```
In [1]: # Pseudocode using Pytorch :
        # 1. Import the necessary libraries
        # 2. Load the image from the folder
        # 3. Data preprocessing using various data augmentation pipeline and Image generate
        # 4. Split the train data with validation data.
        # 4. Analysis of data such as no of images in each class and no of classes
        # 5.Define Forward and Backprop functions
        # 6. Build the CNN model
        # 7. Perform the training with the hyperparameters like epoch size, batch size, led
        # 8. Plot the loss and accuracy curves
        # 9. Use the test data and estimate the confidence score.
In [2]:
        #import libraries
        import matplotlib.pyplot as plt
        import numpy as np
        import pandas as pd
        import os
        import seaborn as sns
        import skimage
        from skimage import io,transform
        import torch
        import torch.nn as nn
        import torch.optim as optim
        import torchvision
        from torchvision import datasets, models, transforms
        from PIL import Image
In [3]: from google.colab import drive
        drive.mount('/content/drive')
        Mounted at /content/drive
In [4]: #Load data
        batch size=20
        data_dir = "/content/drive/MyDrive/Projects/Pet classification using CNN/1577957291
        TEST = 'test'
        TRAIN = 'train'
        VALID = 'val'
In [5]: #Data preprocessing
        transform = transforms.Compose([
            transforms.RandomRotation(30),
            transforms.Resize((256,256)),
            transforms.RandomHorizontalFlip(),
            transforms.ToTensor(),
            transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
            1)
        device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
        print(device)
        cuda:0
        image datasets={x: datasets.ImageFolder(os.path.join(data dir,x),transform=transfo
In [7]:
        num_validation = int(np.floor(0.2* len(image_datasets[TRAIN])))
        num_train= len(image_datasets[TRAIN]) - num_validation
        #Split the data
        train_ds,val_ds=torch.utils.data.random_split(image_datasets[TRAIN],[num_train,num]
        test_ds=torch.utils.data.DataLoader(image_datasets[TEST])
```

```
# num train = len(train data)
         # indices = list(range(num_train))
         # np.random.shuffle(indices)
         # split = int(np.floor(valid_size * num_train))
         # train idx, valid idx = indices[split:], indices[:split]
         # define samplers for obtaining training and validation batches
         # train sampler = SubsetRandomSampler(train idx)
         # valid sampler = SubsetRandomSampler(valid idx)
In [8]: dataloaders = {TRAIN: torch.utils.data.DataLoader(train_ds,batch_size=batch_size,sl
                         TEST: torch.utils.data.DataLoader(image datasets[TEST],batch size,sl
                         VALID: torch.utils.data.DataLoader(val ds,batch size=batch size,shuf
In [8]:
         len(dataloaders[TRAIN])
 In [9]:
         len(dataloaders[TEST])
Out[9]:
         dataset_sizes=len(image_datasets[TRAIN])
In [10]:
         class_names=image_datasets[TRAIN].classes
         num_classes=len(class_names)
         print(class_names)
         ['cats', 'dogs']
In [11]: #Visualize the data
         #Plot sample images for all the classes
         plt.figure(figsize=(10,10))
         for images, labels in dataloaders[TRAIN]:
           print(images.shape,labels.shape)
           for i in range(9):
             plt.subplot(3,3,i+1)
             plt.imshow(images[i].numpy().transpose(1,2,0))
             plt.title(class_names[labels[i]])
             plt.axis("off")
         WARNING: matplotlib.image: Clipping input data to the valid range for imshow with RG
         B data ([0..1] for floats or [0..255] for integers).
         WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG
         B data ([0..1] for floats or [0..255] for integers).
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         WARNING: matplotlib.image: Clipping input data to the valid range for imshow with RG
         B data ([0..1] for floats or [0..255] for integers).
         torch.Size([20, 3, 256, 256]) torch.Size([20])
```

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B data ([0..1] for floats or [0..255] for integers).

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WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

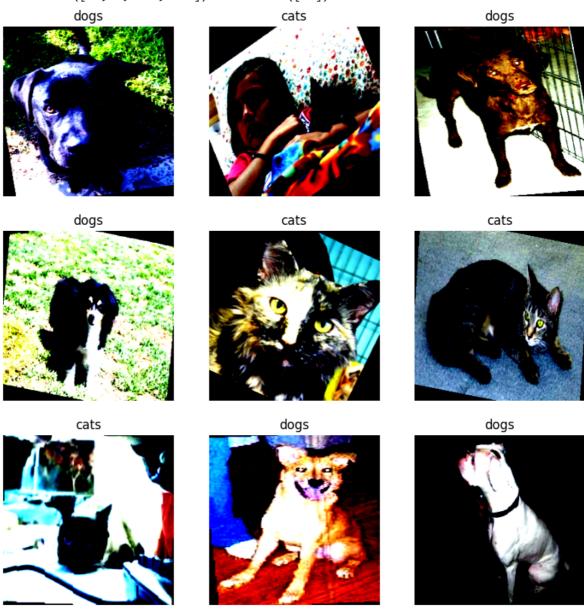
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

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WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

torch.Size([12, 3, 256, 256]) torch.Size([12])



In [12]: #Visualize the test data
 #Plot sample images for all the classes
plt.figure(figsize=(10,10))
for images,labels in dataloaders[TEST]:
 print(images.shape,labels)
 for i in range(9):

```
plt.subplot(3,3,i+1)
plt.imshow(images[i].numpy().transpose(1,2,0))
plt.title(class_names[labels[i]])
plt.axis("off")
```

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

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WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

