Assignment1_EE5178

October 23, 2022

1 Modern Computer Vision Assignment 1: Report

2 Importing Necessory Libraries

[1]:
```
import torchvision
import numpy as np
import matplotlib.pyplot as plt
import torch
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import DataLoader
import sklearn.metrics
import torch.nn as nn
import torch.nn.functional as F
import time
import sys
import os
import gc
import numpy as np
import PIL.Image
```

[2]:
```
# Checking if cuda available
device=torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda
```

3 Defining Hyperparameters and Necessary Global Variables

[3]:
```
epochs = 10
learningRate = 0.01
inputs = 3*32*32
noOfNodesL1 = 500
noOfNodesL2 = 250
noOfNodesL3 = 100
```

```
outputs = 10
batchSize = 100
outputLabel = {0: 'airplane' , 1: 'automobile' , 2: 'bird' , 3: 'cat' , 4:␣
↪'deer' , 5: 'dog' , 6: 'frog' , 7: 'horse' , 8: 'ship' , 9: 'truck'}
```

4 Helpful Functions

[4]:
```
def displayImages2(data , model ,device=torch.device("cuda" if torch.cuda.
↪is_available() else "cpu") ):
  """
  Displaying 'numberOfImages' Random Images
  numberOfImages - Even Number
  """
  ix=1
  fig, ax = plt.subplots(10, 5, figsize=(15,15))
  fig.tight_layout()
  model.eval()
  for filter in range(50):
    randInt = torch.randint(0 , 10000 , (1,))
    #print(randInt)
    #randInt = 1
    ax = plt.subplot(10, 5, ix)
    ax.set_xticks([])
    ax.set_yticks([])
    image , target = data[int(randInt)]
    temp = image.cpu()
    image = torch.reshape(image , (1 , 3 , 32 , 32))
    image = image.to(device)
    temp = torch.clamp(temp , 0 , 1)
    out = model(image)
    yPred = F.softmax(out , dim =1)
    predictedNumber = torch.argmax(yPred , dim = 1)
    ax.title.set_text('P | R: {}|{}'.format(outputLabel[int(predictedNumber)] ,␣
↪outputLabel[int(target)]))
    plt.imshow(temp.T)
    ix+=1
```

[15]:
```
def loadDataSetPy(): # Loading DataSet for pyTorch
  """
  60k Train Data in batches of "batchSize"
  10k Test Data
  Also Does Appropriate Transformations Required
  """
  train_transform = transforms.Compose([
  transforms.ToTensor(),
```

```
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)),])

    test_transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)),])

    train = torchvision.datasets.CIFAR10('./data' , train=True, transform=␣
↪train_transform, download=True)

    testData = torchvision.datasets.CIFAR10('./data' , train=False, transform=␣
↪test_transform,  download = True)
    trainData, validData = torch.utils.data.random_split(train, [45000, 5000])

    trainDataLoader = DataLoader(trainData , batch_size = batchSize , shuffle =␣
↪True)
    testDataLoader = DataLoader(trainData , batch_size = 10000 , shuffle = True)
    validDataLoader = DataLoader(validData, batch_size = 5000 , shuffle = True ,␣
↪num_workers = 2)

    return trainDataLoader , testDataLoader , trainData, validDataLoader, testData
```

[104]:
```
# Defining the MLP

class NeuralNet(nn.Module):
    def __init__(self):
        super(NeuralNet, self).__init__()
        self.relu = nn.ReLU()
        self.l1 = nn.Linear(inputs, noOfNodesL1)
        self.l2 = nn.Linear(noOfNodesL1, noOfNodesL2)
        self.l3 = nn.Linear(noOfNodesL2 , noOfNodesL3)
        self.l4 = nn.Linear(noOfNodesL3 , outputs)
    def forward(self, x):
        out = self.relu(self.l1(x))
        out = self.relu(self.l2(out))
        out = self.relu(self.l3(out))
        out = self.l4(out)
        # no activation and no4softmax at the end
        return out
```

[6]:
```
def creatingOutputVector(trainLabels):
    """
    trainLabels - Labels of Input Train Data of a Partiular Batch. (Size:␣
↪batchSize X 1)
    yReal - True Output. Size: (batchSize X 10)
    """
    batchSize = len(trainLabels)
```

```
  yReal = np.zeros([batchSize , 10]) # BatchSize X 10 Matrix
  for j in range(batchSize):
    yReal[j][trainLabels[j]] = 1
  return yReal
```

[106]:
```
def predictPy(testDataLoader , model):
  for data in testDataLoader:
    img , label = data
  X = torch.reshape(img , (len(img) , 32*32*3))
  model.eval()
  yPred = F.softmax(model(X) , dim =1)
  predictedNumber = torch.argmax(yPred , dim = 1)
  noOfRightPrediction = torch.sum(predictedNumber == label)
  totalPrediction = len(img)
  accuracy = noOfRightPrediction/totalPrediction
  confusionMatrix = sklearn.metrics.confusion_matrix( label , predictedNumber)



  return accuracy , confusionMatrix
```

[5]:
```
def predictPyCNN(testDataLoader , model , device=torch.device("cuda" if torch.
↪cuda.is_available() else "cpu")):
  if device == 'cuda':
    torch.cuda.empty_cache()
    gc.collect()
  for data in testDataLoader:
    img , label = data
  X = torch.reshape(img , (len(img) , 3 , 32 , 32))
  X = X.to(device)
  label = label.to(device)
  model.eval()
  yPred = F.softmax(model(X) , dim =1)
  predictedNumber = torch.argmax(yPred , dim = 1)
  noOfRightPrediction = torch.sum(predictedNumber == label)
  totalPrediction = len(img)
  accuracy = noOfRightPrediction/totalPrediction

  confusionMatrix = sklearn.metrics.confusion_matrix( label.cpu() ,␣
↪predictedNumber.cpu())



  return accuracy , confusionMatrix
```

[13]:
```python
def displayImages(data , model):
  """
  Displaying 32 Random Images
  """
  ix=1
  fig, ax = plt.subplots(8, 4, figsize=(10,10))
  fig.tight_layout()
  model.eval()
  for filter in range(32):
    randInt = torch.randint(0 , 10000 , (1,))
    ax = plt.subplot(8, 4, ix)
    ax.set_xticks([])
    ax.set_yticks([])
    image , target = data[int(randInt)]
    temp = image
    temp = torch.clamp(temp , 0 , 1)
    image = torch.reshape(image , (1 , 32*32*3))
    out = model(image)
    yPred = F.softmax(out , dim =1)
    predictedNumber = torch.argmax(yPred , dim = 1)
    ax.title.set_text('P | R: {}|{}'.format(outputLabel[int(predictedNumber)] ,␣
 ↪outputLabel[int(target)]))
    plt.imshow(temp.T)
    ix+=1
```

5 Training The Model

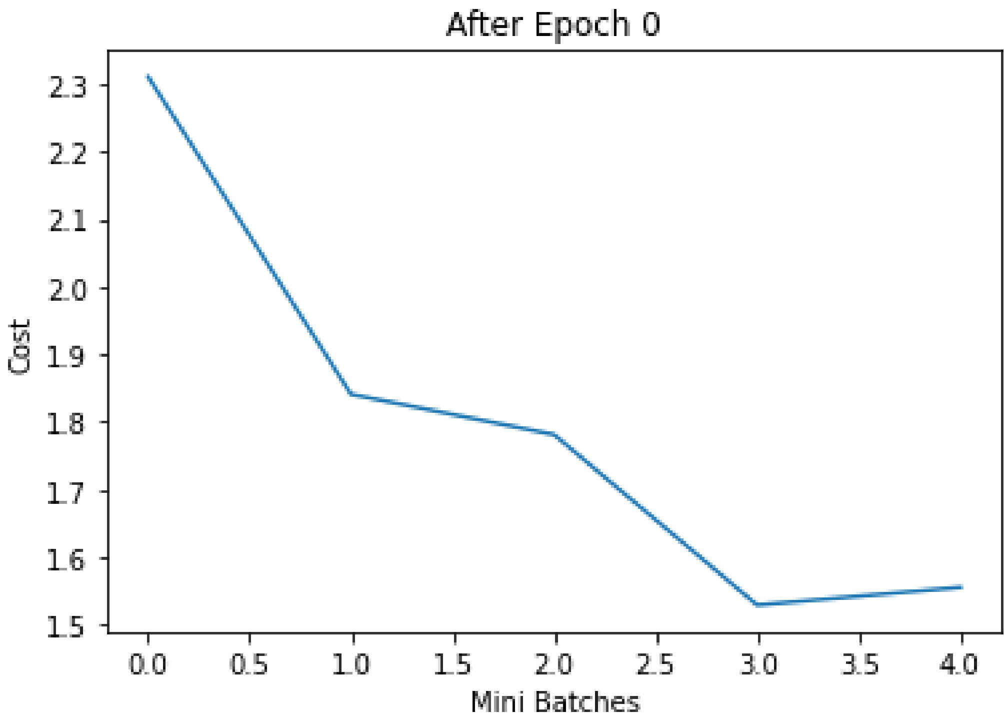
[16]:
```python
"""
Loading Datasets
"""
trainDataLoader , testDataLoader , trainData, validDataLoader, testData =␣
 ↪loadDataSetPy()
```

```
Files already downloaded and verified
Files already downloaded and verified
```

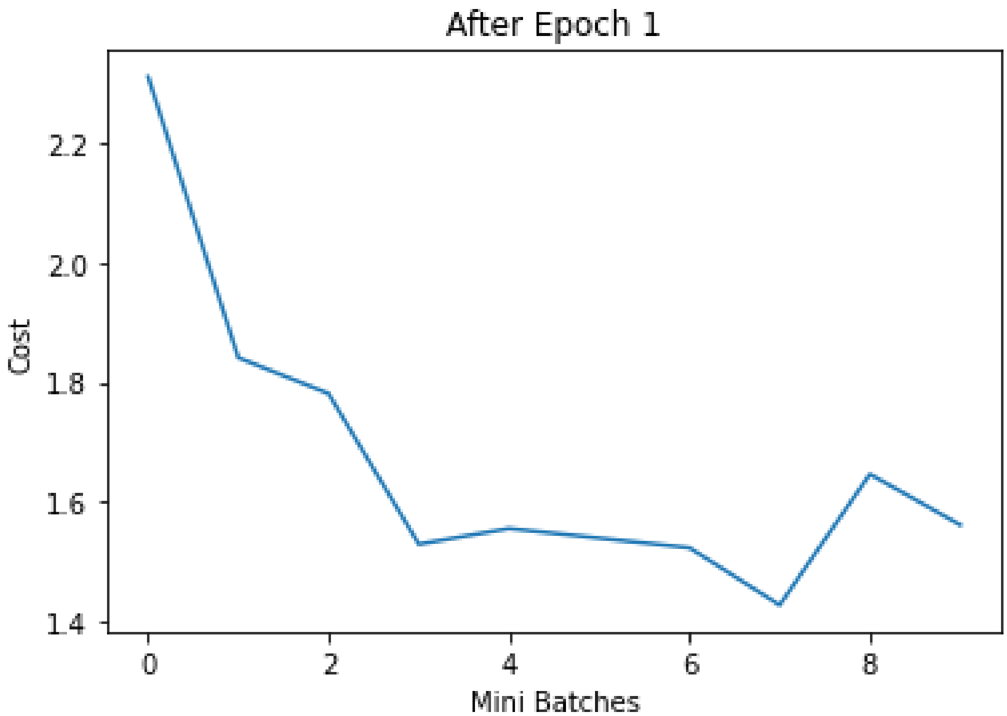
[9]:
```python
"""
Intilizing the model
"""
model = NeuralNet()
optim = torch.optim.SGD(model.parameters(), lr=learningRate , momentum = 0.9)
criterion = nn.CrossEntropyLoss()

"""
Training
```

```
"""
start_time = time.time()
n_total_steps = batchSize
totalCost = []
model.train()
for epoch in range(epochs):
  print('Epoch {} '.format(epoch))
  for i , (images,labels) in enumerate(trainDataLoader):
    # FLATTENING
    images = torch.reshape(images , (batchSize , 3072)) # Size : [batchSize X 3072]
    # FORWARD PASS
    yPred = model(images)
    loss = criterion(yPred , labels)

    # OPTIMISATION
    optim.zero_grad()
    loss.backward()
    optim.step()
    cost = loss.item()
    if i%100 == 0:
      print('Cost After Mini Batch %i: %f' %(i , cost))
      totalCost.append(loss.item())
  model.eval()
  accuracy, confusionMatrix = predictPy(validDataLoader , model)
  print('After Epoch {}, Validation accuracy = {}'.format(epoch , accuracy*100))
  plt.plot(totalCost)
  plt.title('After Epoch {}'.format(epoch))
  plt.xlabel('Mini Batches')
  plt.ylabel('Cost')
  plt.show()
print("Execution Time --- %s seconds ---" % (time.time() - start_time))
```

