Assignment 6: Object detection using Transfer Learning of CNN architectures

In [ ]:
```
#ADITYA PANDIT
#B512024
```

In [5]:
```
#Importing all the necessary libraries

from IPython.core.interactiveshell import InteractiveShell
import seaborn as sns
# PyTorch
from torchvision import transforms, datasets, models
import torch
from torch import optim, cuda
from torch.utils.data import DataLoader, sampler
import torch.nn as nn

import warnings
warnings.filterwarnings('ignore', category=FutureWarning)

# Data science tools
import numpy as np
import pandas as pd
import os

# Image manipulations
from PIL import Image
# Useful for examining network
from torchsummary import summary
# Timing utility
from timeit import default_timer as timer

# Visualizations
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['font.size'] = 14

# Printing out all outputs
InteractiveShell.ast_node_interactivity = 'all'
```

In [6]:
```
# Location of data
datadir = '/home/wjk68/'
traindir = datadir + 'train/'
validdir = datadir + 'valid/'
testdir = datadir + 'test/'

save_file_name = 'vgg16-transfer-4.pt'
checkpoint_path = 'vgg16-transfer-4.pth'

# Change to fit hardware
batch_size = 128

# Whether to train on a gpu
train_on_gpu = cuda.is_available()
print(f'Train on gpu: {train_on_gpu}')

# Number of gpus
if train_on_gpu:
    gpu_count = cuda.device_count()
    print(f'{gpu_count} gpus detected.')
    if gpu_count > 1:
        multi_gpu = True
    else:
        multi_gpu = False
```