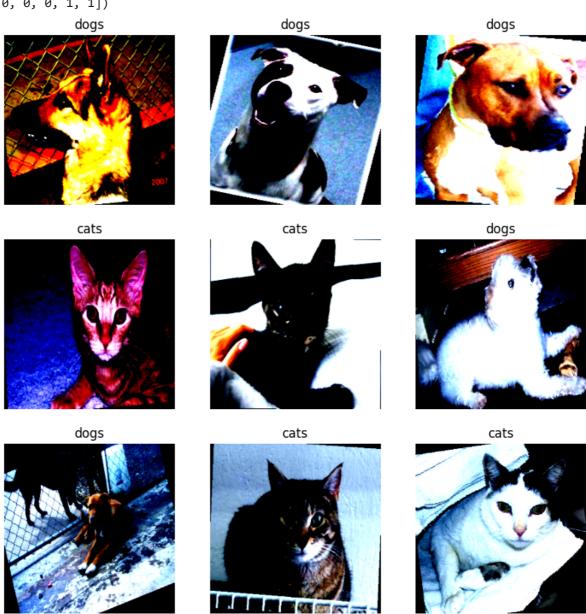
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

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WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RG B data ([0..1] for floats or [0..255] for integers).

torch.Size([20, 3, 256, 256]) tensor([1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1])



In [13]:

class PetNN(nn.Module):

```
def __init__(self, num_classes, fc_size=20, dropout_prob=0.4):
              super(PetNN, self).__init__()
              self.layer1 = nn.Sequential(
                  nn.Conv2d(in_channels=3, out_channels=32, kernel_size=5),
                  nn.BatchNorm2d(32),
                  nn.ReLU(),
                  nn.MaxPool2d(kernel size=2,stride=2)
              self.layer2 = nn.Sequential(
                  nn.Conv2d(in_channels=32, out_channels=64 , kernel_size=5),
                  nn.BatchNorm2d(64),
                  nn.ReLU(),
                  nn.MaxPool2d(kernel_size=2,stride=2)
              )
              self.fc1 = nn.Linear(in_features=64 * 61 * 61, out_features=fc_size)
              #self.bn1 = nn.BatchNorm2d(fc size)
              self.dropout = nn.Dropout(p=dropout prob)
              self.fc2 = nn.Linear(in_features=fc_size, out_features=num_classes)
           def forward(self,x):
             out=self.layer1(x)
              out=self.layer2(out)
              out=out.view(out.size(0),-1) #flatten to 2D tensor (batch_size, num_channels *
              out=torch.relu(self.fc1(out))
              #out=self.bn1(out)
              out=self.dropout(out)
              out=torch.softmax(self.fc2(out),dim=1)
              return(out)
In [14]: |
         #define hyperparamters, loss function and optimiser
         model=PetNN(num_classes)
         model.to(device)
         error=nn.CrossEntropyLoss()
         learning_rate=0.01
         optimizer=torch.optim.Adam(model.parameters(),lr=learning rate)
         print(model)
         PetNN(
            (layer1): Sequential(
             (0): Conv2d(3, 32, kernel_size=(5, 5), stride=(1, 1))
             (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats
         =True)
              (2): ReLU()
              (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=Fals
         e)
           (layer2): Sequential(
              (0): Conv2d(32, 64, kernel_size=(5, 5), stride=(1, 1))
             (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats
         =True)
             (2): ReLU()
             (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=Fals
         e)
           (fc1): Linear(in_features=238144, out_features=20, bias=True)
            (dropout): Dropout(p=0.4, inplace=False)
           (fc2): Linear(in_features=20, out_features=2, bias=True)
         )
```

```
#Initialisation of training variables
In [15]:
         epochs = 300
         count=0
         train_accuracy_list = [] # Store train accuracy values
         train_loss_list = [] # Store train loss values
         valid_accuracy_list = [] # Store validation accuracy values
         valid_loss_list = [] # Store validation loss values
         test_accuracy_list = [] # Store test accuracy values
         labels_list=[]
         prediction_list=[]
         #iteration_list=list(range(epochs))
         iteration_list=[]
         #print(iteration_list)
         #Training
         for epoch in range(epochs):
           for images,labels in dataloaders[TRAIN]:
             images,labels=images.to(device),labels.to(device)
             train outputs=model(images)
             #print(outputs.shape)
             loss=error(train_outputs,labels)
             optimizer.zero_grad()
             loss.backward()
             optimizer.step()
             count += 1
             iteration_list.append(count)
           with torch.no_grad():
             #train_outputs=model(images)
             train_predictions=torch.max(train_outputs,1)[1]
             train_correct=(train_predictions==labels).sum().item()
             train_total=len(labels)
             train_accuracy=train_correct*100/train_total
             train_accuracy_list.append(train_accuracy)
             train_loss_list.append(loss.item())
             total=0
             correct=0
           for images,labels in dataloaders[VALID]:
             images,labels=images.to(device),labels.to(device)
             labels_list.append(labels)
             outputs=model(images)
             loss=error(outputs,labels)
             predictions=torch.max(outputs,1)[1].to(device)
             prediction_list.append(predictions)
             correct += (predictions==labels).sum()
             total+=len(labels)
           with torch.no grad():
             valid correct = (predictions == labels).sum().item()
             valid total = len(labels)
             valid_accuracy = valid_correct * 100 / valid_total
             valid_accuracy_list.append(valid_accuracy)
               # accuracy list.append(accuracy)
               # loss_list.append(loss.data)pend(valid_accuracy)
             valid_loss_list.append(loss.item())
               # accuracy=correct*100/total
               # iteration list.append(count)
            print("epochs:{},loss:{},train_accuracy:{}%".format(epoch,loss.data,train_accura
```