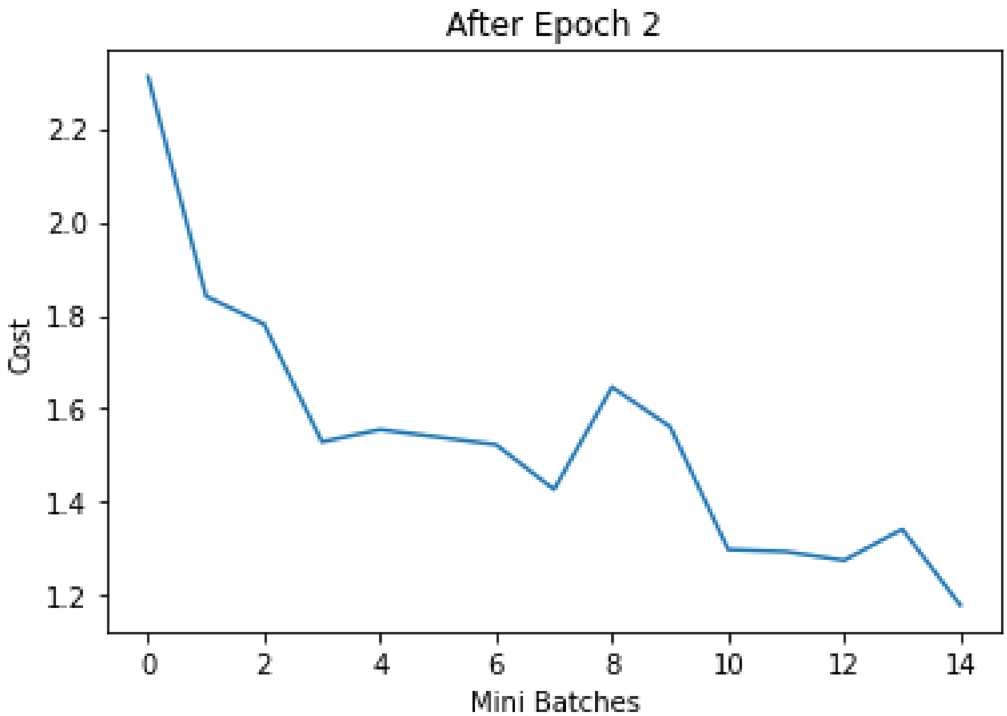
```
Epoch 0
Cost After Mini Batch 0: 2.311132
Cost After Mini Batch 100: 1.840939
Cost After Mini Batch 200: 1.781129
Cost After Mini Batch 300: 1.528851
Cost After Mini Batch 400: 1.555144
After Epoch 0, Validation accuracy = 45.41999816894531
```



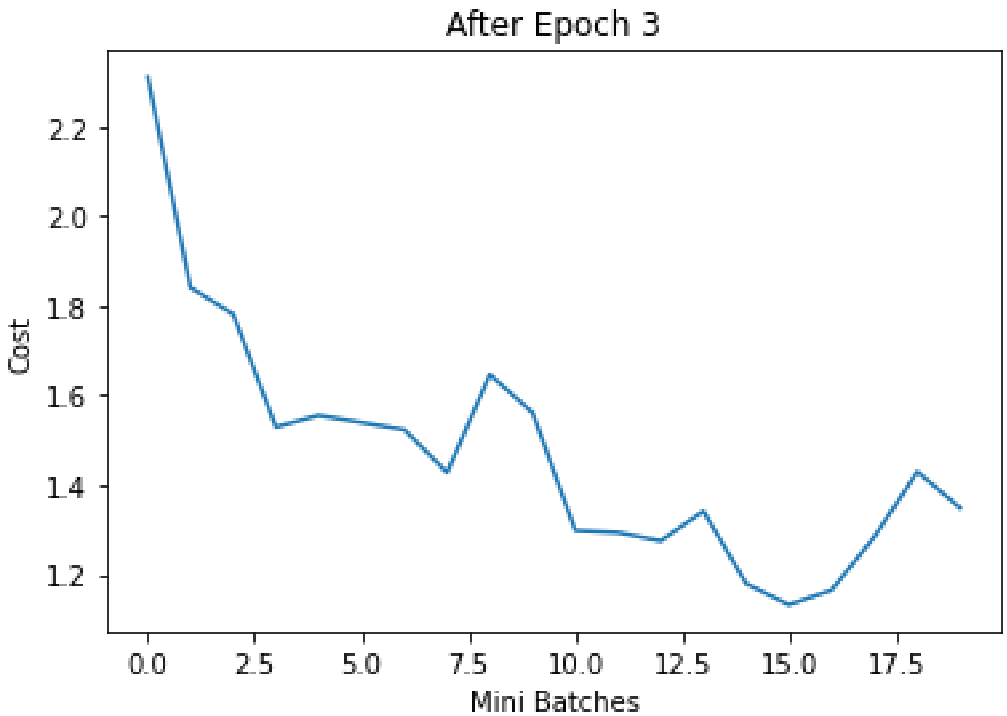

```
Epoch 1
Cost After Mini Batch 0: 1.539053
Cost After Mini Batch 100: 1.522800
Cost After Mini Batch 200: 1.427155
Cost After Mini Batch 300: 1.646216
Cost After Mini Batch 400: 1.561159
After Epoch 1, Validation accuracy = 49.119998931884766
```



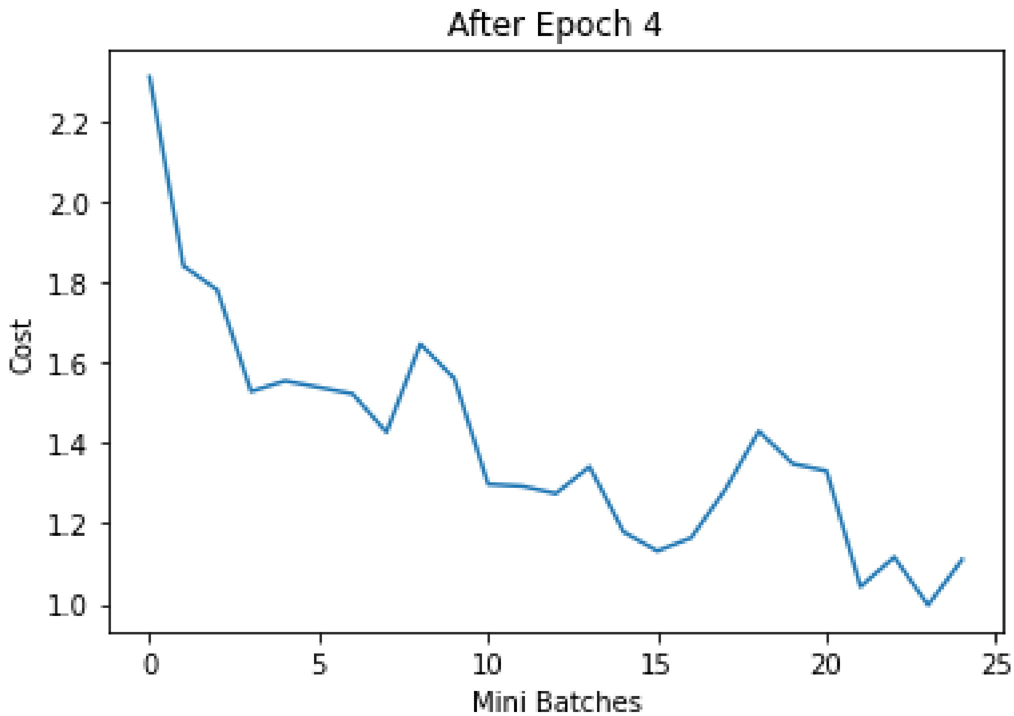

```
Epoch 2
Cost After Mini Batch 0: 1.298357
Cost After Mini Batch 100: 1.293602
Cost After Mini Batch 200: 1.274947
Cost After Mini Batch 300: 1.341696
Cost After Mini Batch 400: 1.179518
After Epoch 2, Validation accuracy = 51.279998779296875
```



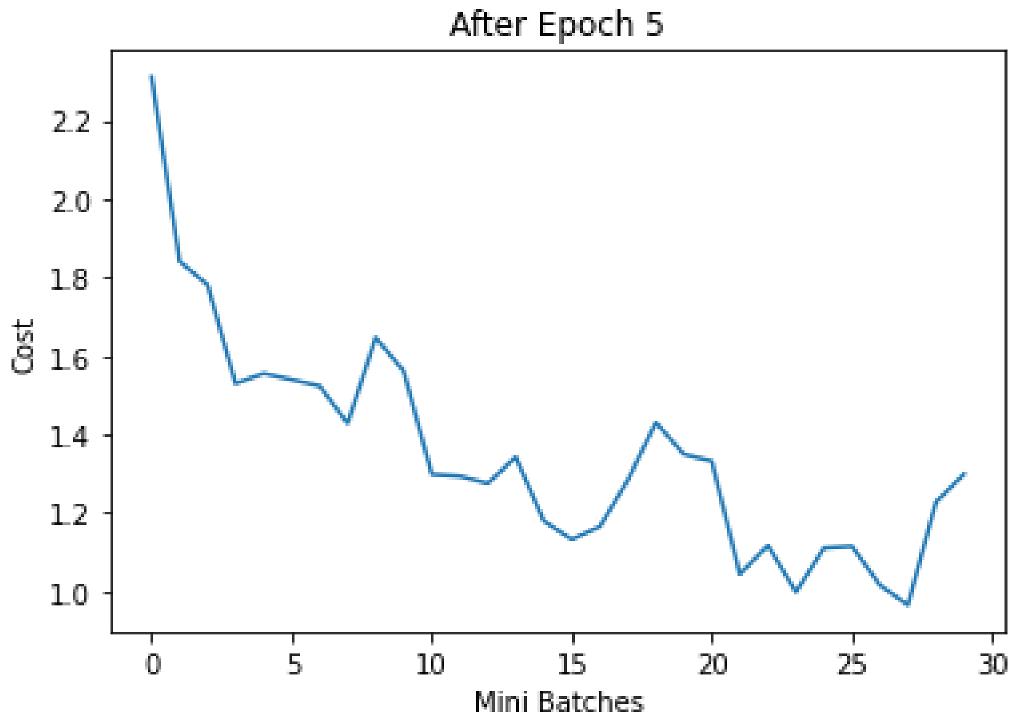

```
Epoch 3
Cost After Mini Batch 0: 1.132018
Cost After Mini Batch 100: 1.164940
Cost After Mini Batch 200: 1.283786
Cost After Mini Batch 300: 1.429813
Cost After Mini Batch 400: 1.348689
After Epoch 3, Validation accuracy = 51.12000274658203
```



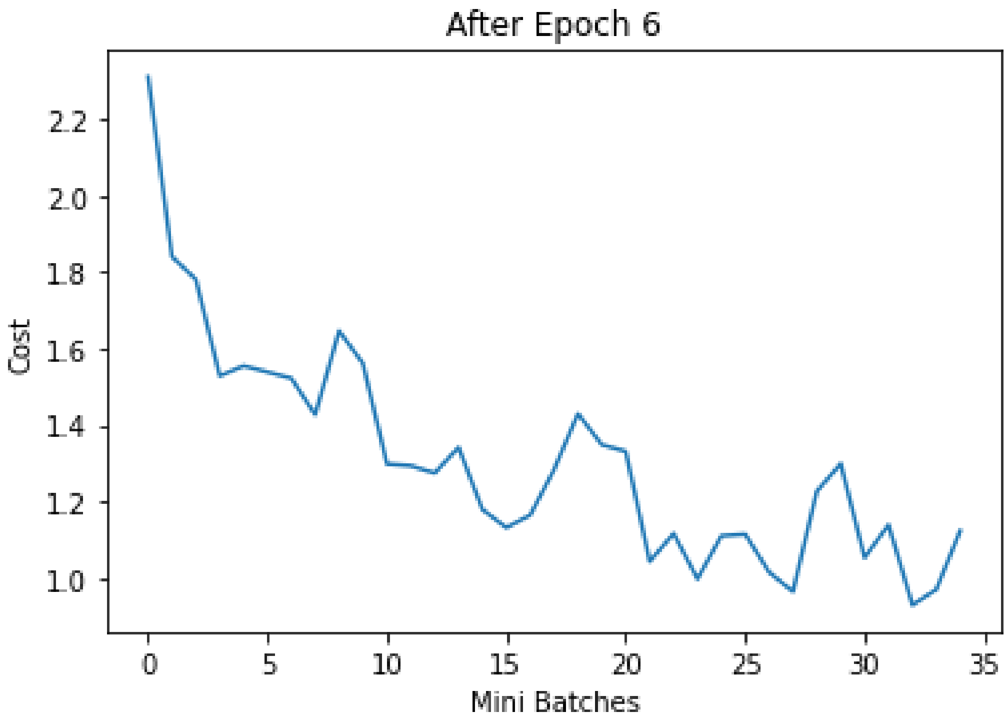

```
Epoch 4
Cost After Mini Batch 0: 1.331268
Cost After Mini Batch 100: 1.043499
Cost After Mini Batch 200: 1.116550
Cost After Mini Batch 300: 0.997852
Cost After Mini Batch 400: 1.110326
After Epoch 4, Validation accuracy = 52.439998626708984
```



