```
## Importing the necessary packages
import numpy as np
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader, TensorDataset, random split
from torchvision import transforms, utils
import time
# get the device type of machine
device = torch.device('cuda' if torch.cuda.is available() else 'cpu')
# device = 'cpu'
print(device)
     cuda
from google.colab import drive
drive.mount('/content/drive')
% cd 'drive/My Drive/ECE C147'
% cd 'project'
% 1s
     Mounted at /content/drive
     /content/drive/My Drive/ECE C147
     /content/drive/My Drive/ECE C147/project
     EEG loading.ipynb person train valid.npy X train valid.npy y train valid.npy
     person_test.npy
                        X_test.npy
                                                y_test.npy
```

### Loading the dataset and creating a windowed version

```
## Loading the numpy arrays

X_test = np.load("X_test.npy")
y_test = np.load("y_test.npy")
person_train_valid = np.load("person_train_valid.npy")
X_train_valid = np.load("X_train_valid.npy")
y_train_valid = np.load("y_train_valid.npy")
person_test = np.load("person_test.npy")

## Adjusting the labels so that

# Cue onset left - 0
# Cue onset right - 1
# Cue onset foot - 2
# Cue onset tongue - 3
```

```
y_train_valid -= 769
y test -= 769
print ('Training/Valid data shape: {}'.format(X_train_valid.shape))
print ('Test data shape: {}'.format(X test.shape))
print ('Training/Valid target shape: {}'.format(y train valid.shape))
print ('Test target shape: {}'.format(y_test.shape))
print ('Person train/valid shape: {}'.format(person train valid.shape))
print ('Person test shape: {}'.format(person_test.shape))
     Training/Valid data shape: (2115, 22, 1000)
     Test data shape: (443, 22, 1000)
     Training/Valid target shape: (2115,)
     Test target shape: (443,)
     Person train/valid shape: (2115, 1)
     Person test shape: (443, 1)
def make_steps(samples,samples_per_frame,stride):
    in:
    samples - number of samples in the session
    samples per frame - number of samples in the frame
    stride - the gap between succesive frames
    out: list of tuple ranges
    111
    i = 0
    intervals = []
    while i+samples per frame <= samples:
        intervals.append((i,i+samples per frame))
        i = i + stride
    return intervals
def make win data pipeline(data arr,label arr,num samples frame,stride):
    in:
    data arr - original data array without windowing
    label_arr - labels of the data array without windowing
    num samples frame - number of samples in the frame
    stride - the gap between succesive frames
    out:
    data_win_arr - windowed data array
    label win arr - labels of the windowed data array
    . . .
```

```
num trials = data arr.shape[0]
num_channels = data_arr.shape[1]
num samples = data arr.shape[2]
steps list = make steps(num samples,num samples frame,stride)
num windows = len(steps list)
data win arr = np.zeros((num trials*num windows,num channels,num samples frame))
label_win_arr = []
k = 0
for i in range(num_trials):
   trial_label = label_arr[i]
   trial_data = data_arr[i,:,:]
    for m,n in enumerate(steps_list):
        start ind = n[0]
        end_ind = n[1]
        win_data = trial_data[:,start_ind:end_ind]
        data_win_arr[k,:,:] = win_data
        label win arr.append(trial label)
        k = k+1
label_win_arr = np.asarray(label_win_arr)
return data win arr, label win arr
```

# Creating the custom dataset for torch

```
# Creating the custom dataset

class EEGDataset(Dataset):
    """EEG dataset"""
    def __init__(self, subset, transform=None):
        'Initialization'
        self.subset = subset
        self.transform = transform

def __getitem__(self, index):
        'Generates one sample of data'
        x, y = self.subset[index]
        if self.transform:
```

```
pass
    # x = self.transform(x)
    # y = self.transform(y)
    return x, y

def __len__(self):
    'Denotes the total number of samples'
    return len(self.subset)
```