print("epochs:{},loss:{},valid\_accuracy:{}%".format(epoch,loss.data,valid\_accuracy
#print(len(train\_accuracy\_list))

```
epochs:0,loss:0.938261866569519,train accuracy:50.0%
epochs:0,loss:0.938261866569519,valid_accuracy:37.5%
epochs:1,loss:0.8132617473602295,train accuracy:25.0%
epochs:1,loss:0.8132617473602295,valid_accuracy:50.0%
epochs:2,loss:0.938261866569519,train accuracy:66.66666666666667%
epochs:2,loss:0.938261866569519,valid accuracy:37.5%
epochs:3,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:3,loss:0.938261866569519,valid accuracy:37.5%
epochs:4,loss:0.938261866569519,train_accuracy:50.0%
epochs:4,loss:0.938261866569519,valid_accuracy:37.5%
epochs:5,loss:0.938261866569519,train accuracy:33.333333333333333333
epochs:5,loss:0.938261866569519,valid_accuracy:37.5%
epochs:6,loss:0.938261866569519,train accuracy:66.66666666666667%
epochs:6,loss:0.938261866569519,valid accuracy:37.5%
epochs:7,loss:0.938261866569519,train accuracy:50.0%
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epochs:8,loss:0.9382617473602295,train_accuracy:50.0%
epochs:8,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:9,loss:0.938261866569519,train_accuracy:41.666666666666664%
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epochs:11,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:11,loss:0.938261866569519,valid_accuracy:37.5%
epochs:12,loss:0.938261866569519,train_accuracy:33.3333333333333336%
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epochs:14,loss:0.938261866569519,train_accuracy:75.0%
epochs:14,loss:0.938261866569519,valid_accuracy:37.5%
epochs:15,loss:0.9382617473602295,train accuracy:33.33333333333333336%
epochs:15,loss:0.9382617473602295,valid accuracy:37.5%
epochs:16,loss:0.9382617473602295,train_accuracy:25.0%
epochs:16,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:17,loss:0.9382617473602295,train accuracy:50.0%
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epochs:25,loss:0.938261866569519,train accuracy:66.66666666666667%
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epochs:29,loss:0.9382617473602295,train accuracy:58.3333333333333336%
epochs: 29, loss: 0.9382617473602295, valid accuracy: 37.5%
epochs:30,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:30,loss:0.938261866569519,valid_accuracy:37.5%
epochs:31,loss:0.938261866569519,train accuracy:50.0%
epochs:31,loss:0.938261866569519,valid accuracy:37.5%
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epochs:32,loss:0.938261866569519,train accuracy:50.0%
epochs:32,loss:0.938261866569519,valid_accuracy:37.5%
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epochs:33,loss:0.938261866569519,valid_accuracy:37.5%
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epochs:63,loss:0.938261866569519,valid accuracy:37.5%
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epochs:64,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:64,loss:0.938261866569519,valid_accuracy:37.5%
epochs:65,loss:0.938261866569519,train accuracy:66.66666666666667%
epochs:65,loss:0.938261866569519,valid_accuracy:37.5%
epochs:66,loss:0.938261866569519,train accuracy:50.0%
epochs:66,loss:0.938261866569519,valid accuracy:37.5%
epochs:67,loss:0.9382617473602295,train accuracy:58.33333333333333336%
epochs:67,loss:0.9382617473602295,valid accuracy:37.5%
epochs:68,loss:0.938261866569519,train_accuracy:41.666666666666664%
epochs:68,loss:0.938261866569519,valid_accuracy:37.5%
epochs:69,loss:0.938261866569519,train accuracy:50.0%
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epochs:70,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:70,loss:0.938261866569519,valid accuracy:37.5%
epochs:71,loss:0.938261866569519,train accuracy:75.0%
epochs:71,loss:0.938261866569519,valid_accuracy:37.5%
epochs:72,loss:0.938261866569519,train_accuracy:58.333333333333336%
epochs:72,loss:0.938261866569519,valid_accuracy:37.5%
epochs:73,loss:0.938261866569519,train_accuracy:41.666666666666664%
epochs:73,loss:0.938261866569519,valid accuracy:37.5%
epochs:74,loss:0.9382617473602295,train_accuracy:58.333333333333336%
epochs:74,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:75,loss:0.938261866569519,train accuracy:50.0%
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epochs:76,loss:0.9382617473602295,train_accuracy:75.0%
epochs:76,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:77,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:77,loss:0.938261866569519,valid_accuracy:37.5%
epochs:78,loss:0.9382617473602295,train_accuracy:58.33333333333336%
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epochs:79,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:79,loss:0.938261866569519,valid accuracy:37.5%
epochs:80,loss:0.938261866569519,train_accuracy:58.333333333333336%
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epochs:83,loss:0.938261866569519,valid accuracy:37.5%
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epochs:85,loss:0.938261866569519,train accuracy:50.0%
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epochs:89,loss:0.813261866569519,valid accuracy:50.0%
epochs:90,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:90,loss:0.938261866569519,valid_accuracy:37.5%
epochs:91,loss:0.938261866569519,train accuracy:58.333333333333336%
epochs:91,loss:0.938261866569519,valid accuracy:37.5%
epochs:92,loss:0.938261866569519,train accuracy:50.0%
epochs:92,loss:0.938261866569519,valid accuracy:37.5%