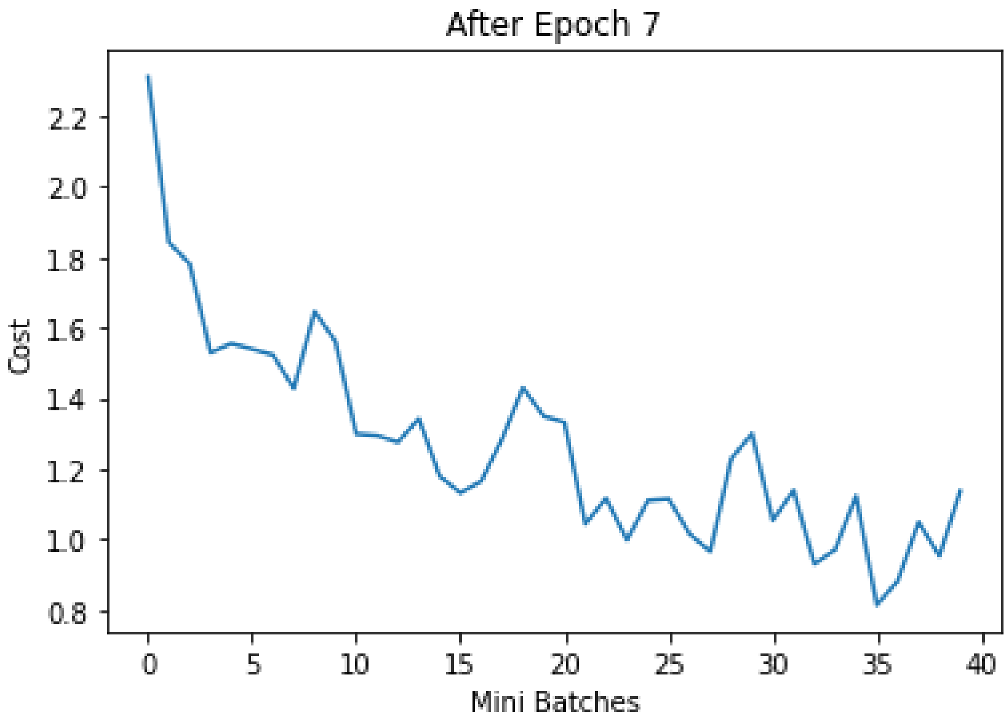

```
Epoch 5
Cost After Mini Batch 0: 1.114824
Cost After Mini Batch 100: 1.015516
Cost After Mini Batch 200: 0.964952
Cost After Mini Batch 300: 1.227359
Cost After Mini Batch 400: 1.299149
After Epoch 5, Validation accuracy = 52.70000076293945
```



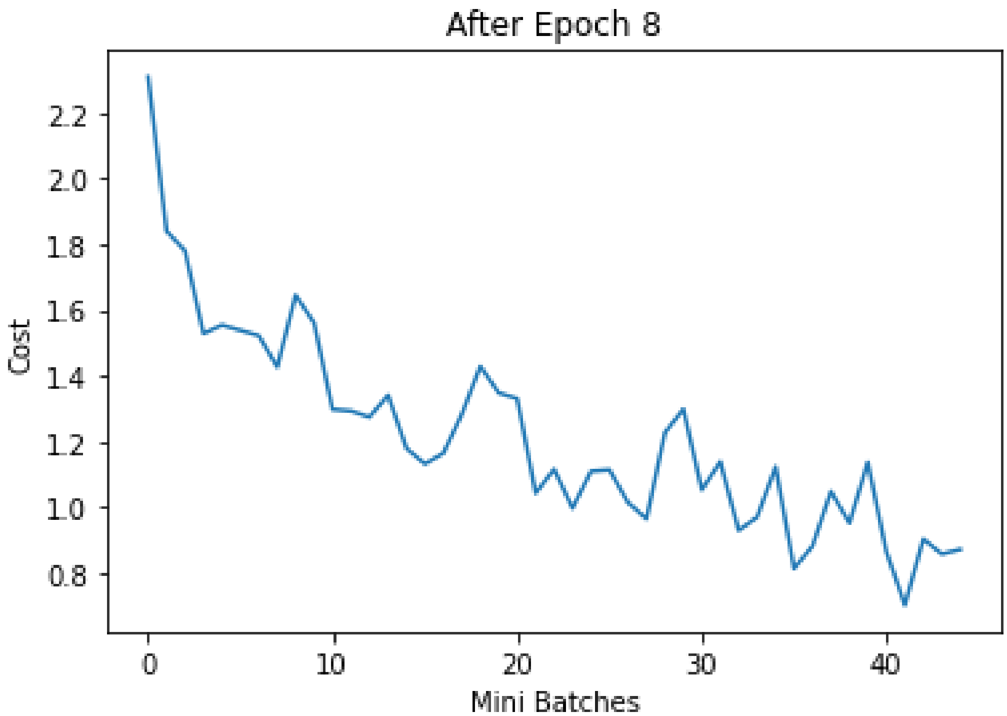

```
Epoch 6
Cost After Mini Batch 0: 1.053469
Cost After Mini Batch 100: 1.139132
Cost After Mini Batch 200: 0.929680
Cost After Mini Batch 300: 0.970843
Cost After Mini Batch 400: 1.123901
After Epoch 6, Validation accuracy = 53.70000076293945
```



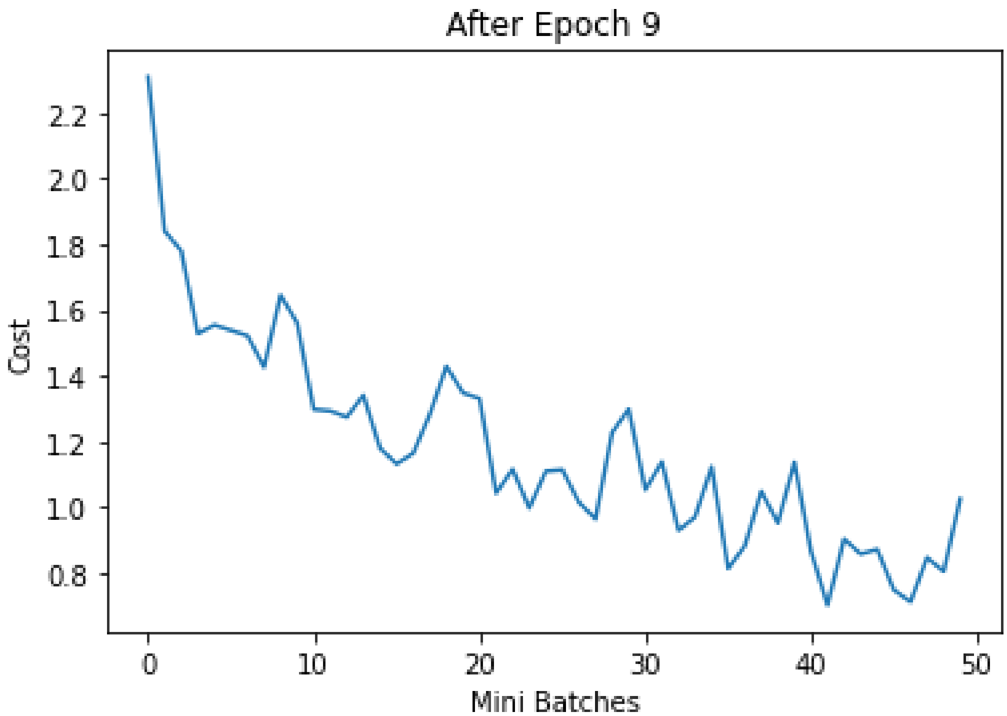

```
Epoch 7
Cost After Mini Batch 0: 0.813730
Cost After Mini Batch 100: 0.882246
Cost After Mini Batch 200: 1.048999
Cost After Mini Batch 300: 0.952442
Cost After Mini Batch 400: 1.137312
After Epoch 7, Validation accuracy = 52.78000259399414
```




```
Epoch 8
Cost After Mini Batch 0: 0.865818
Cost After Mini Batch 100: 0.702905
Cost After Mini Batch 200: 0.904021
Cost After Mini Batch 300: 0.857858
Cost After Mini Batch 400: 0.872158
After Epoch 8, Validation accuracy = 52.619998931884766
```




```
Epoch 9
Cost After Mini Batch 0: 0.748782
Cost After Mini Batch 100: 0.712571
Cost After Mini Batch 200: 0.846918
Cost After Mini Batch 300: 0.804748
Cost After Mini Batch 400: 1.026457
After Epoch 9, Validation accuracy = 53.500003814697266
```




```
Execution Time --- 171.6047477722168 seconds ---
```

6 Confusion Matrix

[10]:
```python
accuracy , confusionMatrix = predictPy(testDataLoader , model)
print('Accuracy on Test Data = {}%'.format(accuracy*100))
print('Confusion Matrix on Test Data')
print(confusionMatrix)
```

```
Accuracy on Test Data = 73.6199951171875%
Confusion Matrix on Test Data
[[349  10  27  12  24   4   4   3  43  22]
 [  3 434   5   7   6   3   6   2  24  45]
 [ 21   1 263  50  67  23  27   9   5   2]
 [  7   2  28 306  26  85  23  11   6   6]
 [ 11   5  28  21 383   4  37  11   6   3]
 [  5   1  15  82  27 347  14   8   1   3]
 [  2   3  13  41  28   8 394   3   0   3]
 [  5   2   6  25  57  22   3 369   4   8]
 [ 21  27   4  11   8   1   2   0 423  12]
 [  5  29   3  11   6   4   2   3   6 413]]
```

7 Plotting Randomly Selected Images

- Without Batch Normalization
- P : Predicted Class, R : Real Class

[12]:
```
displayImages(testData , model)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:25: UserWarning:
The use of `x.T` on tensors of dimension other than 2 to reverse their shape is
deprecated and it will throw an error in a future release. Consider `x.mT` to
transpose batches of matricesor `x.permute(*torch.arange(x.ndim - 1, -1, -1))`
to reverse the dimensions of a tensor. (Triggered internally at
../aten/src/ATen/native/TensorShape.cpp:2981.)
```

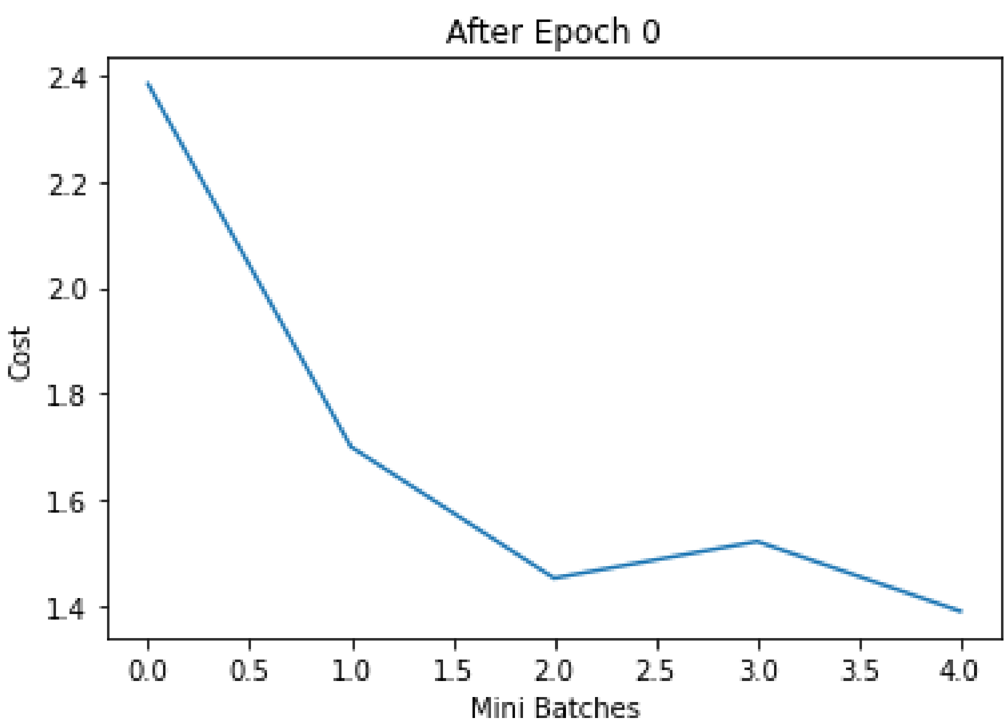
8 With Batch Normalization

[ ]:
```python
class NeuralNetWithBN(nn.Module):
    def __init__(self):
        super(NeuralNetWithBN, self).__init__()
        self.relu = nn.ReLU()
        self.l1 = nn.Linear(inputs, noOfNodesL1)
        self.b1 = nn.BatchNorm1d(noOfNodesL1)
        self.l2 = nn.Linear(noOfNodesL1, noOfNodesL2)
        self.b2 = nn.BatchNorm1d(noOfNodesL2)
        self.l3 = nn.Linear(noOfNodesL2 , noOfNodesL3)
        self.b3 = nn.BatchNorm1d(noOfNodesL3)
        self.l4 = nn.Linear(noOfNodesL3 , outputs)
    def forward(self, x):
        out = self.relu(self.b1(self.l1(x)))
        out = self.relu(self.b2(self.l2(out)))
        out = self.relu(self.b3(self.l3(out)))
        out = self.l4(out)
        # no activation and no4softmax at the end
        return out
```

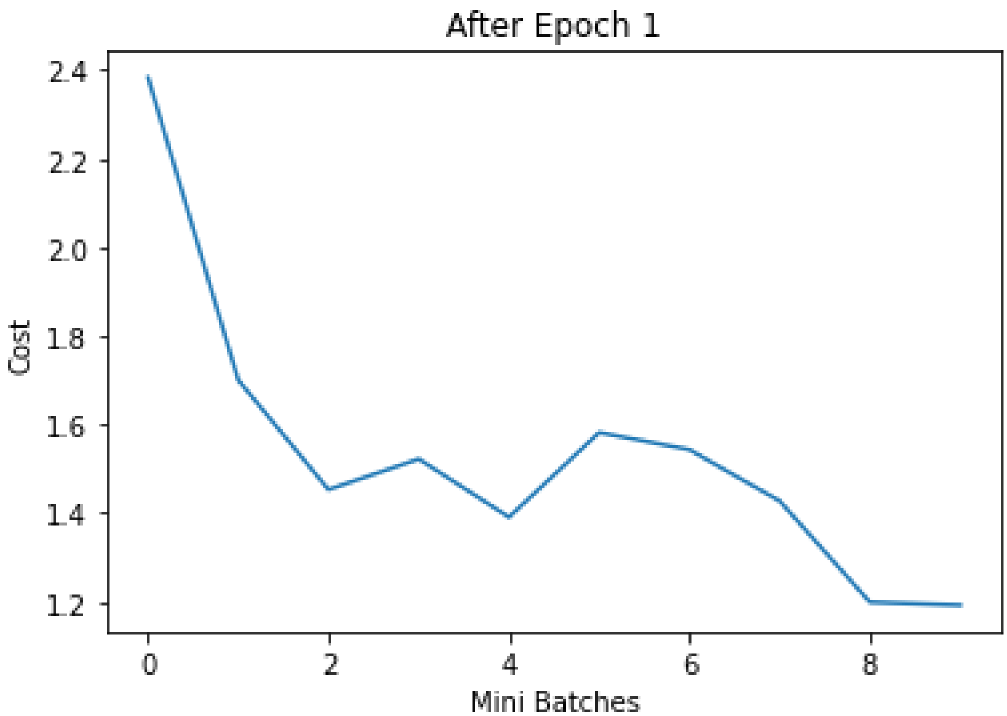
[ ]:
```python
"""
Intilizing the model
"""
modelWithBN = NeuralNetWithBN()
optim = torch.optim.SGD(modelWithBN.parameters(), lr=learningRate , momentum =␣
↪0.9)
criterion = nn.CrossEntropyLoss()

"""
Training
"""
modelWithBN.train()
start_time = time.time()
n_total_steps = batchSize
totalCost = []
for epoch in range(epochs):
  print('Epoch {} '.format(epoch))
  for i , (images,labels) in enumerate(trainDataLoader):
    # FLATTENING
    images = torch.reshape(images , (batchSize , 3072)) # Size : [batchSize X␣
↪3072]
    # FORWARD PASS
    yPred = modelWithBN(images)
    loss = criterion(yPred , labels)

    # OPTIMISATION
```

```
    optim.zero_grad()
    loss.backward()
    optim.step()
    cost = loss.item()
    if i%100 == 0:
      print('Cost After Mini Batch %i: %f' %(i , cost))
      totalCost.append(loss.item())
  modelWithBN.eval()
  accuracy, confusionMatrix = predictPy(validDataLoader , modelWithBN)
  print('After Epoch {}, Validation accuracy = {}'.format(epoch , accuracy*100))
  plt.plot(totalCost)
  plt.title('After Epoch {}'.format(epoch))
  plt.xlabel('Mini Batches')
  plt.ylabel('Cost')
  plt.show()
print("Execution Time --- %s seconds ---" % (time.time() - start_time))
```

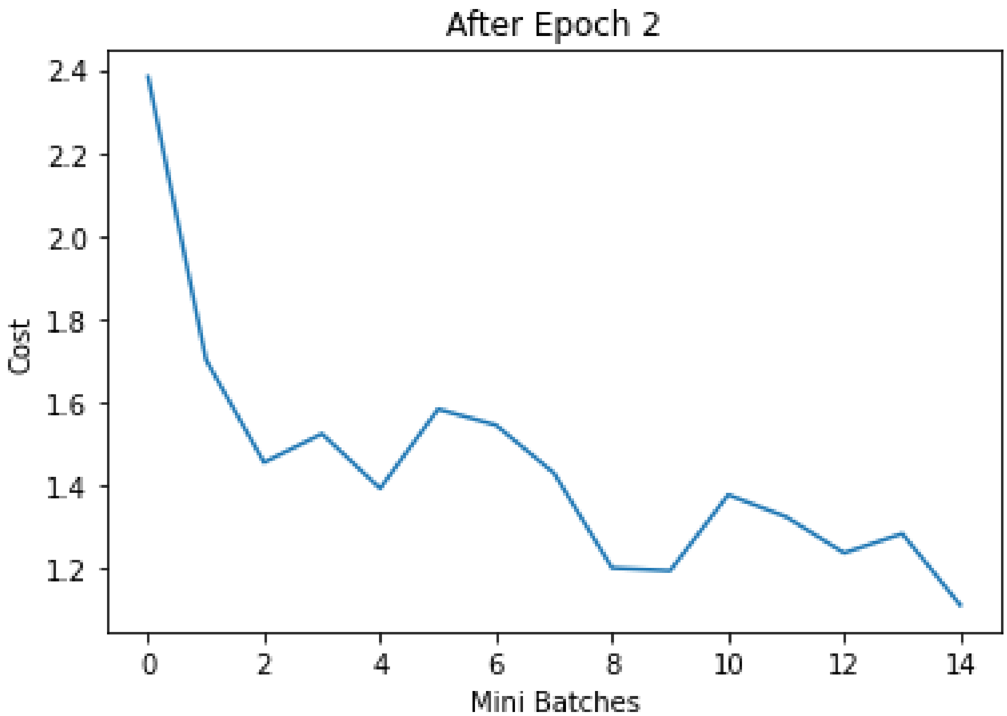
```
Epoch 0
Cost After Mini Batch 0: 2.383224
Cost After Mini Batch 100: 1.700450
Cost After Mini Batch 200: 1.453422
Cost After Mini Batch 300: 1.522559
Cost After Mini Batch 400: 1.391195
After Epoch 0, Validation accuracy = 48.5
```



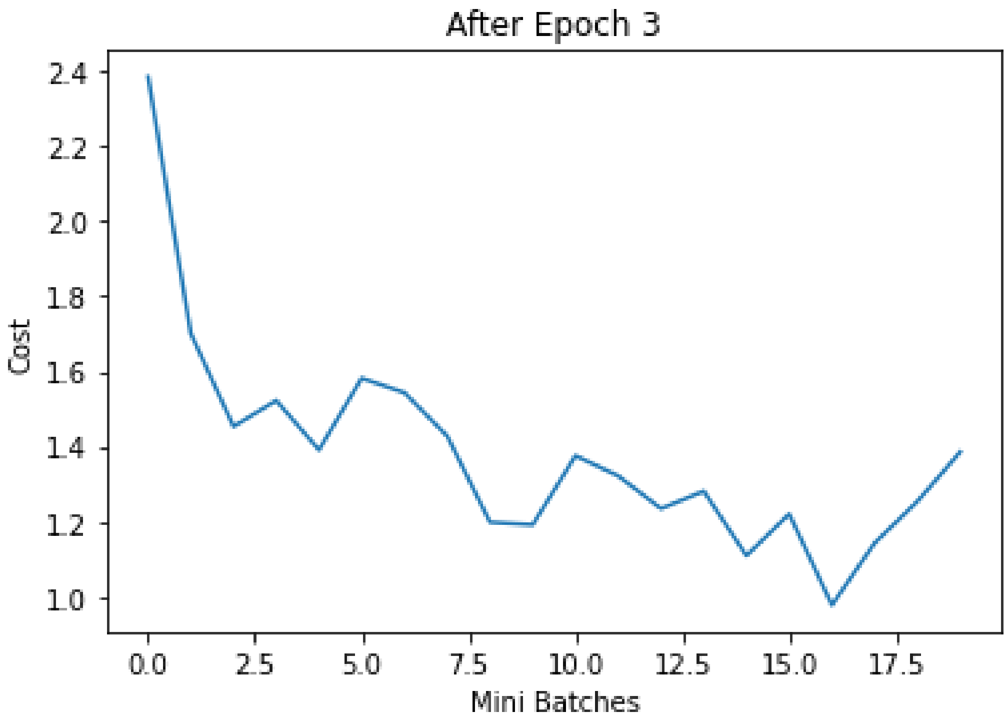
```
Epoch 1
Cost After Mini Batch 0: 1.582003
Cost After Mini Batch 100: 1.543284
Cost After Mini Batch 200: 1.427740
Cost After Mini Batch 300: 1.199081
Cost After Mini Batch 400: 1.192501
After Epoch 1, Validation accuracy = 48.97999954223633
```



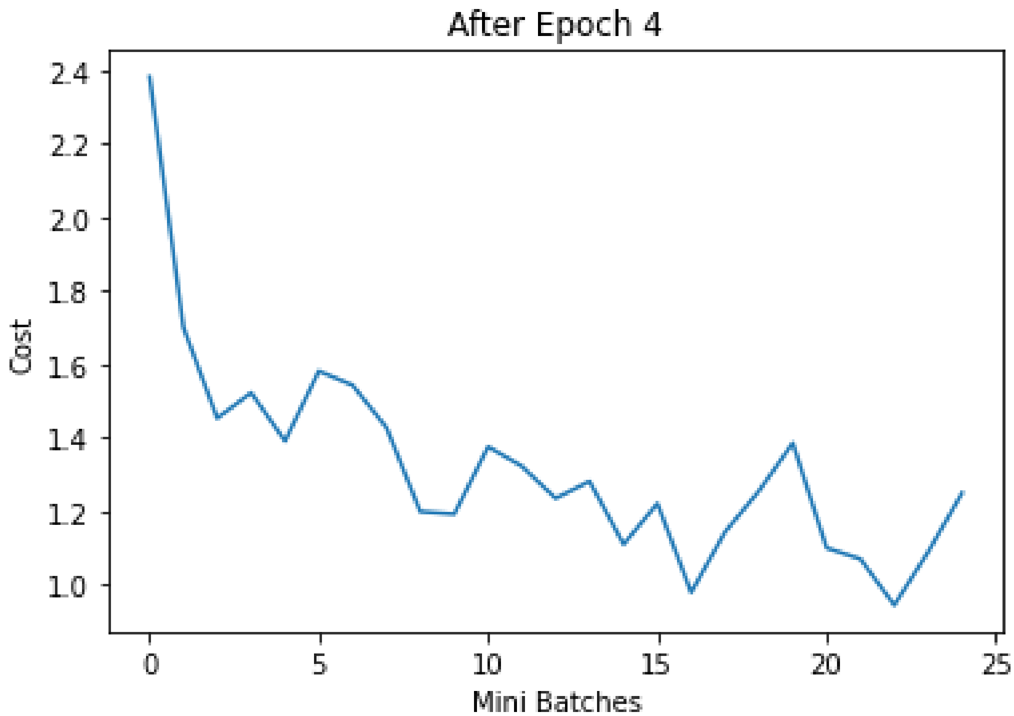

```
Epoch 2
Cost After Mini Batch 0: 1.375597
Cost After Mini Batch 100: 1.322512
Cost After Mini Batch 200: 1.235305
Cost After Mini Batch 300: 1.281783
Cost After Mini Batch 400: 1.109986
After Epoch 2, Validation accuracy = 49.63999938964844
```



