PURDUE UNIVERSITY

Elmore Family School of Electrical and Computer Engineering

Deep Learning

Homework 9

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1 Experiment

In this homework, we have to implement a Vision Transformer and compare its performance with the three models developed for HW4 on the same subset of the MS-COCO dataset:

I have referred to my own HW4 and this medium article for this assignment.

1.1 Dataset

Like HW4, we first download the JSON annotation file. Then using the COCO API, we load 2000 images each for the above mentioned classes and resize them into (64×64) and save 1500 of them into the training dataset and 500 of them into the test dataset.

1.2 Model Training

The optimizer used was Adam with beta values of (0.9,0.99), the learning rate was 0.0001 for 10 epochs and the batch size was 32. The loss function was Binary Cross Entropy Loss.

1.3 Model Architecture

A Vision Transformer consists of the following parts:

1. **Patch Embedding**

   The following steps are involved in this:

   (a) We divide the image into patches of fixed size (16x16 for this homework) and generate the embeddings for each patch. This is done by passing the image through a convolutional layer with stride and kernel size equal to the size of the patch and the number of output channels being equal to the embedding size (384 for this homework). We then permute this tensor so that its of shape (batch size, number of patches, embedding size).

(b) Then we append the same learnable class token of size (1,embedding size) for each image of the batch to the overall embeddings.

(c) Finally we create the learnable parameters for the position embedding of each patch. It is of shape (number of patches +1 , embedding size) for each image of the batch. We then add this to the elementwise to the overall embeddings for each batch.

Therefore the final output of this block is of shape (batch size, number of patches +1, embedding size). This block's learnable parameters help capture the image's short-range dependencies.

2. **Transformer Master block**

Each transformer master block consists of "d" transformer blocks within them (for this homework, I have taken it as 6). Each transformer block consists of Layer Normalization followed by a Multi-Head attention block and another Layer Normalization followed by a MLP layer. There are skip connections between the layers.

In the Multi-headed attention block, we use learnable weights to compute the Query, Key and Value for every patch. Then we split the embeddings for every patch into multiple heads (64 heads in this HW) so that multiple relationships can be learnt between the input patches. Next, we compute the relationship between all the patches (which is called attention) using the Query and Key. This value is then normalized using softmax and the new Value is computed using the attention and the old Value. Finally, the outputs Value embeddings of the multiple heads are reshaped together.

3. **Classification head**

   The class embedding obtained from the transformer block is passed into the classification head, which gives out the 5-class logits.