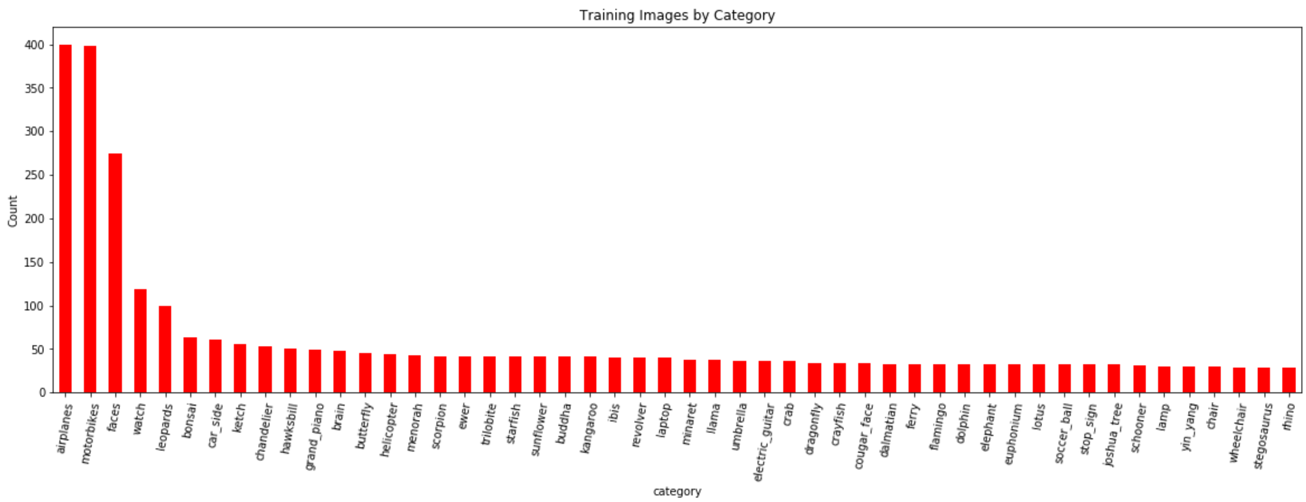
```
Train on gpu: False
```

In [7]:

```python
#Liiking at the number of images in each category and the size of the images

# Empty lists
categories = []
img_categories = []
n_train = []
n_valid = []
n_test = []
hs = []
ws = []

# Iterate through each category
for d in os.listdir(traindir):
    categories.append(d)

    # Number of each image
    train_imgs = os.listdir(traindir + d)
    valid_imgs = os.listdir(validdir + d)
    test_imgs = os.listdir(testdir + d)
    n_train.append(len(train_imgs))
    n_valid.append(len(valid_imgs))
    n_test.append(len(test_imgs))

    # Find stats for train images
    for i in train_imgs:
        img_categories.append(d)
        img = Image.open(traindir + d + '/' + i)
        img_array = np.array(img)
        # Shape
        hs.append(img_array.shape[0])
        ws.append(img_array.shape[1])

# Dataframe of categories
cat_df = pd.DataFrame({'category': categories,
                       'n_train': n_train,
                       'n_valid': n_valid, 'n_test': n_test}).\
    sort_values('category')

# Dataframe of training images
image_df = pd.DataFrame({
    'category': img_categories,
    'height': hs,
    'width': ws
})

cat_df.sort_values('n_train', ascending=False, inplace=True)
cat_df.head()
cat_df.tail()
```

In [8]:
```python
#Distribution of images
cat_df.set_index('category')['n_train'].plot.bar(
    color='r', figsize=(20, 6))
plt.xticks(rotation=80)
plt.ylabel('Count')
plt.title('Training Images by Category')
```

In [5]:
```python
# Only top 50 categories
cat_df.set_index('category').iloc[:50]['n_train'].plot.bar(
    color='r', figsize=(20, 6))
plt.xticks(rotation=80)
plt.ylabel('Count')
plt.title('Training Images by Category')
```