epochs:93,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:93,loss:0.938261866569519,valid accuracy:37.5%
epochs:94,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:94,loss:0.938261866569519,valid_accuracy:37.5%
epochs:95,loss:0.9382617473602295,train accuracy:58.33333333333333333
epochs:95,loss:0.9382617473602295,valid accuracy:37.5%
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epochs:96,loss:0.938261866569519,train accuracy:50.0%
epochs:96,loss:0.938261866569519,valid accuracy:37.5%
epochs:97,loss:0.9382617473602295,train accuracy:50.0%
epochs:97,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:98,loss:0.938261866569519,train accuracy:50.0%
epochs:98,loss:0.938261866569519,valid accuracy:37.5%
epochs:99,loss:0.938261866569519,train accuracy:50.0%
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epochs:101,loss:0.938261866569519,train accuracy:50.0%
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epochs:103,loss:0.938261866569519,train accuracy:33.33333333333333333
epochs:103,loss:0.938261866569519,valid accuracy:37.5%
epochs:104,loss:0.938261866569519,train accuracy:50.0%
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epochs:105,loss:0.938261866569519,valid accuracy:37.5%
epochs:106,loss:0.938261866569519,train_accuracy:41.666666666666664%
epochs:106,loss:0.938261866569519,valid accuracy:37.5%
epochs:107.loss:0.938261866569519.train accuracy:50.0%
epochs:107,loss:0.938261866569519,valid_accuracy:37.5%
epochs:108,loss:0.938261866569519,train_accuracy:58.3333333333333336%
epochs:108,loss:0.938261866569519,valid_accuracy:37.5%
epochs:109,loss:0.938261866569519,train_accuracy:58.333333333333333
epochs:109,loss:0.938261866569519,valid_accuracy:37.5%
epochs:110,loss:0.938261866569519,train accuracy:25.0%
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epochs:111,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs:111,loss:0.938261866569519,valid accuracy:37.5%
epochs:112,loss:0.938261866569519,train_accuracy:58.333333333333333
epochs:112,loss:0.938261866569519,valid_accuracy:37.5%
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epochs:115,loss:0.938261866569519,train accuracy:66.66666666666667%
epochs:115,loss:0.938261866569519,valid accuracy:37.5%
epochs:116,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs:116,loss:0.938261866569519,valid accuracy:37.5%
epochs:117,loss:0.938261866569519,train accuracy:50.0%
epochs:117,loss:0.938261866569519,valid_accuracy:37.5%
epochs:118,loss:0.9382617473602295,train_accuracy:41.6666666666666664%
epochs:118,loss:0.9382617473602295,valid accuracy:37.5%
epochs:119,loss:0.938261866569519,train_accuracy:50.0%
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epochs:121,loss:0.8715721368789673,valid accuracy:37.5%
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epochs:122,loss:0.938261866569519,valid_accuracy:37.5%
epochs:123,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:123,loss:0.938261866569519,valid accuracy:37.5%
epochs:124,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs:124,loss:0.938261866569519,valid accuracy:37.5%
epochs:125,loss:0.938261866569519,train accuracy:50.0%
epochs:125,loss:0.938261866569519,valid accuracy:37.5%
epochs:126,loss:0.9382617473602295,train_accuracy:66.66666666666667%
epochs:126,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:127,loss:0.938261866569519,train accuracy:41.6666666666666664%
epochs:127,loss:0.938261866569519,valid accuracy:37.5%
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epochs:128,loss:0.938261866569519,valid_accuracy:37.5%
epochs:129,loss:0.938261866569519,train accuracy:58.333333333333336%
epochs:129,loss:0.938261866569519,valid_accuracy:37.5%
epochs:130,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:130,loss:0.938261866569519,valid accuracy:37.5%
epochs:131,loss:0.938261866569519,train accuracy:50.0%
epochs:131,loss:0.938261866569519,valid accuracy:37.5%
epochs:132,loss:0.938261866569519,train_accuracy:50.0%
epochs:132,loss:0.938261866569519,valid_accuracy:37.5%
epochs:133,loss:0.9382617473602295,train accuracy:66.66666666666667%
epochs:133,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:134,loss:0.938261866569519,train accuracy:50.0%
epochs:134,loss:0.938261866569519,valid accuracy:37.5%
epochs:135,loss:0.938261866569519,valid_accuracy:37.5%
epochs:136,loss:0.938261866569519,train accuracy:50.0%
epochs:136,loss:0.938261866569519,valid_accuracy:37.5%
epochs:137,loss:0.938261866569519,train_accuracy:50.0%
epochs:137,loss:0.938261866569519,valid accuracy:37.5%
epochs:138,loss:0.938261866569519,train_accuracy:58.33333333333333336%
epochs:138,loss:0.938261866569519,valid_accuracy:37.5%
epochs:139,loss:0.9382617473602295,train accuracy:66.66666666666667%
epochs:139,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:140,loss:0.938261866569519,train_accuracy:66.6666666666667%
epochs:140,loss:0.938261866569519,valid_accuracy:37.5%
epochs:141,loss:0.938261866569519,train_accuracy:50.0%
epochs:141,loss:0.938261866569519,valid_accuracy:37.5%
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epochs:149,loss:0.938261866569519,train accuracy:50.0%
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epochs:151,loss:0.938261866569519,train_accuracy:58.3333333333333336%
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epochs:153,loss:0.9382617473602295,valid accuracy:37.5%
epochs:154,loss:0.938261866569519,train_accuracy:50.0%
epochs:154,loss:0.938261866569519,valid_accuracy:37.5%
epochs:155,loss:0.938261866569519,train accuracy:50.0%