2 Results

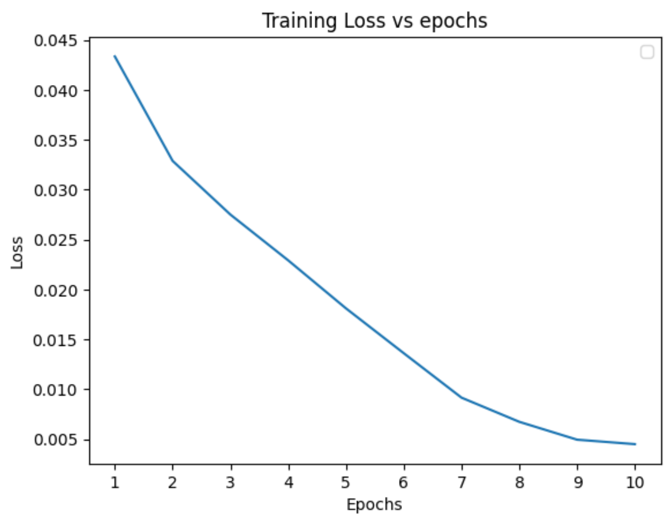


Figure 1: Training loss vs epochs

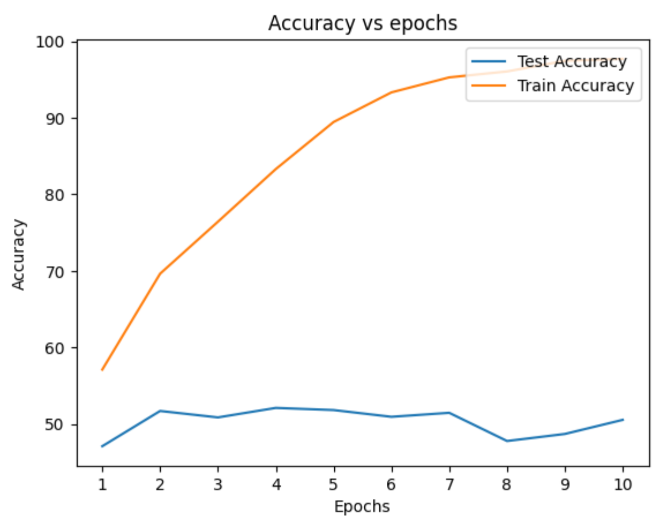


Figure 2: Training and Test Accuracy vs epochs

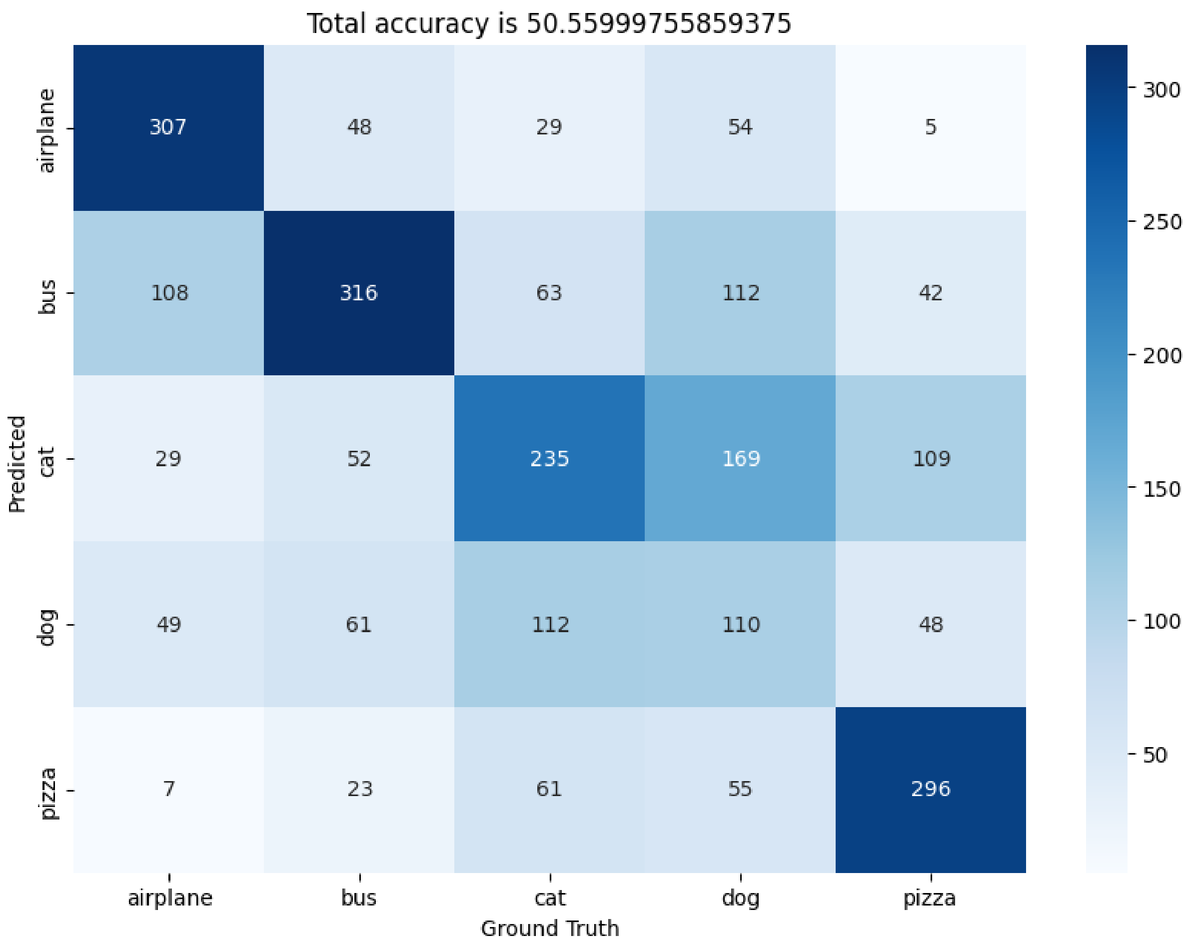


Figure 3: Confusion Matrix

3 Conclusion

The test accuracy of the models in HW4 on the same dataset after 10 epochs were as follows:

1. Net 1 : 57.40%
2. Net 2 : 59.08%
3. Net 3 : 61.48%

In comparison, the Vision Transformer model used in this homework gave a test accuracy of only 50.56% after 10 epochs. From Figure 2, its clear to see overfitting is taking place as the Vision Transformer model is quite powerful for such a small dataset (only 7500 training images). My implementation of the ViT has 10,950,917 parameters compared to 406,885 parameters for Net1, 529,765 parameters for Net2 and 622,245 parameters for Net3 from HW4.

Similar to the models from HW4, the ViT struggles with the classification of cats and dogs.

In [ ]:

```
#Importing the libraries
import torch
import torch.nn as nn
from torch.utils.data import DataLoader, Dataset
import torch.nn.functional as F
import os
import torchvision.transforms as transforms
from torchvision import datasets,models
from tqdm import tqdm
from PIL import Image
import numpy as np
import time
import matplotlib.pyplot as plt
import seaborn as sn
import pandas as pd
from tqdm import tqdm
```

In [ ]:

```
#From HW 4
class IndexedDataset(Dataset):

    def __init__(self, dir_path):
        self.dir_path = dir_path

        if os.path.basename(self.dir_path) == 'train': #transforms for the train dataset
          self.transform = transforms.Compose([
            transforms.ToTensor(),
            transforms.Normalize([0.5,0.5,0.5],[0.5,0.5,0.5])
        ])
        elif os.path.basename(self.dir_path) == 'test': #transforms for the test dataset
          self.transform = transforms.Compose([
            transforms.ToTensor(),
            transforms.Normalize([0.5,0.5,0.5],[0.5,0.5,0.5])
        ])

        image_filenames = []
        for (dirpath, dirnames, filenames) in os.walk(dir_path): #Saving all the image l
            image_filenames += [os.path.join(dirpath, file) for file in filenames]
        self.image_filenames = image_filenames
        self.labels_map = {"airplane" : 0, "bus": 1, "cat" : 2, "dog" : 3, "pizza" : 4}

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

    def __getitem__(self, idx):
        img_name = self.image_filenames[idx]
        image = Image.open(img_name).convert('RGB')
        image = self.transform(image)
        return image, self.labels_map[os.path.basename(os.path.dirname(img_name))]
```

In [ ]:

```
#Converts the images to patches
class Patch_Embedding(nn.Module):
    def __init__(self,in_channels=3,embedding_size=768,patch_size=16,img_size=224):
        #Assuming that the image size is perfectly divisible by patch_size
        super().__init__()
        self.embedding_size = embedding_size
        self.num_patches = (img_size//patch_size)**2 #(h*w)/patch_size**2
        self.conv = nn.Conv2d(in_channels,embedding_size,patch_size,stride=patch_size) #
        self.cls = nn.Parameter(torch.randn((1,embedding_size))) #The cls token
        self.pos = nn.Parameter(torch.randn((self.num_patches+1,embedding_size))) #Posit

    def forward(self,x):
        # x is of shape (b,c,h,w)
        batch_size = x.shape[0]
        y = self.conv(x) #y is of shape (b,embedding_size,h/patch_size,w/patch_size)
        out = y.view(-1,self.embedding_size,self.num_patches) #out is of shape (b,embedd
        out = torch.permute(out,(0,2,1)) #out is of shape (b,num_patches,embedding_size)

        #Appending the cls token
        cout = torch.concat((out,self.cls.repeat(batch_size,1,1)),1) #cout is of shape (

        #Adding the position embedding
        pcout = cout+self.pos.repeat(batch_size,1,1)  #pcout is of shape (b,num_patches+

        return pcout
```

In [ ]:

```
#Final classification head
class ClassificationHead(nn.Module):
    def __init__(self,embedding_size=768,num_classes=5):
        super().__init__()
        self.fc = nn.Linear(embedding_size,num_classes)

    def forward(self,x):
        #x is of shape (b,num_patches,embedding_size)
        x = x[:,-1,:] #Taking the output of the last patch
        out = self.fc(x)
        return out
```