# ▼ Defining the models

```
# Defining the shallow conv net
class ShallowConv(nn.Module):
   # Defining the building blocks of shallow conv net
   def init (self, in channels, num conv filters, num samples frame, num eeg channels, cla
       # Defining as a subclass
       super(ShallowConv, self). init ()
       self.num samples frame = num samples frame
        self.num conv filters = num conv filters
        self.num_eeg_channels = num_eeg_channels
       # Define the convolution layer, https://pytorch.org/docs/stable/generated/torch.nn.Co
        self.conv1 = nn.Conv2d(in channels, self.num conv filters, (1, 25), stride=1)
        self.conv_output_width = int(self.num_samples_frame - (25-1) - 1 + 1)
       # Define the 2d batchnorm layer
       self.bnorm2d = nn.BatchNorm2d(self.num conv filters)
       # Define the 1d batchnorm layer
       self.bnorm1d = nn.BatchNorm1d(self.num conv filters)
       # Define the fc layer, https://pytorch.org/docs/stable/generated/torch.nn.Linear.html
       self.fc1 = nn.Linear(self.num_eeg_channels*self.num_conv_filters, self.num_conv_filte
       # Define the elu activation
       self.elu = nn.ELU(0.2)
       # Define the avg pooling layer
       self.avgpool = nn.AvgPool1d(75, stride=15)
```

```
self.num_features_linear = int(np.floor(((self.conv_output_width - 75)/15)+1))
    # Define the fc layer for generating the scores for classes
    self.fc2 = nn.Linear(self.num_features_linear*self.num_conv_filters, classes)
 # Defining the connections of shallow conv net
def forward(self, x):
    # Reshaping the input for 2-D convolution (B,22,num_samples_frame) -> (B,1,22,num_sam
   x = x.view(-1, 1, 22, self.num_samples_frame)
    # Performing the 2-D convolution (B,1,22,300) -> (B,40,22,x_shape_4dim)
   x = self.conv1(x)
    x_{shape_4dim} = x.shape[3]
   # ELU activation
   x = self.elu(x)
   # 2d Batch normalization
   x = self.bnorm2d(x)
   # Reshaping the input to dense layer (B,40,22,x_shape_4dim) -> (B,x_shape_4dim,880)
   x = x.permute(0,3,1,2) # (B,40,22,x_shape_4dim) -> (B,x_shape_4dim,40,22)
   x = x.view(-1,x shape 4dim,880)
   # Passing through the dense layer (B,x shape 4dim,880) -> (B,x shape 4dim,40)
   x = self.fc1(x)
   # ELU activation
   x = self.elu(x)
   # Square activation
   x = torch.square(x)
    # Reshaping the input for average pooling layer (B,x_shape_4dim,40) -> (B,40,x_shape_
    x = x.nermute(0.2.1)
```

```
7. PCI MUCC (0) 2) 2/
# Passing through the average pooling layer (B,40,x shape 4dim) -> (B,40,x pool 3dim)
x = self.avgpool(x)
x_{pool}=x.shape[2]
# Log activation
x = torch.log(x)
# 1D Batch normalization
x = self.bnorm1d(x)
#print(x.shape)
# Reshaping the input to dense layer (B,40,x pool 3dim) -> (B,40*x pool 3dim)
x = x.reshape(-1, 40*x_pool_3dim)
# Passing through the dense layer (B,40*x_pool_3dim) -> (B,classes)
x = self.fc2(x)
# Passing through the softmax layer
return x
```