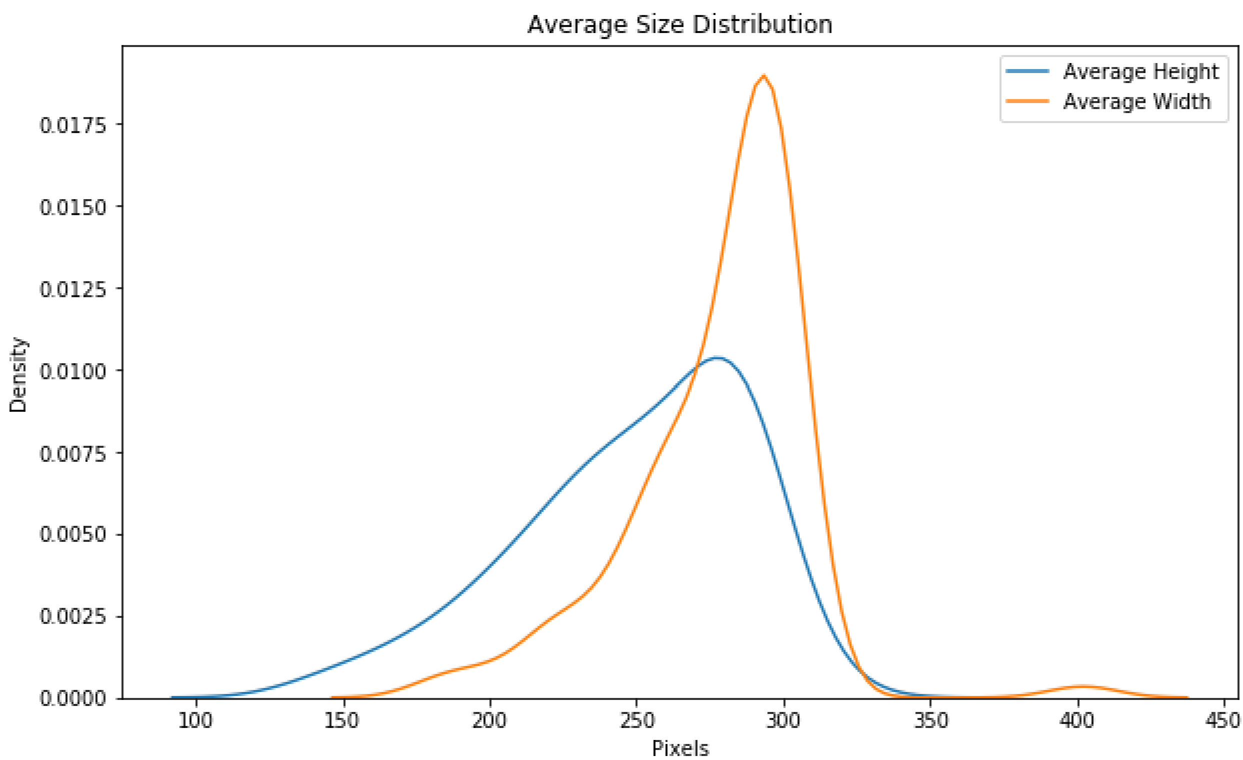


In [6]:
```
#Distribution of Images sizes
img_dsc = image_df.groupby('category').describe()
img_dsc.head()
```

Out[6]:

	height										
	count	mean	std	min	25%	50%	75%	max	count	mean	std
category											
accordion	27.0	263.851852	35.769243	199.0	233.00	265.0	300.00	300.0	27.0	280.333333	30.849511
airplanes	400.0	158.455000	30.847397	101.0	141.00	154.0	170.25	494.0	400.0	402.137500	8.804965
anchor	20.0	241.000000	38.608698	170.0	219.75	236.0	264.50	300.0	20.0	291.300000	22.209766
ant	20.0	211.950000	47.137509	103.0	177.00	203.0	236.75	300.0	20.0	298.600000	6.029751
barrel	23.0	284.086957	36.455344	188.0	300.00	300.0	300.00	300.0	23.0	241.869565	41.592508

In [7]:
```
plt.figure(figsize=(10, 6))
sns.kdeplot(
    img_dsc['height']['mean'], label='Average Height')
sns.kdeplot(
    img_dsc['width']['mean'], label='Average Width')
plt.xlabel('Pixels')
plt.ylabel('Density')
plt.title('Average Size Distribution')
```



In [ ]:
```
#When we use the images in the pre-trained network, we'll have to reshape them to 224 x
```

In [8]:
```
def imshow(image):
    """Display image"""
    plt.figure(figsize=(6, 6))
    plt.imshow(image)
    plt.axis('off')
    plt.show()


# Example image
x = Image.open(traindir + 'ewer/image_0002.jpg')
np.array(x).shape
imshow(x)
```

Out[8]:
```
(300, 187, 3)
```

In [10]:
```python
# Data Augmentation and Image transformations


image_transforms = {
    # Train uses data augmentation
    'train':
    transforms.Compose([
        transforms.RandomResizedCrop(size=256, scale=(0.8, 1.0)),
        transforms.RandomRotation(degrees=15),
        transforms.ColorJitter(),
        transforms.RandomHorizontalFlip(),
        transforms.CenterCrop(size=224),  # Image net standards
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],
                             [0.229, 0.224, 0.225])  # Imagenet standards
    ]),
    # Validation does not use augmentation
    'val':
    transforms.Compose([
        transforms.Resize(size=256),
        transforms.CenterCrop(size=224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    # Test does not use augmentation
    'test':
    transforms.Compose([
        transforms.Resize(size=256),
        transforms.CenterCrop(size=224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}
```