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epochs:156,loss:0.938261866569519,valid accuracy:37.5%
epochs:157,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:157,loss:0.938261866569519,valid accuracy:37.5%
epochs:158,loss:0.938261866569519,train accuracy:66.66666666666667%
epochs:158,loss:0.938261866569519,valid_accuracy:37.5%
epochs:159,loss:0.9382617473602295,train accuracy:41.6666666666666664%
epochs:159,loss:0.9382617473602295,valid accuracy:37.5%
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epochs:160,loss:0.938261866569519,train accuracy:50.0%
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epochs:161,loss:0.9382617473602295,train accuracy:41.666666666666664%
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epochs:163,loss:0.9382617473602295,train accuracy:58.3333333333333336%
epochs:163,loss:0.9382617473602295,valid accuracy:37.5%
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epochs:178,loss:0.938261866569519,train_accuracy:41.6666666666666664%
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epochs:183,loss:0.938261866569519,valid accuracy:37.5%
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epochs:185,loss:0.938261866569519,train accuracy:58.3333333333333336%
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epochs:186,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:187,loss:0.938261866569519,train accuracy:25.0%
epochs:187,loss:0.938261866569519,valid accuracy:37.5%
epochs:188,loss:0.938261866569519,train accuracy:50.0%
epochs:188,loss:0.938261866569519,valid accuracy:37.5%
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epochs:189,loss:0.938261866569519,valid accuracy:37.5%
epochs:190,loss:0.938261866569519,train accuracy:50.0%
epochs:190,loss:0.938261866569519,valid_accuracy:37.5%
epochs:191,loss:0.813261866569519,train accuracy:66.66666666666667%
epochs:191,loss:0.813261866569519,valid accuracy:50.0%
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epochs:192,loss:0.938261866569519,train accuracy:50.0%
epochs:192,loss:0.938261866569519,valid_accuracy:37.5%
epochs:193,loss:0.938261866569519,train accuracy:58.333333333333336%
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epochs:194,loss:0.8692269325256348,valid accuracy:37.5%
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epochs:195,loss:0.938261866569519,valid accuracy:37.5%
epochs:196,loss:0.938261866569519,train_accuracy:41.66666666666664%
epochs:196,loss:0.938261866569519,valid_accuracy:37.5%
epochs:197,loss:0.938261866569519,train accuracy:50.0%
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epochs:198,loss:0.938261866569519,valid accuracy:37.5%
epochs:199,loss:0.938261866569519,train accuracy:41.6666666666666664%
epochs:199,loss:0.938261866569519,valid_accuracy:37.5%
epochs:200,loss:0.9382617473602295,train_accuracy:50.0%
epochs:200,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:201,loss:0.938261866569519,train_accuracy:58.333333333333336%
epochs:201,loss:0.938261866569519,valid accuracy:37.5%
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epochs:203,loss:0.9382617473602295,train accuracy:58.3333333333333336%
epochs:203,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:204,loss:0.938261866569519,train_accuracy:58.333333333333336%
epochs:204,loss:0.938261866569519,valid_accuracy:37.5%
epochs:205,loss:0.9382617473602295,train_accuracy:41.666666666666664%
epochs:205,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:206,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:206,loss:0.938261866569519,valid_accuracy:37.5%
epochs:207,loss:0.938261866569519,train accuracy:75.0%
epochs:207,loss:0.938261866569519,valid accuracy:37.5%
epochs:208,loss:0.938261866569519,train_accuracy:50.0%
epochs:208,loss:0.938261866569519,valid_accuracy:37.5%
epochs:209,loss:0.938261866569519,train accuracy:58.333333333333333333
epochs:209,loss:0.938261866569519,valid_accuracy:37.5%
epochs:210,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:210,loss:0.938261866569519,valid_accuracy:37.5%
epochs:211,loss:0.938261866569519,train accuracy:41.6666666666666664%
epochs:211,loss:0.938261866569519,valid accuracy:37.5%
epochs:212,loss:0.938261866569519,train accuracy:41.6666666666666664%
epochs:212,loss:0.938261866569519,valid accuracy:37.5%
epochs:213,loss:0.9382617473602295,train accuracy:58.3333333333333336%
epochs:213,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:214,loss:0.9382617473602295,train_accuracy:50.0%
epochs:214,loss:0.9382617473602295,valid accuracy:37.5%
epochs:215,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:215,loss:0.938261866569519,valid accuracy:37.5%
epochs:216,loss:0.9382617473602295,train accuracy:58.33333333333333336%
epochs:216,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:217,loss:0.938261866569519,train accuracy:50.0%
epochs:217,loss:0.938261866569519,valid accuracy:37.5%
epochs:218,loss:0.938261866569519,train_accuracy:75.0%
epochs:218,loss:0.938261866569519,valid_accuracy:37.5%
epochs:219,loss:0.938261866569519,train accuracy:50.0%
epochs:219,loss:0.938261866569519,valid accuracy:37.5%
epochs:220,loss:0.938261866569519,valid accuracy:37.5%
epochs:221,loss:0.938261866569519,train accuracy:50.0%
epochs:221,loss:0.938261866569519,valid accuracy:37.5%
epochs:222,loss:0.938261866569519,train accuracy:50.0%
epochs:222,loss:0.938261866569519,valid_accuracy:37.5%
epochs:223,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:223,loss:0.938261866569519,valid accuracy:37.5%
```