# Defining the training and validation of the model

```
## Defining the training and validation function

def train_val(model,optimizer,criterion,num_epochs):

    train_loss = []
    train_acc = []
    val_loss = []
    val_acc = []

    for epoch in range(num_epochs):

        print('Epoch {}/{}'.format(epoch, num_epochs - 1))
        print('-' * 10)
```

```
for phase in ['train','val']:
    #Initializing the losses and accuracy
    training_loss = 0
    correct_train_preds = 0
    total_train_preds = 0
    batch_train_idx = 0
    validation loss = 0
    correct_val_preds = 0
    total_val_preds = 0
    batch val idx = 0
    # Implementing the training phase
    if phase == 'train':
        # setting the model to training mode
        model.train()
        # Loading the training dataset in batches
        for inputs, labels in dataloaders['train']:
            # Transfer input data and labels to device
            inputs = inputs.to(device)
            labels = labels.to(device)
            # Incrementing the batch counter
            batch train idx += 1
            # Zeroing the gradient buffer
            optimizer.zero_grad()
            # Perform the forward pass
            outputs = model(inputs)
            # Compute loss
            loss = criterion(outputs,labels)
```

```
# Perform the backward pass
        loss.backward()
        # Perform optimization step
        optimizer.step()
        # Compute training statistics
        training_loss += loss.item()
        _, predicted = outputs.max(1)
        total_train_preds += labels.size(0)
        correct train preds += predicted.eq(labels).sum().item()
    train loss.append(training loss)
    t_acc = correct_train_preds/total_train_preds
    train acc.append(t acc)
    print('Training loss:',training_loss)
    print('Training accuracy:',t_acc)
else:
    # setting the model to evaluation mode
    model.eval()
    # Disable gradient computation
    with torch.no grad():
        # Loading the training dataset in batches
        for val inputs, val labels in dataloaders['val']:
            # Transfer input data and labels to device
            val inputs = val inputs.to(device)
            val labels = val labels.to(device)
            # Incrementing the batch counter
            batch val idx += 1
            # Perform forward pass
```

```
val_outputs = model(val_inputs)

# Compute loss

valid_loss = criterion(val_outputs,val_labels)

# Compute validation statistics

validation_loss += valid_loss.item()
_, val_predicted = val_outputs.max(1)
 total_val_preds += val_labels.size(0)
 correct_val_preds += val_predicted.eq(val_labels).sum().item()

val_loss.append(validation_loss)
v_acc = correct_val_preds/total_val_preds
val_acc.append(v_acc)
print('Validation loss:',validation_loss)
print('Validation accuracy:',v_acc)
```

return model, train\_loss, train\_acc, val\_loss, val\_acc

### Training, validating and testing the model with 1000 samples per trial

```
## Preparing the training and validation data
num_samples_frame = 1000
stride = 50
X_train_win,y_train_win = make_win_data_pipeline(X_train_valid,y_train_valid,num_samples_fram
print ('Windowed Training/Valid data shape: {}'.format(X_train_win.shape))
print ('Windowed Training/Valid label shape: {}'.format(y_train_win.shape))

# Converting the numpy data to torch tensors

X_train_valid_tensor = torch.from_numpy(X_train_win).float().to(device)
y_train_valid_tensor = torch.from_numpy(y_train_win).float().long().to(device)

print ('Training/Valid tensor shape: {}'.format(X_train_valid_tensor.shape))
print ('Training/Valid target tensor shape: {}'.format(y_train_valid_tensor.shape))
init_dataset = TensorDataset(X_train_valid_tensor, y_train_valid_tensor)

# Soliting the dataset into training and validation
```

```
lengths = [int(len(init_dataset)*0.8), int(len(init_dataset)*0.2)]
subset train, subset val = random split(init dataset, lengths)
train data = EEGDataset(subset train, transform=None)
val data = EEGDataset(subset val, transform=None)
# Constructing the training and validation dataloaders
dataloaders = {
    'train': torch.utils.data.DataLoader(train data, batch size=32, shuffle=True, num workers
    'val': torch.utils.data.DataLoader(val data, batch size=8, shuffle=False, num workers=0)
}
    Windowed Training/Valid data shape: (2115, 22, 1000)
    Windowed Training/Valid label shape: (2115,)
    Training/Valid tensor shape: torch.Size([2115, 22, 1000])
    Training/Valid target tensor shape: torch.Size([2115])
# Defining the parameters for model training
weight decay = 0.15 # weight decay to alleviate overfiting
shallow_model = ShallowConv(in_channels=1, num_conv_filters=40,num_samples_frame=1000,num_eeg
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(shallow_model.parameters(), lr = 1e-4, weight_decay=weight_decay
# Training and validating the model
num epoch=200
shallow model,t l,t a,v l,v a=train val(shallow model, optimizer, criterion, num epochs=num e
    Training loss: 13.62040539085865
    Training accuracy: 0.9905437352245863
    Validation loss: 46.24142950773239
    Validation accuracy: 0.640661938534279
    Epoch 191/199
     _____
    Training loss: 11.871786415576935
    Training accuracy: 0.99822695035461
    Validation loss: 46.138053804636
    Validation accuracy: 0.640661938534279
    Epoch 192/199
    Training loss: 11.304404214024544
    Training accuracy: 0.9994089834515366
    Validation loss: 45.59165704250336
    Validation accuracy: 0.6524822695035462
```

```
ShallowCNN differenttime.ipynb - Colaboratory
Epoch 193/199
-----
Training loss: 11.66141477227211
Training accuracy: 0.9994089834515366
Validation loss: 45.31048172712326
Validation accuracy: 0.6713947990543735
Epoch 194/199
-----
Training loss: 11.064806789159775
Training accuracy: 0.9988179669030733
Validation loss: 46.9757679104805
Validation accuracy: 0.6312056737588653
Epoch 195/199
------
Training loss: 11.57563641667366
Training accuracy: 0.9994089834515366
Validation loss: 45.78339001536369
Validation accuracy: 0.6572104018912529
Epoch 196/199
-----
Training loss: 11.33141578733921
Training accuracy: 0.99822695035461
Validation loss: 46.35113310813904
Validation accuracy: 0.6501182033096927
Epoch 197/199
-----
Training loss: 11.987960189580917
Training accuracy: 0.9976359338061466
Validation loss: 45.7522796690464
Validation accuracy: 0.6477541371158393
Epoch 198/199
-----
Training loss: 11.420435383915901
Training accuracy: 0.9988179669030733
Validation loss: 45.86351674795151
Validation accuracy: 0.6359338061465721
Epoch 199/199
-----
Training loss: 11.868240520358086
Training accuracy: 0.9940898345153665
Validation loss: 45.230103462934494
Validation accuracy: 0.6548463356973995
```