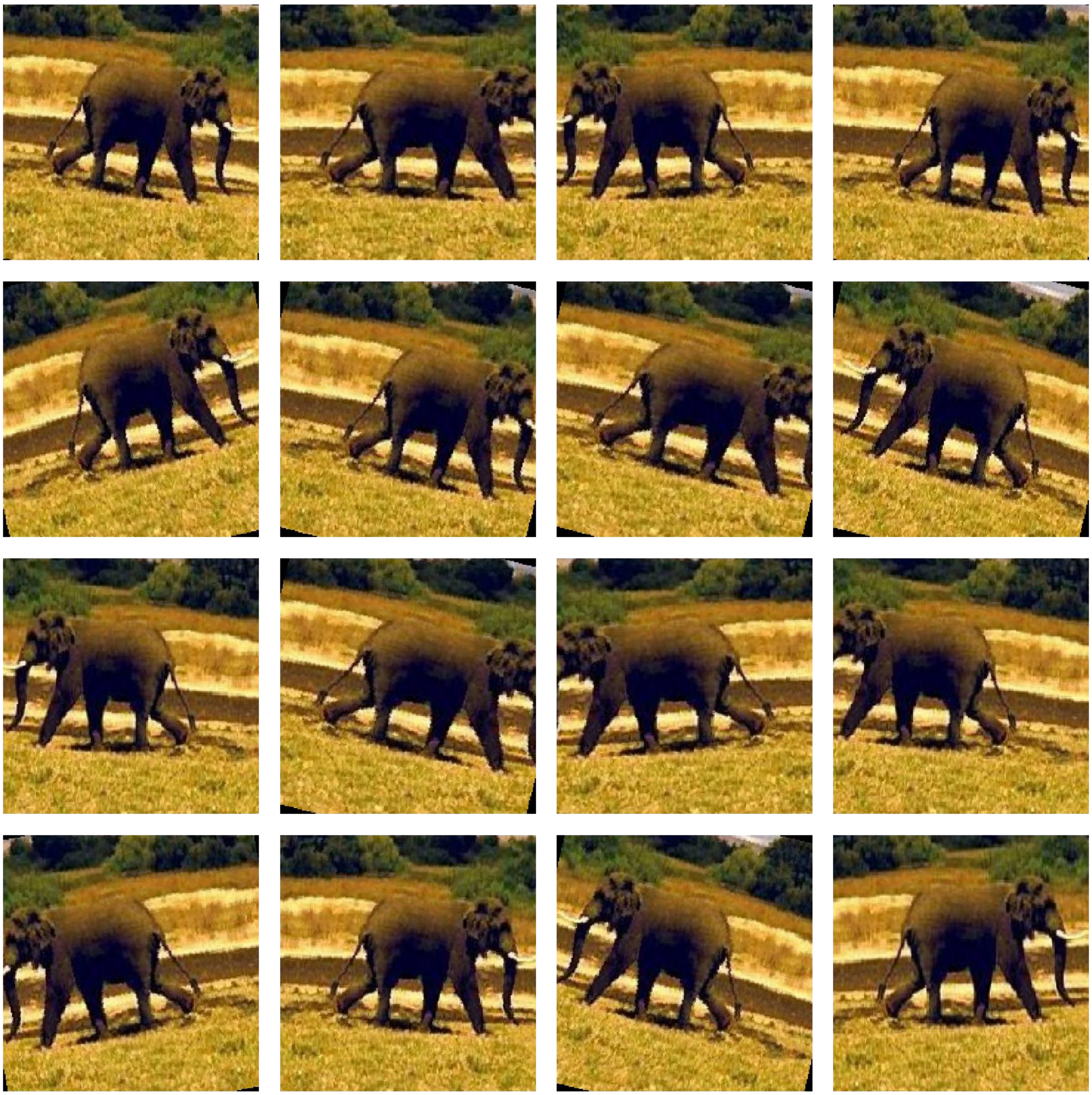
In [11]:
```python
def imshow_tensor(image, ax=None, title=None):
    """Imshow for Tensor."""

    if ax is None:
        fig, ax = plt.subplots()

    # Set the color channel as the third dimension
    image = image.numpy().transpose((1, 2, 0))

    # Reverse the preprocessing steps
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    image = std * image + mean

    # Clip the image pixel values
    image = np.clip(image, 0, 1)

    ax.imshow(image)
    plt.axis('off')

    return ax, image
```

In [12]:

```
ex_img = Image.open('/home/wjk68/train/elephant/image_0024.jpg')
imshow(ex_img)
```

In [13]:
```python
t = image_transforms['train']
plt.figure(figsize=(24, 24))

for i in range(16):
    ax = plt.subplot(4, 4, i + 1)
    _ = imshow_tensor(t(ex_img), ax=ax)

plt.tight_layout()
```