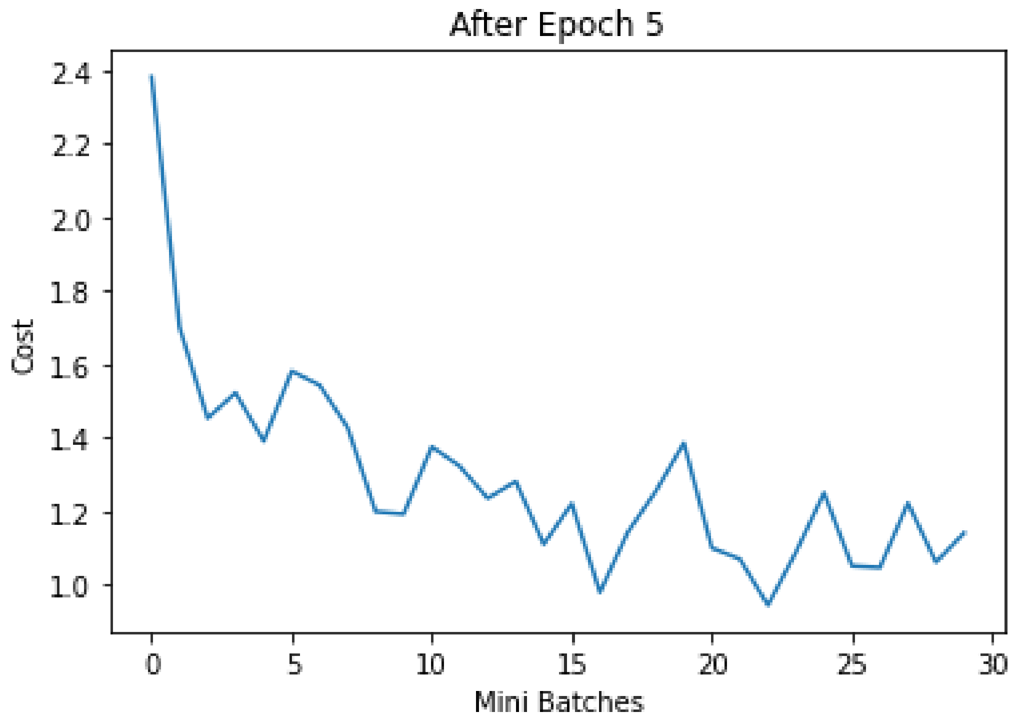

```
Epoch 3
Cost After Mini Batch 0: 1.221174
Cost After Mini Batch 100: 0.979037
Cost After Mini Batch 200: 1.143501
Cost After Mini Batch 300: 1.254964
Cost After Mini Batch 400: 1.385743
After Epoch 3, Validation accuracy = 52.47999954223633
```



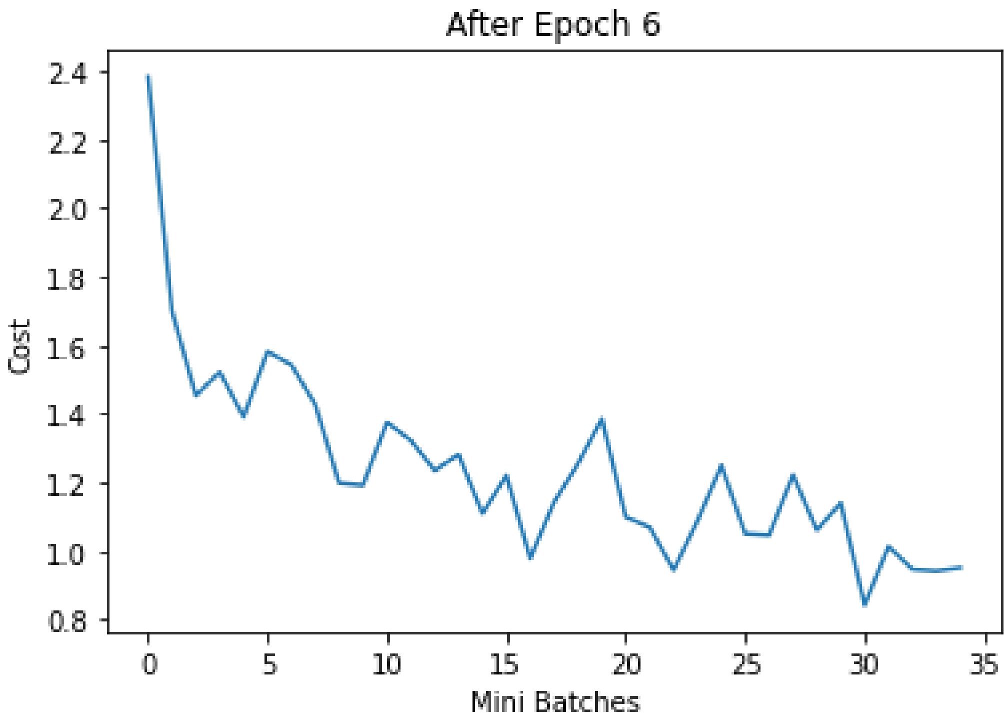

```
Epoch 4
Cost After Mini Batch 0: 1.100049
Cost After Mini Batch 100: 1.069984
Cost After Mini Batch 200: 0.944833
Cost After Mini Batch 300: 1.088776
Cost After Mini Batch 400: 1.249971
After Epoch 4, Validation accuracy = 52.439998626708984
```



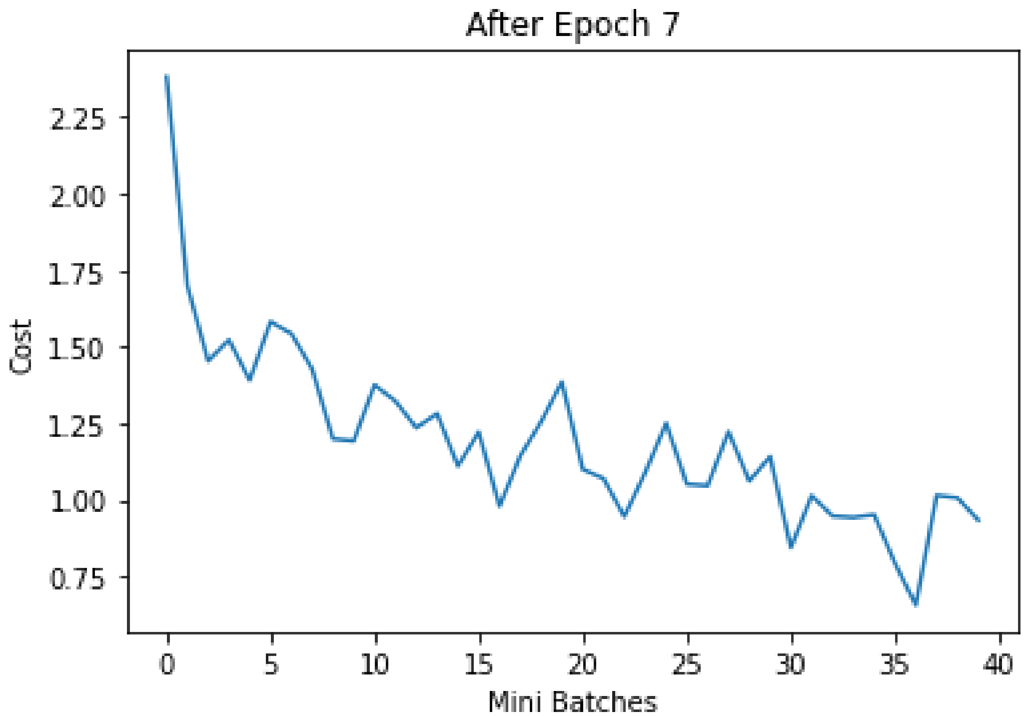

```
Epoch 5
Cost After Mini Batch 0: 1.051230
Cost After Mini Batch 100: 1.046620
Cost After Mini Batch 200: 1.222595
Cost After Mini Batch 300: 1.061490
Cost After Mini Batch 400: 1.140897
After Epoch 5, Validation accuracy = 55.159996032714844
```



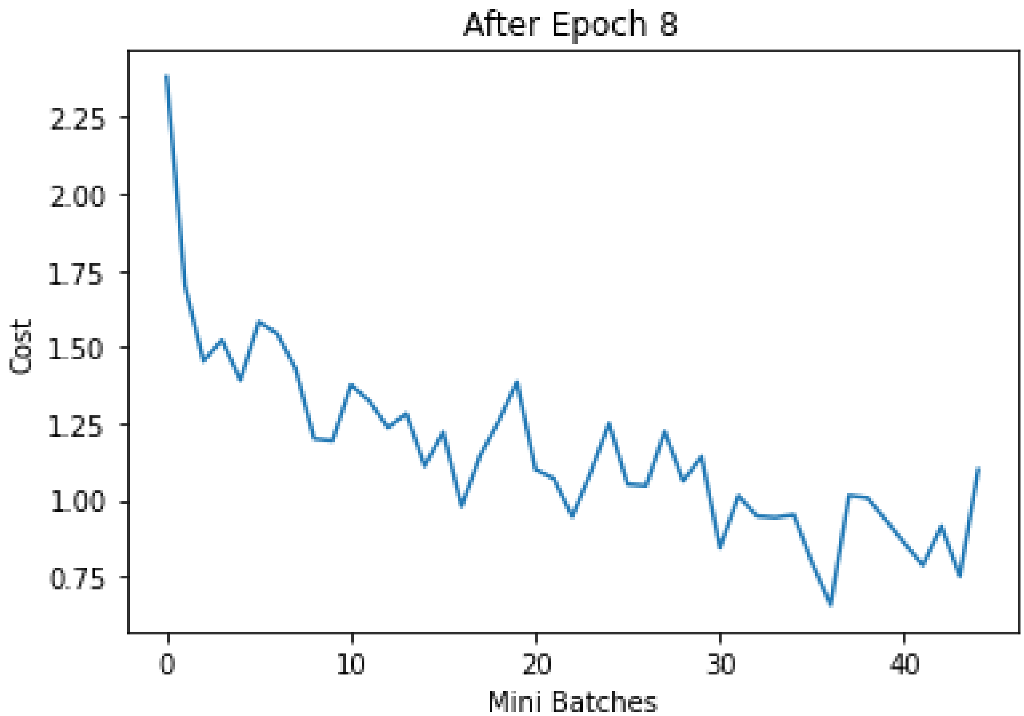

```
Epoch 6
Cost After Mini Batch 0: 0.843136
Cost After Mini Batch 100: 1.013773
Cost After Mini Batch 200: 0.947004
Cost After Mini Batch 300: 0.942487
Cost After Mini Batch 400: 0.951548
After Epoch 6, Validation accuracy = 54.07999801635742
```



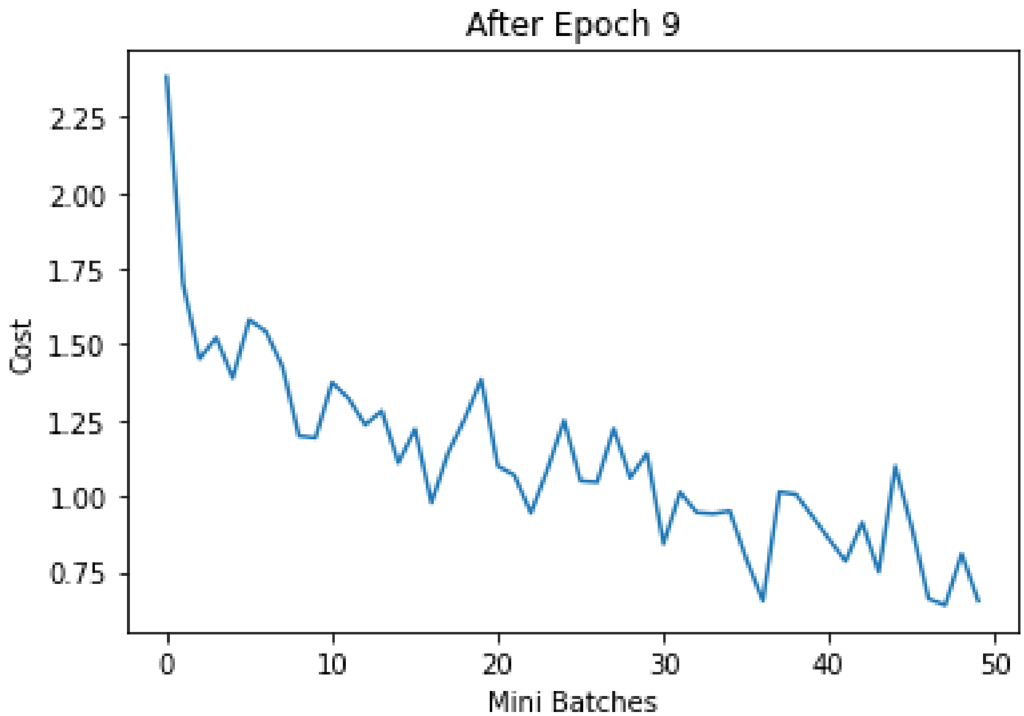

```
Epoch 7
Cost After Mini Batch 0: 0.792948
Cost After Mini Batch 100: 0.656006
Cost After Mini Batch 200: 1.014510
Cost After Mini Batch 300: 1.006602
Cost After Mini Batch 400: 0.933423
After Epoch 7, Validation accuracy = 53.820003509521484
```




```
Epoch 8
Cost After Mini Batch 0: 0.858434
Cost After Mini Batch 100: 0.785785
Cost After Mini Batch 200: 0.913952
Cost After Mini Batch 300: 0.749897
Cost After Mini Batch 400: 1.099093
After Epoch 8, Validation accuracy = 53.15999984741211
```




```
Epoch 9
Cost After Mini Batch 0: 0.894441
Cost After Mini Batch 100: 0.662178
Cost After Mini Batch 200: 0.641659
Cost After Mini Batch 300: 0.810018
Cost After Mini Batch 400: 0.655432
After Epoch 9, Validation accuracy = 53.96000289916992
```



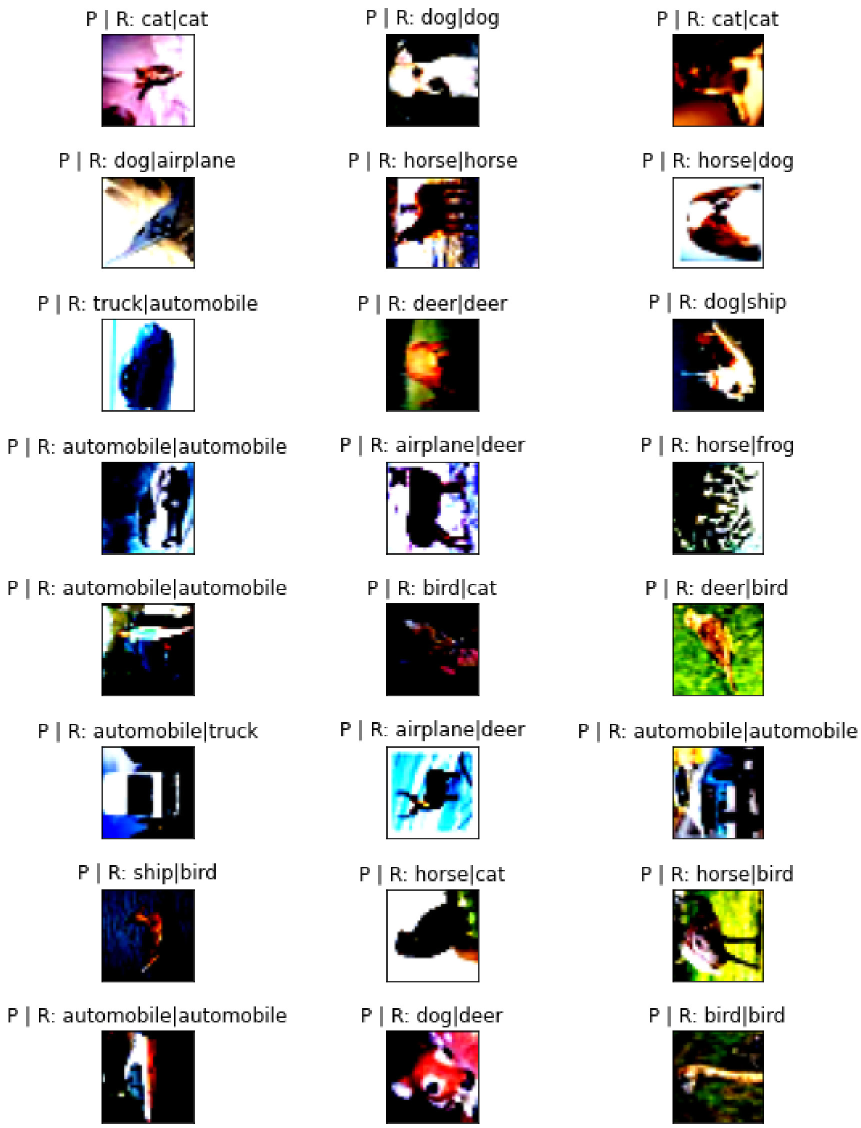

```
Execution Time --- 225.135009765625 seconds ---
```

9 Confusion Matrix

[ ]:
```
accuracy , confusionMatrix = predictPy(testDataLoader , modelWithBN)
print('Accuracy on Test Data = {}%'.format(accuracy*100))
print('Confusion Matrix on Test Data')
print(confusionMatrix)
```

```
Accuracy on Test Data = 76.5%
Confusion Matrix on Test Data
[[437  11  13   2   5   3   5   8  21  10]
 [ 13 401   5   1   2   2   6   0   6  43]
 [ 29   5 302  34  34  16  33  12   3   4]
 [ 13   9  27 337  14  77  36  17   2   7]
 [ 17   5  41  17 350  13  22  23   1   2]
 [  5   3  26  81   9 340   8  24   1   1]
 [  4   1   8  21  13   5 443   1   0   1]
 [ 11   2  10  12  12  26   5 420   2   3]
 [ 72  24  10   5   7   7   3   2 368  12]
 [ 14  22   5   5   4   8   1   5   5 427]]
```

```
[ ]: displayImages(testData , modelWithBN)
```



10 Report

1. Prediction Accuracy on Test Data (Without Batch Normalization) - 73.6%

   Prediction Accuracy on Test Data (With Batch Normalization) - 76.5 %

2. **Use batch-normalization. Does it improve the test accuracy? Does it affect training time?**

   Yes as seen, from above, Batch Normalization has improved the accuracy by a small margin.

Maybe this can also be associated with the initialization of weights.

Execution Time

With Batch Normalization - 225.14 secs

Without BN - 171.60 secs

We can see a considerable increase in Execution Time

11 CNN

Loading Datasets and Performing Necessory Transformations

[6]:
```
train_transform = transforms.Compose([
  transforms.RandomCrop(32, padding=4),
  transforms.RandomHorizontalFlip(),
  transforms.ToTensor(),
  transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)),
])
test_transform = transforms.Compose([
  transforms.ToTensor(),
  transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)),
])

train_dset = torchvision.datasets.CIFAR10(root="data/", train=True,␣
↪transform=train_transform, download=True)
test_dset = torchvision.datasets.CIFAR10(root="data/", train=False,␣
↪transform=test_transform, download=True)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
data/cifar-10-python.tar.gz

  0%|          | 0/170498071 [00:00<?, ?it/s]


Extracting data/cifar-10-python.tar.gz to data/
Files already downloaded and verified
```

[7]:
```
train_loader = DataLoader(train_dset, batch_size=100, shuffle=True,␣
↪num_workers=2)
test_loader = DataLoader(test_dset, batch_size=100, shuffle=False,␣
↪num_workers=2)
```

Defining the Architecture

[8]:
```
class VGG(nn.Module):
  CONFIGS = {
```

```
    "vgg11": [64, "pool", 128, "pool", 256, 256, "pool", 512, 512, "pool",␣
↪512, 512, "pool"],
 }
 def __init__(self, cfg):
   super(VGG, self).__init__()
   in_dim = 3
   layers = []
   for layer in self.CONFIGS[cfg]:
       if layer == "pool":
           maxpool = nn.MaxPool2d(kernel_size = 2 , stride = 2)
           layers.append(maxpool)
       else:
           block = nn.Sequential(nn.Conv2d(in_dim , layer , kernel_size = 3 ,␣
↪padding = 1),
                                 nn.BatchNorm2d(layer),
                                 nn.ReLU())
           layers.append(block)
           in_dim = layer
   avgpool = nn.AvgPool2d(kernel_size=1)
   layers.append(avgpool)
   self.layers = nn.Sequential(*layers)
   self.fc1 = nn.Linear(512, 100)
   self.fc2 = nn.Linear(100,10)

 def forward(self, x):
   out = self.layers(x)
   out = torch.flatten(out , start_dim = 1)
   out = self.fc1(out)
   out = self.fc2(out)
   return out
```

[9]:
```
def pbar(p=0, msg="", bar_len=20):
    sys.stdout.write("\033[K")
    sys.stdout.write("\x1b[2K" + "\r")
    block = int(round(bar_len * p))
    text = "Progress: [{}] {}% {}".format(
        "\x1b[32m" + "=" * (block - 1) + ">" + "\033[0m" + "-" * (bar_len -␣
↪block),
        round(p * 100, 2),
        msg,
    )
    print(text, end="\r")
    if p == 1:
        print()


class AvgMeter:
```

```
    def __init__(self):
        self.reset()

    def reset(self):
        self.metrics = {}

    def add(self, batch_metrics):
        if self.metrics == {}:
            for key, value in batch_metrics.items():
                self.metrics[key] = [value]
        else:
            for key, value in batch_metrics.items():
                self.metrics[key].append(value)

    def get(self):
        return {key: np.mean(value) for key, value in self.metrics.items()}

    def msg(self):
        avg_metrics = {key: np.mean(value) for key, value in self.metrics.
↪items()}
        return "".join(["[{}] {:.5f} ".format(key, value) for key, value in␣
↪avg_metrics.items()])
```

[10]:
```
def train(model, optim, lr_sched=None, epochs=200, device=torch.device("cuda"␣
↪if torch.cuda.is_available() else "cpu"), criterion=None, metric_meter=None,␣
↪out_dir="out/"):
  if device == 'cuda':
    torch.cuda.empty_cache()
    gc.collect()
  model.to(device)
  best_acc = 0
  trainError = []
  validError = []
  predAcc = []
  for epoch in range(epochs):
    model.train()
    metric_meter.reset()
    for indx, (img, target) in enumerate(train_loader):
      img = img.to(device)
      target = target.to(device)

      out = model(img)
      loss = criterion(out, target)
      optim.zero_grad()
      loss.backward()
      optim.step()
      cost = loss.item()
```

```
    if indx % 5 == 0:
      trainError.append(cost)

    metric_meter.add({"train loss": cost})
    pbar(indx / len(train_loader), msg=metric_meter.msg())
  print('Please Work')
  pbar(1, msg=metric_meter.msg())

  model.eval()
  metric_meter.reset()
  for indx, (img, target) in enumerate(test_loader):
    img = img.to(device)
    target = target.to(device)

    out= model(img)
    loss = criterion(out, target)
    cost = loss.item()
    if indx % 5 == 0:
      validError.append(cost)
    yPred = F.softmax(out , dim =1)
    predictedNumber = torch.argmax(yPred , dim = 1)
    noOfRightPrediction = torch.sum(predictedNumber == target)
    totalPrediction = yPred.shape[0]
    acc = noOfRightPrediction/totalPrediction
    acc = acc.cpu().detach().numpy()
    if indx % 5 == 0:
      predAcc.append(acc)

    metric_meter.add({"test loss": loss.item(), "test acc": acc})
    pbar(indx / len(test_loader), msg=metric_meter.msg())
  pbar(1, msg=metric_meter.msg())

  test_metrics = metric_meter.get()
  if test_metrics["test acc"] > best_acc:
    print(
        "\x1b[33m"
        + f"test acc improved from {round(best_acc, 5)} to {round(test_metrics['test acc'], 5)}"
        + "\033[0m"
    )
    best_acc = test_metrics['test acc']
    torch.save(model.state_dict(), os.path.join(out_dir, "best.ckpt"))
  lr_sched.step()
plt.plot(trainError)
plt.xlabel('Epochs')
plt.ylabel('Training Error')
plt.show()
```

```python
    plt.plot(validError)
    plt.xlabel('Epochs')
    plt.ylabel('Validation Error')
    plt.show()
    plt.plot(predAcc)
    plt.xlabel('Epochs')
    plt.ylabel('Prediction Accuracy')
    plt.show()
```

[11]:
```python
def run_experiment(epochs=200):
    model_name = "VGG"
    model_cfg = "vgg11"
    model = VGG('vgg11')
    optim = torch.optim.SGD(model.parameters(), lr=1e-1, momentum=0.9,␣
 ↪weight_decay=5e-4)
    lr_sched = torch.optim.lr_scheduler.CosineAnnealingLR(optim, T_max=epochs)
    criterion = nn.CrossEntropyLoss()
    metric_meter = AvgMeter()
    out_dir = f"{model_name}_{model_cfg}"
    os.makedirs(out_dir, exist_ok=True)
    train(model, optim, lr_sched, epochs=epochs, criterion=criterion,␣
 ↪metric_meter=metric_meter, out_dir=out_dir)
    return model
```