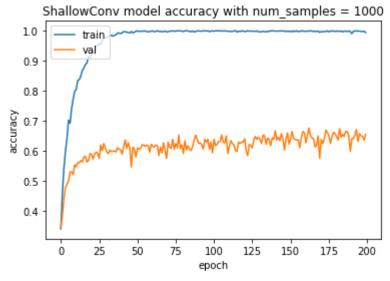
# Plotting the training and validation history

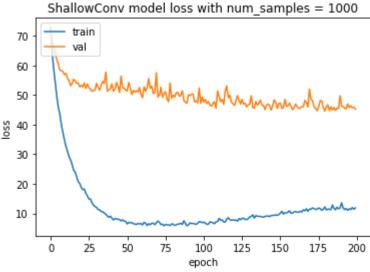
```
import matplotlib.pyplot as plt
print(v a)
plt.plot(range(num epoch),t a)
plt.plot(range(num_epoch),v_a)
plt.title('ShallowConv model accuracy with num samples = 1000')
plt.ylabel('accuracy')
plt.xlabel('epoch')
```

```
pit.legena(['train','val'], loc='upper left')
plt.show()
```

```
plt.plot(range(num_epoch),t_l)
plt.plot(range(num_epoch),v_l)
plt.title('ShallowConv model loss with num_samples = 1000')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','val'], loc='upper left')
plt.show()
```

#### $[0.34515366430260047,\ 0.3829787234042553,\ 0.44208037825059104,\ 0.47754137115839246,\ 0.488037825059104]$





```
# Testing the model
```

```
num_samples_frame = 1000
stride = 50
```

```
X test win,y test win = make win data pipeline(X test,y test,num samples frame,stride)
# Preparing the test dataset
X_test_tensor = torch.from_numpy(X_test_win).float().to(device)
y test tensor = torch.from numpy(y test win).float().long().to(device)
test_dataset = TensorDataset(X_test_tensor, y_test_tensor)
test_data = EEGDataset(test_dataset, transform=None)
def test model(model,test data,criterion):
    # Creating the test dataloader
    test_dataloader = torch.utils.data.DataLoader(test_data, batch_size=8, shuffle=True, num_
    # Making the predictions on the dataset
    total test preds = 0
    correct_test_preds = 0
    test loss = 0
    model.eval()
    with torch.no_grad():
        for test inputs, test labels in test dataloader:
            # Transfer test data and labels to device
            test_inputs = test_inputs.to(device)
            test labels = test labels.to(device)
            # Perform forward pass
            test outputs = model(test inputs)
            # Compute loss
            test loss = criterion(test outputs,test labels)
            # Compute test statistics
            test loss += test loss.item()
            , test predicted = test outputs.max(1)
            total_test_preds += test_labels.size(0)
            correct test preds += test predicted.eq(test labels).sum().item()
        test acc = correct test preds/total test preds
        print('Test loss', test loss)
        print('Test accuracy',test_acc*100)
```

```
test_a = test_model(shallow_model,test_data,criterion)
   Test loss tensor(1.1953, device='cuda:0')
   Test accuracy 65.23702031602708
```