In [ ]:

```
#Main attention implementation
class MultiAttentionhead(nn.Module):
    def __init__(self,embedding_size=768,num_heads=8,p=0.0):
        super().__init__()
        self.embedding_size = embedding_size #The embedding size of each 16x16 sized ima
        self.num_heads = num_heads #Into how many parts the embedding is split into
        self.QKV = nn.Linear(embedding_size,3*embedding_size) #The learnable matrices fo
        self.fc = nn.Linear(embedding_size,embedding_size) #To be applied at the output
        self.drop = nn.Dropout(p) #'p' is Dropped out

    def forward(self,x):
        #x is of shape (b,num_patches,embedding_size)
        b = x.shape[0]
        num_patches = x.shape[1]

        #Getting the Q,K,V for every patch in all the batches
        QKV1 = self.QKV(x) #QKV1 is of shape (b,num_patches,3*embedding_size)
        QKV2 = QKV1.reshape(b,num_patches,self.num_heads,self.embedding_size//self.num_h


        Q,K,V = torch.permute(QKV2,(4,0,2,1,3)) #Q,K,V are of shape (b,heads,num_patches

        #Computing the attention
        QKT = torch.einsum('bhid,bhjd -> bhij',Q,K) #QKT is of shape (b,heads,num_patche
                                                    #This gives the relationship between

        attention = F.softmax(QKT,dim=-1)/(self.embedding_size**(0.5)) #Softmax converts
                                                                       # to all the othe
        attention = self.drop(attention)

        #Updating the value
        QKtV = torch.einsum('bhik,bhkj -> bhij',QKT,V) #is of shape (b,heads,num_patches
        z = torch.permute(QKtV,(0,2,1,3)) #is of shape (b,num_patches,heads,embedding/he
        Z = z.reshape(b,num_patches,-1) #is of shape (b,num_patches,embedding_size)
        out = self.fc(Z) #is of shape (b,num_patches,embedding_size)
        return out
```

In [ ]:

```
#Multi layer perceptron at the end of every Transformer block
class MLP(nn.Module):
    #The MLP block within the transformer
    def __init__(self,embedding_size=768,p=0.0,expansion=4):
        super().__init__()
        self.fc1 = nn.Linear(embedding_size,expansion*embedding_size)
        self.fc2 = nn.Linear(expansion*embedding_size,embedding_size)
        self.gelu = nn.GELU()
        self.drop = nn.Dropout(p)

    def forward(self,x):
        #x is of shape (b,num_patches,embedding_size)
        x = self.gelu(self.fc1(x))
        out = self.fc2(self.drop(x))
        return out
```

In [ ]:

```
#One transformer block
class Transformer(nn.Module):
    #The overall Transformer block
    def __init__(self,embedding_size=768,p=0.0,expansion=4,num_heads=8):
        super().__init__()
        self.ln1 = nn.LayerNorm(embedding_size)
        self.MAH = MultiAttentionhead(embedding_size,num_heads,p)
        self.ln2 = nn.LayerNorm(embedding_size)
        self.mlp = MLP(embedding_size,p,expansion)

    def forward(self,x):
        identity1 = x
        x = self.MAH(self.ln1(x))
        identity2 = x + identity1 #skip connection
        out = self.mlp(self.ln2(identity2))
        out = out + identity2 #skip connection
        return out
```

In [ ]:

```
#Overall ViT implementation
class ViT(nn.Module):
    def __init__(self,embedding_size=768,p=0.0,expansion=4,num_heads=8,in_channels=3,pat
        super().__init__()

        self.embedding = Patch_Embedding(in_channels,embedding_size,patch_size,img_size)

        Tlayers = [] #A ViT would have multiple (depth) Transformer blocks
        for i in range(depth):
            Tlayers.append(Transformer(embedding_size,p,expansion,num_heads))

        self.Tlayers = nn.Sequential(*Tlayers)

        self.head = ClassificationHead(embedding_size,num_classes)

    def forward(self,x):
        #Getting the embeddings of each patch of all the batch images
        x = self.embedding(x)

        #Passing them through "depth" Transformer blocks
        x = self.Tlayers(x)

        #Passing the output through classification head
        out = self.head(x)
        return out
```