12 Training the CNN

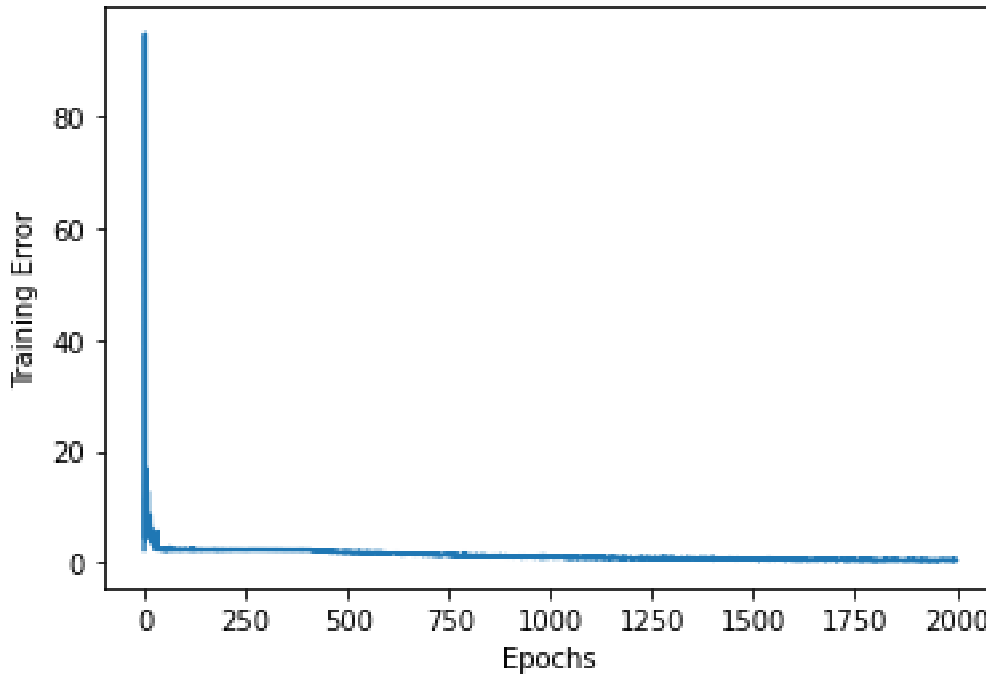
Displayed the Train Cost, Validation Cost and Validation Accuracy

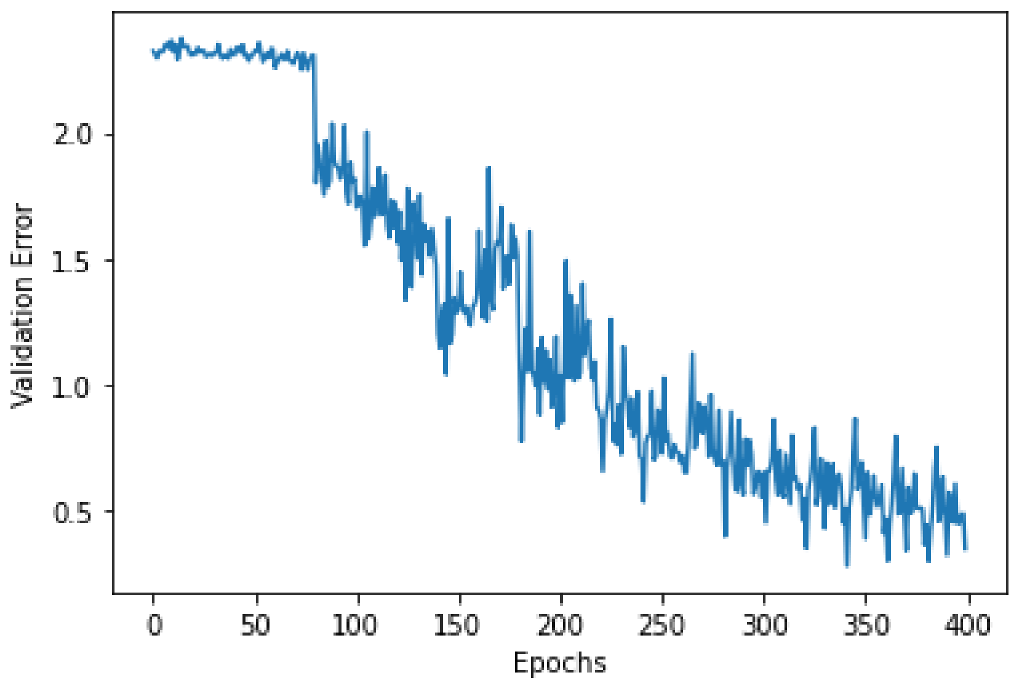
[12]:
```python
modelVGG = run_experiment(epochs=20)
```

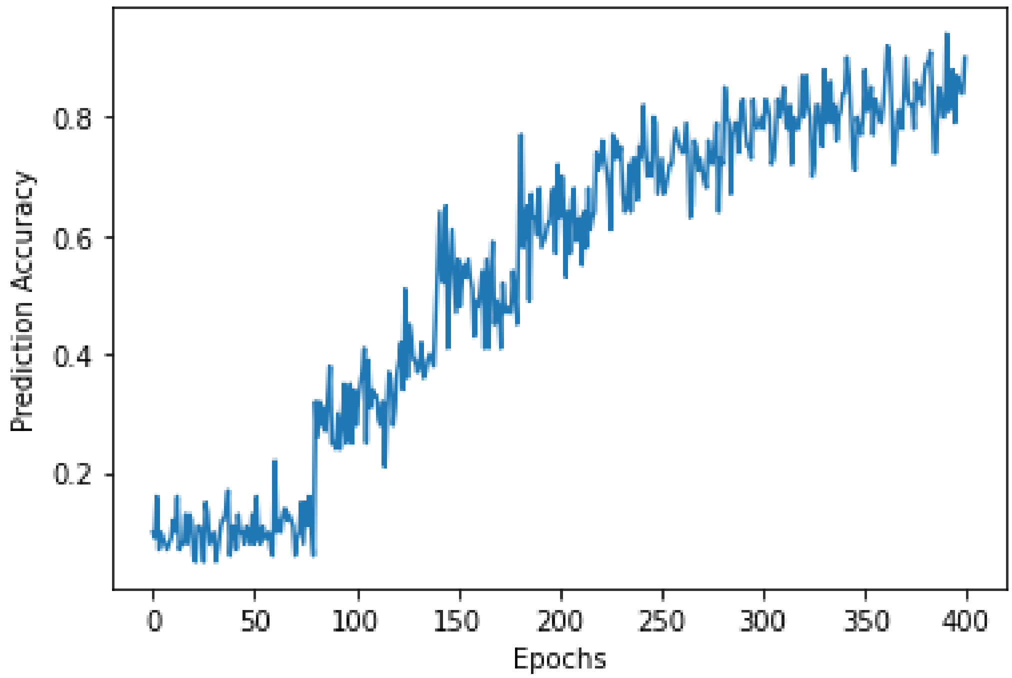
```
Please Work
Progress: [===================>] 100% [train loss] 4.37105
Progress: [===================>] 100% [test loss] 2.33205 [test acc]
0.10000
test acc improved from 0 to 0.10000000149011612
Please Work
Progress: [===================>] 100% [train loss] 2.33519
Progress: [===================>] 100% [test loss] 2.31161 [test acc]
0.10000
Please Work
Progress: [===================>] 100% [train loss] 2.30926
Progress: [===================>] 100% [test loss] 2.31434 [test acc]
0.10090
test acc improved from 0.10000000149011612 to 0.10090000182390213
Please Work
Progress: [===================>] 100% [train loss] 2.29586
```

```
Progress: [====================>] 100% [test loss] 2.28165 [test acc]
0.12980
test acc improved from 0.10090000182390213 to 0.1298000067472458
Please Work
Progress: [====================>] 100% [train loss] 2.03508
Progress: [====================>] 100% [test loss] 1.81641 [test acc]
0.28450
test acc improved from 0.1298000067472458 to 0.28450000286102295
Please Work
Progress: [====================>] 100% [train loss] 1.77731
Progress: [====================>] 100% [test loss] 1.67264 [test acc]
0.33160
test acc improved from 0.28450000286102295 to 0.33160001039505005
Please Work
Progress: [====================>] 100% [train loss] 1.60010
Progress: [====================>] 100% [test loss] 1.56384 [test acc]
0.40560
test acc improved from 0.33160001039505005 to 0.40560001134872437
Please Work
Progress: [====================>] 100% [train loss] 1.40590
Progress: [====================>] 100% [test loss] 1.28519 [test acc]
0.52850
test acc improved from 0.40560001134872437 to 0.5285000205039978
Please Work
Progress: [====================>] 100% [train loss] 1.23223
Progress: [====================>] 100% [test loss] 1.49581 [test acc]
0.48380
Please Work
Progress: [====================>] 100% [train loss] 1.09219
Progress: [====================>] 100% [test loss] 1.06945 [test acc]
0.62690
test acc improved from 0.5285000205039978 to 0.6269000172615051
Please Work
Progress: [====================>] 100% [train loss] 0.98541
Progress: [====================>] 100% [test loss] 1.15533 [test acc]
0.62230
Please Work
Progress: [====================>] 100% [train loss] 0.90046
Progress: [====================>] 100% [test loss] 0.91588 [test acc]
0.69180
test acc improved from 0.6269000172615051 to 0.6917999982833862
Please Work
Progress: [====================>] 100% [train loss] 0.82347
Progress: [====================>] 100% [test loss] 0.80108 [test acc]
0.72270
test acc improved from 0.6917999982833862 to 0.7226999998092651
Please Work
Progress: [====================>] 100% [train loss] 0.74968
```

```
Progress: [====================>] 100% [test loss] 0.81656 [test acc]
0.71700
Please Work
Progress: [====================>] 100% [train loss] 0.68185
Progress: [====================>] 100% [test loss] 0.69564 [test acc]
0.76420
test acc improved from 0.7226999998092651 to 0.76419997215271
Please Work
Progress: [====================>] 100% [train loss] 0.61270
Progress: [====================>] 100% [test loss] 0.63950 [test acc]
0.78480
test acc improved from 0.76419997215271 to 0.7847999930381775
Please Work
Progress: [====================>] 100% [train loss] 0.55754
Progress: [====================>] 100% [test loss] 0.60501 [test acc]
0.79420
test acc improved from 0.7847999930381775 to 0.7942000031471252
Please Work
Progress: [====================>] 100% [train loss] 0.50129
Progress: [====================>] 100% [test loss] 0.56405 [test acc]
0.80670
test acc improved from 0.7942000031471252 to 0.8066999912261963
Please Work
Progress: [====================>] 100% [train loss] 0.46348
Progress: [====================>] 100% [test loss] 0.52243 [test acc]
0.82490
test acc improved from 0.8066999912261963 to 0.8248999714851379
Please Work
Progress: [====================>] 100% [train loss] 0.43607
Progress: [====================>] 100% [test loss] 0.50315 [test acc]
0.83190
test acc improved from 0.8248999714851379 to 0.8319000005722046
```