# Training, validating and testing the model with 500 samples per trial

```
## Preparing the training and validation data
num_samples_frame = 500
stride = 100
X_train_win,y_train_win = make_win_data_pipeline(X_train_valid,y_train_valid,num_samples_fram
print ('Windowed Training/Valid data shape: {}'.format(X_train_win.shape))
print ('Windowed Training/Valid label shape: {}'.format(y train win.shape))
# Converting the numpy data to torch tensors
X_train_valid_tensor = torch.from_numpy(X_train_win).float().to(device)
y_train_valid_tensor = torch.from_numpy(y_train_win).float().long().to(device)
print ('Training/Valid tensor shape: {}'.format(X_train_valid_tensor.shape))
print ('Training/Valid target tensor shape: {}'.format(y train valid tensor.shape))
init dataset = TensorDataset(X train valid tensor, y train valid tensor)
# Spliting the dataset into training and validation
lengths = [int(len(init_dataset)*0.8), int(len(init_dataset)*0.2)]
subset_train, subset_val = random_split(init_dataset, lengths)
train data = EEGDataset(subset train, transform=None)
val_data = EEGDataset(subset_val, transform=None)
# Constructing the training and validation dataloaders
dataloaders = {
    'train': torch.utils.data.DataLoader(train_data, batch_size=32, shuffle=True, num_workers
    'val': torch.utils.data.DataLoader(val data, batch size=8, shuffle=False, num workers=0)
}
    Windowed Training/Valid data shape: (12690, 22, 500)
    Windowed Training/Valid label shape: (12690,)
    Training/Valid tensor shape: torch.Size([12690, 22, 500])
     Training/Valid target tensor shape: torch.Size([12690])
```

# Defining the parameters for model training

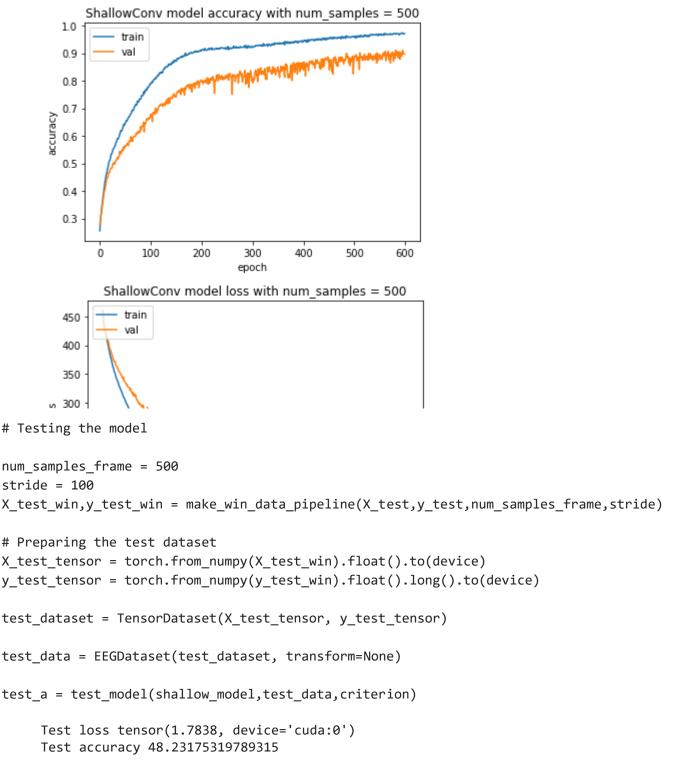
```
weight decay = 0.15 # weight decay to alleviate overfiting
shallow model = ShallowConv(in channels=1, num conv filters=40,num samples frame=500,num eeg
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(shallow model.parameters(), lr = 1e-5, weight decay=weight decay
# Training and validating the model
epoch=600
shallow model, t l,t a,v l,v a=train val(shallow model, optimizer, criterion, num epochs=epoch
     _____
    Training loss: 117.18125839531422
    Training accuracy: 0.969070133963751
    Validation loss: 167.66588066518307
    Validation accuracy: 0.8782505910165485
    Epoch 591/599
     _____
    Training loss: 116.57842734456062
    Training accuracy: 0.9710401891252955
    Validation loss: 158.88496893644333
    Validation accuracy: 0.9026792750197006
    Epoch 592/599
    Training loss: 116.43788632750511
    Training accuracy: 0.9713356973995272
    Validation loss: 160.04617117345333
    Validation accuracy: 0.9003152088258471
    Epoch 593/599
    -----
    Training loss: 114.91826002299786
    Training accuracy: 0.9716312056737588
    Validation loss: 162.16221196949482
    Epoch 594/599
     -----
    Training loss: 115.09499441087246
    Training accuracy: 0.973404255319149
    Validation loss: 160.72544640302658
    Validation accuracy: 0.8987391646966115
    Epoch 595/599
    Training loss: 114.1037253588438
    Training accuracy: 0.9741922773837668
    Validation loss: 157.73168356716633
    Validation accuracy: 0.9109535066981875
    Epoch 596/599
    Training loss: 115.34859521687031
    Training accuracy: 0.9706461780929866
    Validation loss: 159.916859716177
    Validation accuracy: 0.9034672970843184
    Epoch 597/599
     _____
```

 $https://colab.research.google.com/drive/14dtByJAOgYsHeQaG5U9zaL\_HFEQAnYIT\#scrollTo=Roi\_oRfovQe4\&printMode=true-line for the control of the$ 

Training loss: 116.22640573978424

```
Training accuracy: 0.969956658786446
     Validation loss: 159.92002944648266
     Validation accuracy: 0.8975571315996848
     Epoch 598/599
     Training loss: 115.20905143022537
     Training accuracy: 0.9705476753349094
     Validation loss: 159.32293625175953
     Validation accuracy: 0.8975571315996848
     Epoch 599/599
     Training loss: 115.96913474798203
     Training accuracy: 0.9711386918833728
     Validation loss: 159.1123557537794
     Validation accuracy: 0.8975571315996848
# Plotting the training and validation history
import matplotlib.pyplot as plt
print(v_a)
plt.plot(range(epoch),t_a)
plt.plot(range(epoch), v a)
plt.title('ShallowConv model accuracy with num_samples = 500')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train','val'], loc='upper left')
plt.show()
plt.plot(range(epoch),t_l)
plt.plot(range(epoch), v 1)
plt.title('ShallowConv model loss with num_samples = 500')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','val'], loc='upper left')
plt.show()
```

[0.2777777777778, 0.2970843183609141, 0.3073286052009456, 0.3195429472025217, 0.32978



### Training, validating and testing the model with 300 samples per trial

```
## Preparing the training and validation data

num_samples_frame = 300
stride = 60
X_train_win,y_train_win = make_win_data_pipeline(X_train_valid,y_train_valid,num_samples_fram
https://colab.research.google.com/drive/14dtByJAOgYsHeQaG5U9zaL_HFEQAnYIT#scrollTo=Roi_oRfovQe4&printMode=true 17/21
```

```
print ('Windowed Training/Valid data shape: {}'.format(X train win.shape))
print ('Windowed Training/Valid label shape: {}'.format(y train win.shape))
# Converting the numpy data to torch tensors
X train valid tensor = torch.from numpy(X train win).float().to(device)
y train valid tensor = torch.from numpy(y train win).float().long().to(device)
print ('Training/Valid tensor shape: {}'.format(X_train_valid_tensor.shape))
print ('Training/Valid target tensor shape: {}'.format(y_train_valid_tensor.shape))
init dataset = TensorDataset(X train valid tensor, y train valid tensor)
# Spliting the dataset into training and validation
lengths = [int(len(init dataset)*0.8), int(len(init dataset)*0.2)]
subset train, subset val = random split(init dataset, lengths)
train_data = EEGDataset(subset_train, transform=None)
val data = EEGDataset(subset val, transform=None)
# Constructing the training and validation dataloaders
dataloaders = {
    'train': torch.utils.data.DataLoader(train data, batch size=32, shuffle=True, num workers
    'val': torch.utils.data.DataLoader(val_data, batch_size=8, shuffle=False, num_workers=0)
}
     Windowed Training/Valid data shape: (25380, 22, 300)
     Windowed Training/Valid label shape: (25380,)
     Training/Valid tensor shape: torch.Size([25380, 22, 300])
     Training/Valid target tensor shape: torch.Size([25380])
# Defining the parameters for model training
weight decay = 0.15 # weight decay to alleviate overfiting
shallow_model = ShallowConv(in_channels=1, num_conv_filters=40,num_samples_frame=300,num_eeg_
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(shallow_model.parameters(), lr = 1e-5, weight_decay=weight_decay
epoch=500
# Training and validating the model
shallow model, t l,t a,v l,v a=train val(shallow model, optimizer, criterion, num epochs=epoch
 ☐ Training loss: 335.36366787552834
     Training accuracy: 0.9218873128447597
     Validation loss: 432.33226826786995
     Validation accuracy: 0 814026792750197
```

Validacion accuracy. U.OITOZOIDZIDOIDI

Epoch 491/499

-----

Training loss: 335.4767629802227 Training accuracy: 0.9238081166272656 Validation loss: 431.3445480763912 Validation accuracy: 0.8130417651694247

Epoch 492/499

-----

Training loss: 336.6296007633209
Training accuracy: 0.9213455476753349
Validation loss: 418.34600818157196
Validation accuracy: 0.8297872340425532

Epoch 493/499

-----

Training loss: 334.1713341474533
Training accuracy: 0.924645390070922
Validation loss: 448.4650750756264
Validation accuracy: 0.7799448384554768

Epoch 494/499

-----

Training loss: 334.402989000082

Training accuracy: 0.9253349093774625 Validation loss: 416.81055849790573 Validation accuracy: 0.8368794326241135

Epoch 495/499

-----

Training loss: 334.5504116117954
Training accuracy: 0.9237096138691884
Validation loss: 411.161266207695

Validation accuracy: 0.8378644602048857

Epoch 496/499

-----

Training loss: 333.81252458691597
Training accuracy: 0.9253841607565012
Validation loss: 422.41213831305504
Validation accuracy: 0.8264381402679275

Epoch 497/499

-----

Training loss: 333.2014458477497
Training accuracy: 0.9234141055949566
Validation loss: 422.80629459023476
Validation accuracy: 0.8157998423955871

Epoch 498/499

-----

Training loss: 334.38831117749214
Training accuracy: 0.9238573680063041
Validation loss: 417.11436754465103
Validation accuracy: 0.8402285263987391

Epoch 499/499

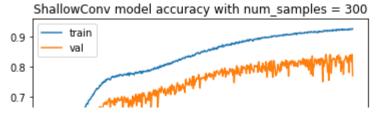
-----

Training loss: 334.5765996873379
Training accuracy: 0.925531914893617
Validation loss: 447.5720668435097
Validation accuracy: 0.7693065405831363

" I TOCCTUP CITC CLATHITUP AND VALLAGETON HISCOLY

```
import matplotlib.pyplot as plt
print(v a)
plt.plot(range(epoch),t_a)
plt.plot(range(epoch), v_a)
plt.title('ShallowConv model accuracy with num samples = 300')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train','val'], loc='upper left')
plt.show()
plt.plot(range(epoch),t_1)
plt.plot(range(epoch),v_1)
plt.title('ShallowConv model loss with num samples = 300')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','val'], loc='upper left')
plt.show()
```

[0.27698975571316, 0.2929472025216706, 0.30437352245862886, 0.3195429472025217, 0.32959(



```
# Testing the model
num samples frame = 300
stride = 60
X_test_win,y_test_win = make_win_data_pipeline(X_test,y_test,num_samples_frame,stride)
# Preparing the test dataset
X test tensor = torch.from numpy(X test win).float().to(device)
y_test_tensor = torch.from_numpy(y_test_win).float().long().to(device)
test dataset = TensorDataset(X test tensor, y test tensor)
test data = EEGDataset(test dataset, transform=None)
test a = test model(shallow model,test data,criterion)
     Test loss tensor(2.7331, device='cuda:0')
     Test accuracy 40.105342362678705
                                                     500
             Ò
                    100
                            200
                                     300
                                             400
                                epoch
```