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epochs:224,loss:0.938261866569519,train accuracy:50.0%
epochs:224,loss:0.938261866569519,valid_accuracy:37.5%
epochs:225,loss:0.938261866569519,train accuracy:58.333333333333336%
epochs:225,loss:0.938261866569519,valid_accuracy:37.5%
epochs:226,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:226,loss:0.938261866569519,valid accuracy:37.5%
epochs:227,loss:0.938261866569519,train accuracy:50.0%
epochs: 227, loss: 0.938261866569519, valid accuracy: 37.5%
epochs:228,loss:0.938261866569519,train_accuracy:75.0%
epochs:228,loss:0.938261866569519,valid_accuracy:37.5%
epochs:229,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs:229,loss:0.938261866569519,valid_accuracy:37.5%
epochs:230,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:230,loss:0.938261866569519,valid accuracy:37.5%
epochs:231,loss:0.938261866569519,train_accuracy:41.666666666666664%
epochs:231,loss:0.938261866569519,valid_accuracy:37.5%
epochs:232,loss:0.938261866569519,train accuracy:50.0%
epochs:232,loss:0.938261866569519,valid_accuracy:37.5%
epochs:233,loss:0.9382617473602295,train_accuracy:41.666666666666664%
epochs:233,loss:0.9382617473602295,valid accuracy:37.5%
epochs:234,loss:0.9382617473602295,train_accuracy:66.6666666666667%
epochs:234,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:235,loss:0.938261866569519,train accuracy:33.3333333333333336%
epochs:235,loss:0.938261866569519,valid_accuracy:37.5%
epochs:236,loss:0.938261866569519,train_accuracy:25.0%
epochs:236,loss:0.938261866569519,valid_accuracy:37.5%
epochs:237,loss:0.9382617473602295,train_accuracy:50.0%
epochs:237,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:238,loss:0.938261866569519,train_accuracy:58.333333333333336%
epochs:238,loss:0.938261866569519,valid_accuracy:37.5%
epochs:239,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs:239,loss:0.938261866569519,valid accuracy:37.5%
epochs:240,loss:0.938261866569519,train_accuracy:33.33333333333333333
epochs:240,loss:0.938261866569519,valid_accuracy:37.5%
epochs:241,loss:0.938261866569519,train accuracy:50.0%
epochs:241,loss:0.938261866569519,valid_accuracy:37.5%
epochs:242,loss:0.9778552055358887,train_accuracy:58.333333333333336%
epochs:242,loss:0.9778552055358887,valid_accuracy:37.5%
epochs:243,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs: 243, loss: 0.938261866569519, valid accuracy: 37.5%
epochs:244,loss:0.938261866569519,train accuracy:25.0%
epochs:244,loss:0.938261866569519,valid accuracy:37.5%
epochs: 245, loss: 0.9382617473602295, train accuracy: 75.0%
epochs:245,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:246,loss:0.938261866569519,train_accuracy:50.0%
epochs:246,loss:0.938261866569519,valid_accuracy:37.5%
epochs:247,loss:0.8691732883453369,train_accuracy:50.0%
epochs:247,loss:0.8691732883453369,valid accuracy:37.5%
epochs:248,loss:0.938261866569519,train accuracy:25.0%
epochs:248,loss:0.938261866569519,valid_accuracy:37.5%
epochs:249,loss:0.938261866569519,train accuracy:50.0%
epochs:249,loss:0.938261866569519,valid_accuracy:37.5%
epochs:250,loss:0.938261866569519,train_accuracy:50.0%
epochs:250,loss:0.938261866569519,valid_accuracy:37.5%
epochs:251,loss:0.938261866569519,train accuracy:58.333333333333336%
epochs:251,loss:0.938261866569519,valid accuracy:37.5%
epochs:252,loss:0.938261866569519,valid accuracy:37.5%
epochs:253,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs:253,loss:0.938261866569519,valid accuracy:37.5%
epochs:254,loss:0.938261866569519,train accuracy:50.0%
epochs:254,loss:0.938261866569519,valid_accuracy:37.5%
epochs:255,loss:0.938261866569519,valid accuracy:37.5%
```

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epochs:256,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:256,loss:0.938261866569519,valid_accuracy:37.5%
epochs:257,loss:0.938261866569519,train accuracy:50.0%
epochs:257,loss:0.938261866569519,valid_accuracy:37.5%
epochs:258,loss:0.938261866569519,train accuracy:50.0%
epochs:258,loss:0.938261866569519,valid accuracy:37.5%
epochs:259,loss:0.813261866569519,train accuracy:58.33333333333333336%
epochs: 259, loss: 0.813261866569519, valid accuracy: 50.0%
epochs:260,loss:0.938261866569519,train_accuracy:58.3333333333333336%
epochs:260,loss:0.938261866569519,valid_accuracy:37.5%
epochs:261,loss:0.9382617473602295,train accuracy:58.33333333333333336%
epochs:261,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:262,loss:0.938261866569519,train accuracy:58.33333333333333333333
epochs:262,loss:0.938261866569519,valid accuracy:37.5%
epochs:263,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:263,loss:0.938261866569519,valid_accuracy:37.5%
epochs: 264, loss: 0.938261866569519, train accuracy: 58.33333333333333336%
epochs:264,loss:0.938261866569519,valid_accuracy:37.5%
epochs:265,loss:0.8132617473602295,train_accuracy:58.3333333333333336%
epochs: 265, loss: 0.8132617473602295, valid accuracy: 50.0%
epochs:266,loss:0.9382617473602295,train_accuracy:58.3333333333333336%
epochs:266,loss:0.9382617473602295,valid_accuracy:37.5%
epochs:267.loss:0.938261866569519.train accuracy:75.0%
epochs:267,loss:0.938261866569519,valid_accuracy:37.5%
epochs:268,loss:0.938261866569519,train_accuracy:41.6666666666666664%
epochs:268,loss:0.938261866569519,valid_accuracy:37.5%
epochs:269,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:269,loss:0.938261866569519,valid_accuracy:37.5%
epochs:270,loss:0.938261866569519,train_accuracy:50.0%
epochs:270,loss:0.938261866569519,valid_accuracy:37.5%
epochs:271,loss:0.9800688028335571,train accuracy:75.0%
epochs:271,loss:0.9800688028335571,valid accuracy:37.5%
epochs:272,loss:0.938261866569519,train_accuracy:75.0%
epochs:272,loss:0.938261866569519,valid_accuracy:37.5%
epochs:273,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs:273,loss:0.938261866569519,valid_accuracy:37.5%
epochs:274,loss:0.938261866569519,train_accuracy:50.0%
epochs:274,loss:0.938261866569519,valid_accuracy:37.5%
epochs:275,loss:0.9382617473602295,train accuracy:41.666666666666666666
epochs: 275, loss: 0.9382617473602295, valid accuracy: 37.5%
epochs:276,loss:0.9382617473602295,train_accuracy:58.333333333333336%
epochs:276,loss:0.9382617473602295,valid accuracy:37.5%
epochs:277,loss:0.938261866569519,train accuracy:66.66666666666667%
epochs:277,loss:0.938261866569519,valid_accuracy:37.5%
epochs:278,loss:0.938261866569519,train_accuracy:33.3333333333333336%
epochs:278,loss:0.938261866569519,valid_accuracy:37.5%
epochs:279,loss:0.938261866569519,train_accuracy:41.666666666666664%
epochs:279,loss:0.938261866569519,valid accuracy:37.5%
epochs:280,loss:0.938261866569519,train accuracy:58.33333333333333336%
epochs:280,loss:0.938261866569519,valid_accuracy:37.5%
epochs:281,loss:0.938261866569519,train accuracy:8.3333333333333334%
epochs:281,loss:0.938261866569519,valid accuracy:37.5%
epochs:282,loss:0.938261866569519,train_accuracy:41.666666666666664%
epochs:282,loss:0.938261866569519,valid_accuracy:37.5%
epochs:283,loss:0.938261866569519,train accuracy:75.0%
epochs:283,loss:0.938261866569519,valid accuracy:37.5%
epochs:284,loss:0.938261866569519,valid accuracy:37.5%
epochs:285,loss:0.938261866569519,train accuracy:75.0%
epochs:285,loss:0.938261866569519,valid accuracy:37.5%
epochs:286,loss:0.938261866569519,valid_accuracy:37.5%
epochs:287,loss:0.938261866569519,train accuracy:41.6666666666666664%
epochs:287,loss:0.938261866569519,valid accuracy:37.5%
```

In [16]:

```
epochs:288,loss:0.938261866569519,train_accuracy:58.3333333333333333
epochs:288,loss:0.938261866569519,valid_accuracy:37.5%
epochs:289,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:289,loss:0.938261866569519,valid_accuracy:37.5%
epochs:290,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:290,loss:0.938261866569519,valid accuracy:37.5%
epochs:291,loss:0.9382617473602295,train accuracy:41.666666666666666666
epochs:291,loss:0.9382617473602295,valid accuracy:37.5%
epochs:292,loss:0.938261866569519,train_accuracy:50.0%
epochs:292,loss:0.938261866569519,valid_accuracy:37.5%
epochs:293,loss:0.938261866569519,train accuracy:58.3333333333333336%
epochs:293,loss:0.938261866569519,valid_accuracy:37.5%
epochs:294,loss:0.938261866569519,train accuracy:66.66666666666667%
epochs:294,loss:0.938261866569519,valid accuracy:37.5%
epochs:295,loss:0.938261866569519,train accuracy:41.666666666666664%
epochs:295,loss:0.938261866569519,valid accuracy:37.5%
epochs:296,loss:0.938261866569519,train accuracy:50.0%
epochs:296,loss:0.938261866569519,valid_accuracy:37.5%
epochs:297,loss:1.063261866569519,train_accuracy:66.6666666666667%
epochs:297,loss:1.063261866569519,valid accuracy:25.0%
epochs:298,loss:0.938261866569519,train_accuracy:66.66666666666667%
epochs:298,loss:0.938261866569519,valid_accuracy:37.5%
epochs:299.loss:0.938261866569519.train accuracy:50.0%
epochs:299,loss:0.938261866569519,valid_accuracy:37.5%
```

```
In [17]: # Plotting train and validation accuracy/loss together

plt.plot(list(range(epochs)), train_accuracy_list, label='Train Accuracy')
    plt.plot(list(range(epochs)), valid_accuracy_list, label='Validation Accuracy')
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy (%)")
    plt.title("Training and Validation Accuracy")
    plt.legend()
    plt.show()

plt.plot(list(range(epochs)), train_loss_list, label='Train Loss')
    plt.plot(list(range(epochs)), valid_loss_list, label='Validation Loss')
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.title("Training and Validation Loss")
    plt.legend()
    plt.show()
```

torch.save(model.state\_dict(), '/content/drive/MyDrive/Projects/Pet classification

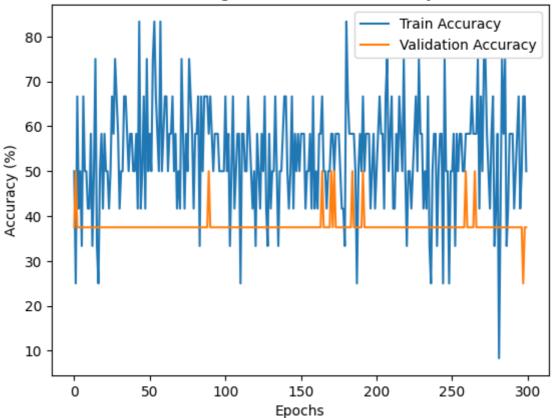
# plt.plot(iteration\_list[4::5], test\_accuracy\_list, label='Test Accuracy', color=

# # Plotting test accuracy in a separate plot

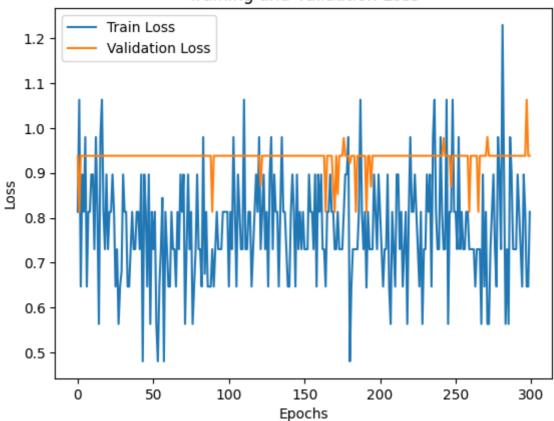
# plt.xlabel("No. of Iteration")
# plt.ylabel("Accuracy (%)")
# plt.title("Test Accuracy")

# plt.legend()
# plt.show()





## Training and Validation Loss



In [18]: test\_path='/content/drive/MyDrive/Projects/Pet classification using CNN/1577957291
print(os.listdir(test\_path))

['cats', 'dogs']

```
In [19]: # #test the model
         # model = PetNN(2).to(device)
         # model.load state dict(torch.load('/content/drive/MyDrive/Projects/Pet classificat
         # model.eval()
         # test_path='/content/drive/MyDrive/Projects/Pet classification using CNN/15779572
         # for class_name in os.listdir(test_path):
             print(f"Class name: {class name}")
             class_path=os.path.join(test_path,class_name)
             for image_name in os.listdir(class_path):
         #
               image_path=os.path.join(class_path,image_name)
         #
               image=Image.open(image path)
         #
               # Define a transformation to convert PIL Image to PyTorch tensor
         #
               transform = transforms.ToTensor()
         #
               # Apply the transformation to the image
               transform = transforms.Compose([
               transforms.RandomRotation(30),
         #
               transforms.Resize((256, 256)),
               transforms.RandomHorizontalFlip(),
         #
         #
                transforms.ToTensor(),
               transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
         #
         #
                   1)
                image_tensor = transform(image)
         #
               image_tensor=image_tensor.unsqueeze(0)
         #
                image tensor=image tensor.to(device)
         #
               #print(image tensor.shape)
         #
               with torch.no_grad():
                 outputs=model(image_tensor)
               predicted_class_index=torch.max(outputs,1)[1].to(device)
         #
         #
               #predicted_class_index=torch.argmax(outputs,dim=1).item()
         #
               print(predicted_class_index)
         #
               predicted_class=class_names[predicted_class_index]
               confidence_scores = torch.softmax(outputs, dim=1)
               print(f'Image : {image_name}, Predicted class : {predicted_class}, confidence
         def predict(img_detect, model):
In [22]:
             img = transform(img detect).unsqueeze(0).cuda() # Apply transformation and add
             model.eval() # Set eval mode
             output = model(img)
             predicted = torch.argmax(output)
             return predicted
In [23]: | model = PetNN(2)
         model = model.to(device)
         model.load_state_dict(torch.load('/content/drive/MyDrive/Projects/Pet classification
         device = torch.device("cuda:0" if torch.cuda.is available() else "cpu")
         print(device)
         test path = '/content/drive/MyDrive/Projects/Pet classification using CNN/157795729
         for class_name in os.listdir(test_path):
           class_path = os.path.join(test_path, class_name)
           for image_name in os.listdir(class_path):
             image_path = os.path.join(class_path, image_name)
             image = Image.open(image_path)
             predicted class index = predict(image, model)
             predicted_class = class_names[predicted_class_index.item()]
             print(f"Image: {image_name}, Predicted class: {predicted_class}")
```

```
cuda:0
         Image: 110.jpg, Predicted class: dogs
         Image: 104.jpg, Predicted class: dogs
         Image: 109.jpg, Predicted class: dogs
         Image: 101.jpg, Predicted class: dogs
         Image: 106.jpg, Predicted class: dogs
         Image: 107.jpg, Predicted class: dogs
         Image: 105.jpg, Predicted class: dogs
         Image: 108.jpg, Predicted class: dogs
         Image: 103.jpg, Predicted class: dogs
         Image: 102.jpg, Predicted class: dogs
         Image: 106.jpg, Predicted class: dogs
         Image: 105.jpg, Predicted class: dogs
         Image: 103.jpg, Predicted class: dogs
         Image: 110.jpg, Predicted class: dogs
         Image: 109.jpg, Predicted class: dogs
         Image: 101.jpg, Predicted class: dogs
         Image: 107.jpg, Predicted class: dogs
         Image: 104.jpg, Predicted class: dogs
         Image: 102.jpg, Predicted class: dogs
         Image: 108.jpg, Predicted class: dogs
In [24]: # Test Loop
         test_correct = 0
         test_total = 0
         test_acc_list=[]
         with torch.no_grad():
             for images, labels in dataloaders[TEST]:
                  images, labels = images.to(device), labels.to(device)
                  outputs = model(images)
                  predictions = torch.argmax(outputs, dim=1)
                 test correct += (predictions == labels).sum().item()
                 test_total += len(labels)
                  test_accuracy = test_correct * 100 / test_total
                  print("Test Accuracy: {}%".format(test_accuracy))
```

Test Accuracy: 50.0%