Training Error
80
60
40
20
0
0
250
500
750
1000
1250
1500
1750
2000
Epochs


Validation Error
2.0
1.5
1.0
0.5
0
50
100
150
200
250
300
350
400
Epochs



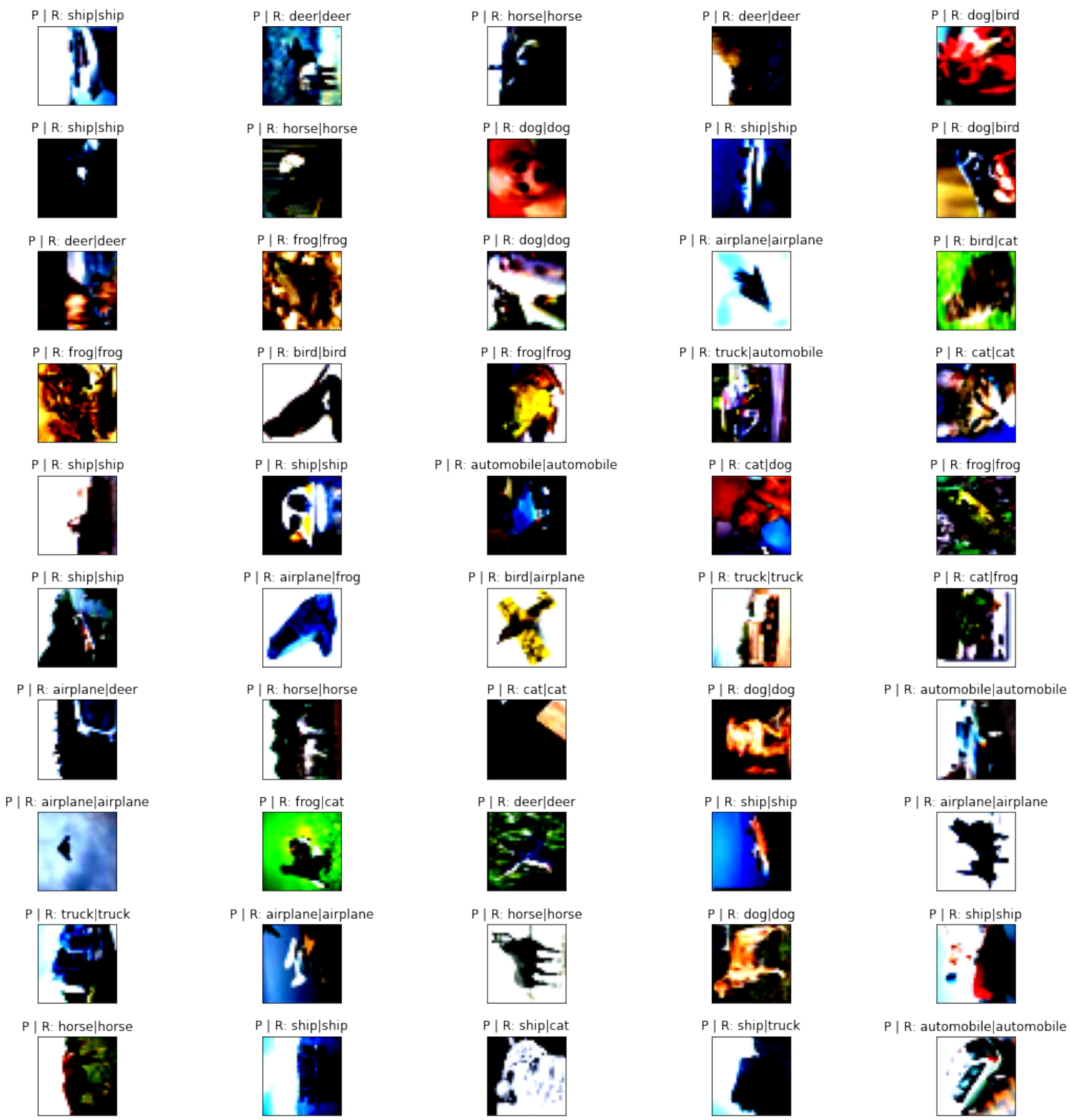
13 Confusion Matrix

[17]:
```
accuracy , confusionMatrix = predictPyCNN(testDataLoader , modelVGG ,␣
↪device=torch.device("cuda" if torch.cuda.is_available() else "cpu"))
print('Accuracy on Test Data = {}%'.format(accuracy*100))
print('Confusion Matrix on Test Data')
print(confusionMatrix)
```

```
Accuracy on Test Data = 87.15999603271484%
Confusion Matrix on Test Data
[[444   1   7   1   3   1   0   2  28   5]
 [  3 469   0   0   0   1   1   0   5  17]
 [ 15   1 378  18  17  11  12   6   1   2]
 [  9   1  17 367  12  73  22   8   0   5]
 [  3   0  15  19 428   6   7  15   2   0]
 [  1   1   6  61  14 397   6  13   0   0]
 [  0   0  10  15  15   5 465   1   2   1]
 [  2   0   4  18   8  14   1 447   0   2]
 [ 10   2   1   6   1   0   0   1 480   5]
 [ 10  26   0   1   0   0   1   2   4 483]]
```

[34]:
```
displayImages2(testData , modelVGG)
```

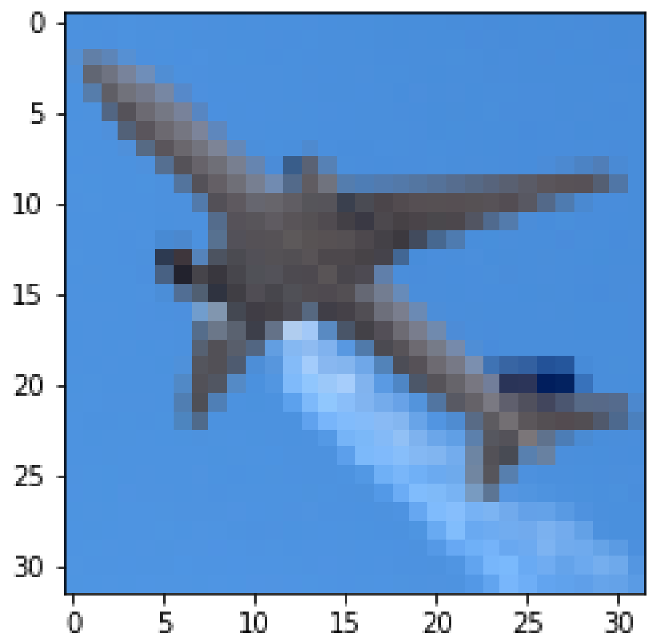
```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:26: UserWarning:
The use of `x.T` on tensors of dimension other than 2 to reverse their shape is
deprecated and it will throw an error in a future release. Consider `x.mT` to
transpose batches of matricesor `x.permute(*torch.arange(x.ndim - 1, -1, -1))`
to reverse the dimensions of a tensor. (Triggered internally at
../aten/src/ATen/native/TensorShape.cpp:2981.)
```



14 Passing 5 Images downloaded from Internet

[19]:

```
airplane = PIL.Image.open("/content/Airplane.png")
airplane = np.array(airplane.convert('RGB'))
plt.imshow(airplane)
plt.show()
```



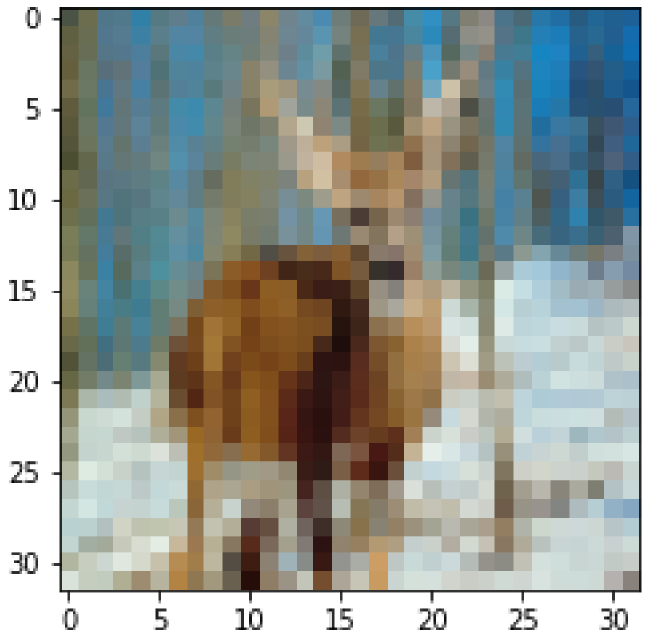
[22]:

```
image = test_transform(airplane)
temp = image.cpu()
image = torch.reshape(image , (1 , 3 , 32 , 32)).float()
image = image.to(device)
temp = torch.clamp(temp , 0 , 1)
out = modelVGG(image)
yPred = F.softmax(out , dim =1)
predictedNumber = torch.argmax(yPred , dim = 1)
print('Predicted Class -', outputLabel[int(predictedNumber)])
```

```
Predicted Class - airplane
```

[23]:

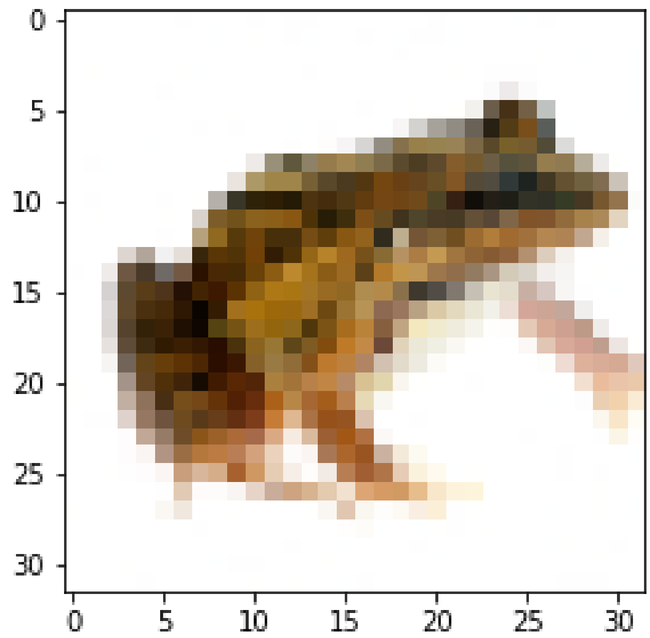
```
deer = PIL.Image.open("/content/Deer.png")
deer = np.array(deer.convert('RGB'))
plt.imshow(deer)
plt.show()
```



[24]:
```
image = test_transform(deer)
temp = image.cpu()
image = torch.reshape(image , (1 , 3 , 32 , 32)).float()
image = image.to(device)
temp = torch.clamp(temp , 0 , 1)
out = modelVGG(image)
yPred = F.softmax(out , dim =1)
predictedNumber = torch.argmax(yPred , dim = 1)
print('Predicted Class -', outputLabel[int(predictedNumber)])
```

```
Predicted Class - deer
```

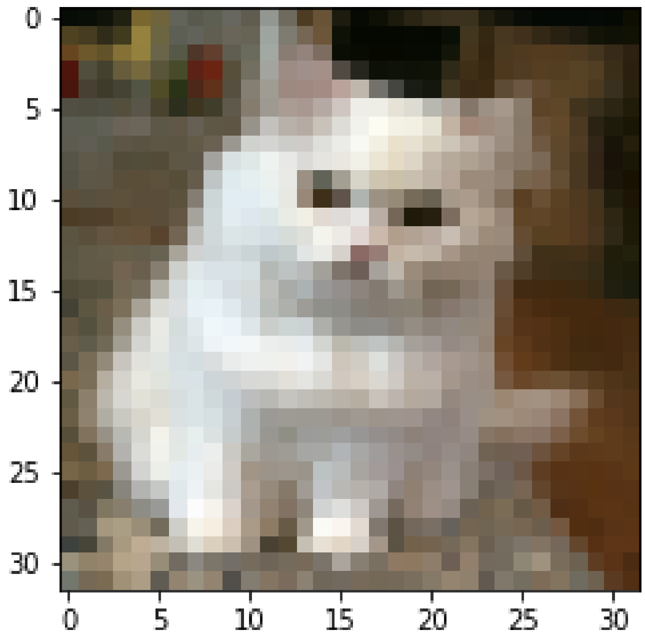
[25]:
```
frog = PIL.Image.open("/content/Frog.png")
frog = np.array(frog.convert('RGB'))
plt.imshow(frog)
plt.show()
```



[26]:
```
image = test_transform(frog)
temp = image.cpu()
image = torch.reshape(image , (1 , 3 , 32 , 32)).float()
image = image.to(device)
temp = torch.clamp(temp , 0 , 1)
out = modelVGG(image)
yPred = F.softmax(out , dim =1)
predictedNumber = torch.argmax(yPred , dim = 1)
print('Predicted Class -', outputLabel[int(predictedNumber)])
```

```
Predicted Class - frog
```

[27]:
```
cat = PIL.Image.open("/content/cat.png")
cat = np.array(cat.convert('RGB'))
plt.imshow(cat)
plt.show()
```



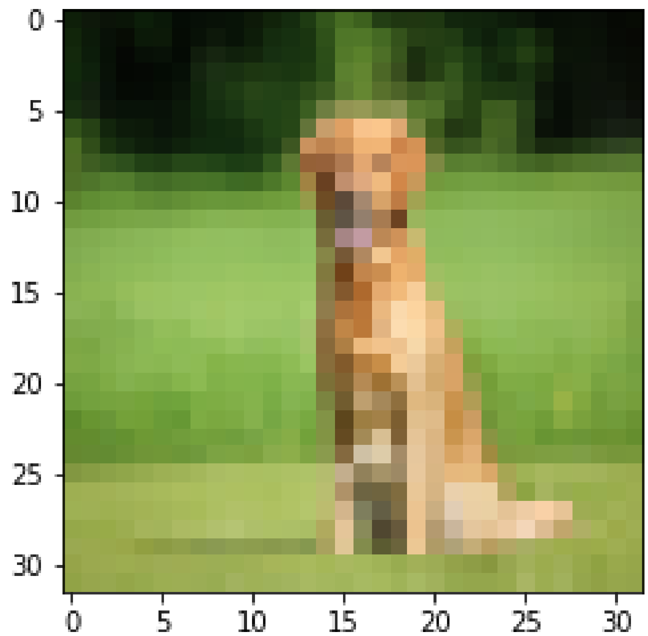
[28]:

```
image = test_transform(cat)
temp = image.cpu()
image = torch.reshape(image , (1 , 3 , 32 , 32)).float()
image = image.to(device)
temp = torch.clamp(temp , 0 , 1)
out = modelVGG(image)
yPred = F.softmax(out , dim =1)
predictedNumber = torch.argmax(yPred , dim = 1)
print('Predicted Class -', outputLabel[int(predictedNumber)])
```

```
Predicted Class - cat
```

[32]:

```
dog = PIL.Image.open("/content/dog.png")
dog = np.array(dog.convert('RGB'))
plt.imshow(dog)
plt.show()
```



[33]:
```
image = test_transform(dog)
temp = image.cpu()
image = torch.reshape(image , (1 , 3 , 32 , 32)).float()
image = image.to(device)
temp = torch.clamp(temp , 0 , 1)
out = modelVGG(image)
yPred = F.softmax(out , dim =1)
predictedNumber = torch.argmax(yPred , dim = 1)
print('Predicted Class -', outputLabel[int(predictedNumber)])
```

```
Predicted Class - deer
```

15 Observation

We can observe, almost all the random images were predicted correctly.