In [ ]:

```
#Function to count the number of parameters from https://discuss.pytorch.org/t/how-do-i-
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)
```

In [ ]:

```
#Function to calculate the accuracy of the model
def find_acc(net,dataloader):
  net.eval()
  correct = 0
  with torch.no_grad():
    loop = tqdm(dataloader)
    for i,data in enumerate(loop):
      inputs, labels = data
      inputs = inputs.to(device)
      labels = labels.to(device)
      outputs = net(inputs)
      predicted = torch.argmax(outputs,1)
      correct  = correct + torch.sum(predicted.cpu()==labels.cpu()).item()
  net.train()
  return (correct*100)/len(dataloader.dataset)
```

In [ ]:

```
#Funtion to train the model
def training(epochs,optimizer,criterion,net,train_data_loader,test_data_loader,device):
  train_losses = []
  train_accs = []
  test_accs = []
  for epoch in range(epochs):
    running_loss = 0.0
    loop = tqdm(train_data_loader)
    for i, data in enumerate(loop):
      inputs, labels = data
      inputs = inputs.to(device)
      labels = labels.to(device)
      optimizer.zero_grad()
      outputs = net(inputs)
      loss = criterion(outputs, labels)
      loss.backward()
      optimizer.step()
      running_loss += loss.cpu().item()
      loop.set_postfix(loss=running_loss/(i+1))

    train_acc = find_acc(net,train_data_loader)
    test_acc = find_acc(net,test_data_loader)

    train_accs.append(train_acc)
    test_accs.append(test_acc)

    print("[epoch: %d] loss: %.3f Train Accuracy: %.3f Test Accuracy: %.3f " % (epoch +
    print("\n")
    train_losses.append(running_loss/len(train_dataset))
  return net, train_losses, train_accs, test_accs
```

In [ ]:

```
#Function to plot the confusion matrix
def confusion_matrix(model,test_data_loader):
  matrix = torch.zeros((5,5))
  with torch.no_grad():
    for b, (X_test, y_test) in enumerate(test_data_loader):
      model.eval()
      X_test, y_test = X_test.to(device), y_test.to(device)
      # Apply the model
      y_val = model(X_test)

      # Tally the number of correct predictions
      predicted = torch.max(y_val.data, 1)[1]
      for i in range(len(predicted)):
        matrix[predicted[i].cpu(),y_test[i].cpu()] += 1

  heat = pd.DataFrame(matrix, index = [i for i in ["airplane","bus","cat","dog","pizza"]
                  columns = [i for i in ["airplane","bus","cat","dog","pizza"]])
  heat = heat.astype(int)
  accuracy = (matrix.trace()/matrix.sum())*100
  plt.figure(figsize = (10,7))
  plt.title("Total accuracy is "+str(accuracy.item()))
  s = sn.heatmap(heat, annot=True,cmap='Blues',fmt='g')
  s.set(xlabel='Ground Truth', ylabel='Predicted')
```

In [ ]:

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
```

Out[13]:

```
device(type='cuda')
```

In [ ]:

```
train_dataset = IndexedDataset("/content/drive/MyDrive/Dataset_HW4/train")
test_dataset = IndexedDataset("/content/drive/MyDrive/Dataset_HW4/test")
train_data_loader = DataLoader(train_dataset,batch_size=32, shuffle=True,num_workers=32)
test_data_loader = DataLoader(test_dataset,batch_size=32, shuffle=True,num_workers=32)

criterion = nn.CrossEntropyLoss()
epochs = 10

model = ViT(embedding_size=384,p=0.0,expansion=4,num_heads=64,in_channels=3,patch_size=1
optimizer = torch.optim.Adam(model.parameters(), lr=0.00001, betas = (0.9,0.99))
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:56
1: UserWarning: This DataLoader will create 32 worker processes in total.
Our suggested max number of worker in current system is 2, which is small
er than what this DataLoader is going to create. Please be aware that exc
essive worker creation might get DataLoader running slow or even freeze,
lower the worker number to avoid potential slowness/freeze if necessary.
  warnings.warn(_create_warning_msg(
```

In [ ]:

```
count_parameters(model)
```

Out[15]:

```
10950917
```

In [ ]:

```
print(len(train_dataset))
print(len(test_dataset))
```

```
7500
2500
```

In [ ]:

```
trained_model,train_losses,train_accs, test_accs  = training(epochs,optimizer,criterion,
confusion_matrix(trained_model,test_data_loader)
```

```
100%|██████████| 235/235 [02:59<00:00,  1.31it/s, loss=1.38]
100%|██████████| 235/235 [00:13<00:00, 17.18it/s]
100%|██████████| 79/79 [01:15<00:00,  1.04it/s]

[epoch: 1] loss: 1.384 Train Accuracy: 57.120 Test Accuracy: 47.120



100%|██████████| 235/235 [00:17<00:00, 13.14it/s, loss=1.05]
100%|██████████| 235/235 [00:14<00:00, 15.92it/s]
100%|██████████| 79/79 [00:05<00:00, 13.29it/s]

[epoch: 2] loss: 1.050 Train Accuracy: 69.640 Test Accuracy: 51.720



100%|██████████| 235/235 [00:18<00:00, 12.82it/s, loss=0.878]
100%|██████████| 235/235 [00:14<00:00, 16.61it/s]
100%|██████████| 79/79 [00:06<00:00, 13.03it/s]

[epoch: 3] loss: 0.878 Train Accuracy: 76.427 Test Accuracy: 50.880
```

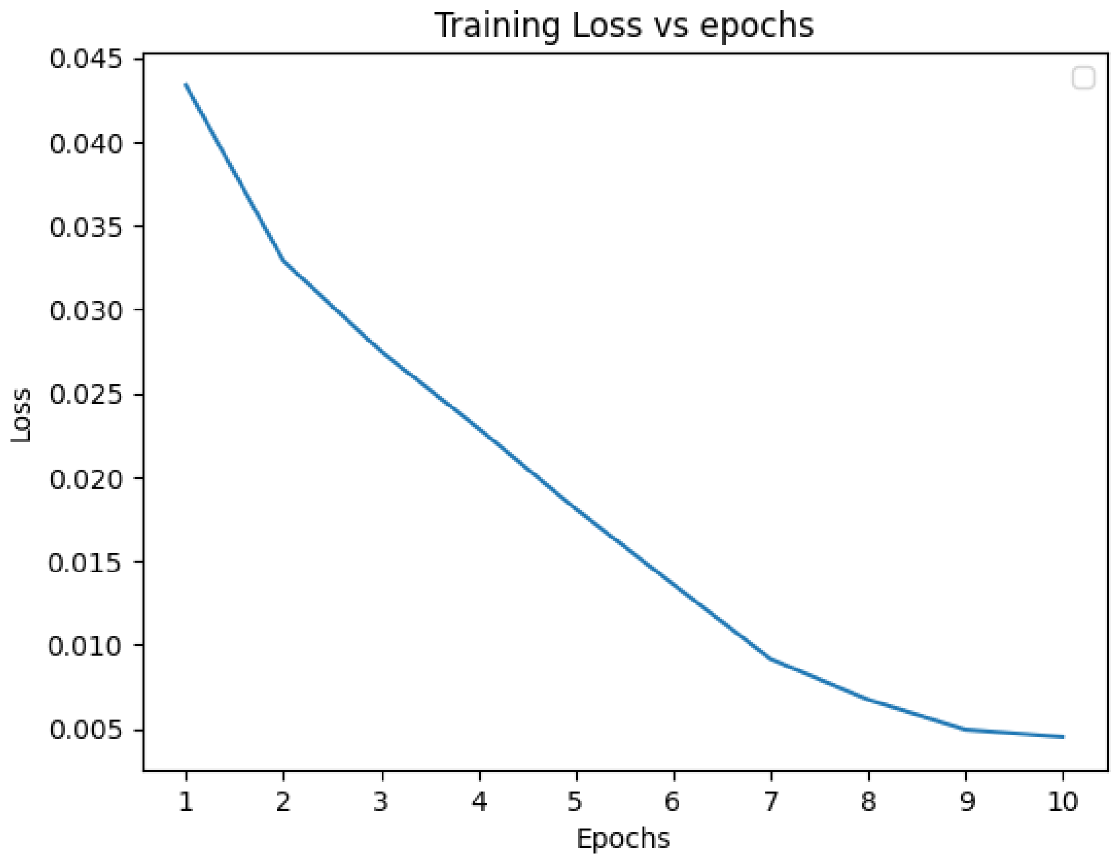
In [ ]:

```
epochs = np.arange(1,11)
plt.xticks(epochs, epochs)
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Training Loss vs epochs")
plt.plot(epochs,train_losses)
plt.legend(loc = "upper right")
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.
Note that artists whose label start with an underscore are ignored when l
egend() is called with no argument.
```

Out[18]:

```
<matplotlib.legend.Legend at 0x7f34290a4490>
```

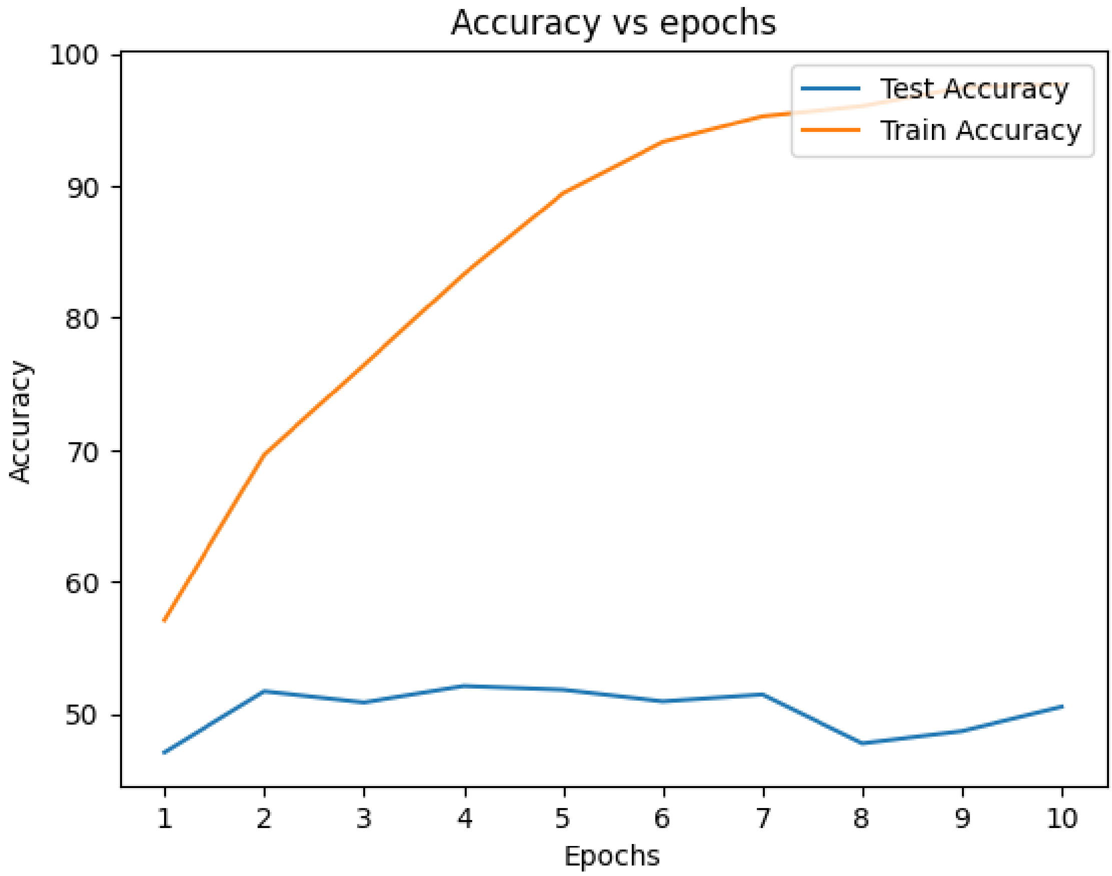


In [ ]:

```
epochs = np.arange(1,11)
plt.xticks(epochs, epochs)
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.title("Accuracy vs epochs")
plt.plot(epochs,test_accs,label="Test Accuracy")
plt.plot(epochs,train_accs,label="Train Accuracy")
plt.legend(loc = "upper right")
```

Out[19]:

```
<matplotlib.legend.Legend at 0x7f342913ab90>
```



In [ ]: