```