Out[13]:
```
<Figure size 1728x1728 with 0 Axes>
```



In [15]:
```
#Using dataloaders for speedy iterations
'''This construction avoids the need to load all the data into memory and also will aut

# Datasets from each folder
data = {
    'train':
    datasets.ImageFolder(root=traindir, transform=image_transforms['train']),
    'val':
    datasets.ImageFolder(root=validdir, transform=image_transforms['val']),
    'test':
    datasets.ImageFolder(root=testdir, transform=image_transforms['test'])
}

# Dataloader iterators
dataloaders = {
    'train': DataLoader(data['train'], batch_size=batch_size, shuffle=True),
    'val': DataLoader(data['val'], batch_size=batch_size, shuffle=True),
    'test': DataLoader(data['test'], batch_size=batch_size, shuffle=True)
}
```

In [16]:
```
trainiter = iter(dataloaders['train'])
features, labels = next(trainiter)
features.shape, labels.shape
```

Out[16]:
```
(torch.Size([128, 3, 224, 224]), torch.Size([128]))
```

In [17]:
```
n_classes = len(cat_df)
print(f'There are {n_classes} different classes.')

len(data['train'].classes)
```

```
There are 100 different classes.
```

Out[17]:
```
100
```

In [19]:
```
#using the pre-trained model -vgg for first few convolutional trained layers
model = models.vgg16(pretrained=True)
model
```

Out[19]:
```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace)
    (2): Dropout(p=0.5)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace)
    (5): Dropout(p=0.5)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
  )
)
```

In [ ]:
```
#manual training to be done only on classifier layer. rest as it is
```

In [20]:
```
# Freeze early layers
for param in model.parameters():
    param.requires_grad = False
```

In [21]:
```
'''train a classifier consisting of the following layers

Fully connected with ReLU activation (n_inputs, 256)
Dropout with 40% chance of dropping
Fully connected with log softmax output (256, n_classes)'''

n_inputs = model.classifier[6].in_features

# Add on classifier
model.classifier[6] = nn.Sequential(
    nn.Linear(n_inputs, 256), nn.ReLU(), nn.Dropout(0.4),
    nn.Linear(256, n_classes), nn.LogSoftmax(dim=1))

model.classifier
```

Out[21]:
```
Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace)
  (2): Dropout(p=0.5)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace)
  (5): Dropout(p=0.5)
  (6): Sequential(
    (0): Linear(in_features=4096, out_features=256, bias=True)
    (1): ReLU()
    (2): Dropout(p=0.4)
    (3): Linear(in_features=256, out_features=100, bias=True)
    (4): LogSoftmax()
  )
)
```

In [22]:
```
total_params = sum(p.numel() for p in model.parameters())
print(f'{total_params:,} total parameters.')
total_trainable_params = sum(
    p.numel() for p in model.parameters() if p.requires_grad)
print(f'{total_trainable_params:,} training parameters.')
```

```
135,335,076 total parameters.
1,074,532 training parameters.
```

In [23]:
```
#moving to gpu
if train_on_gpu:
    model = model.to('cuda')

if multi_gpu:
    model = nn.DataParallel(model)
```

In [24]:

```python
#function to load in pretrained model
def get_pretrained_model(model_name):
    """Retrieve a pre-trained model from torchvision

    Params
    -------
        model_name (str): name of the model (currently only accepts vgg16 and resnet50)

    Return
    --------
        model (PyTorch model): cnn

    """

    if model_name == 'vgg16':
        model = models.vgg16(pretrained=True)

        # Freeze early layers
        for param in model.parameters():
            param.requires_grad = False
        n_inputs = model.classifier[6].in_features

        # Add on classifier
        model.classifier[6] = nn.Sequential(
            nn.Linear(n_inputs, 256), nn.ReLU(), nn.Dropout(0.2),
            nn.Linear(256, n_classes), nn.LogSoftmax(dim=1))

    elif model_name == 'resnet50':
        model = models.resnet50(pretrained=True)

        for param in model.parameters():
            param.requires_grad = False

        n_inputs = model.fc.in_features
        model.fc = nn.Sequential(
            nn.Linear(n_inputs, 256), nn.ReLU(), nn.Dropout(0.2),
            nn.Linear(256, n_classes), nn.LogSoftmax(dim=1))

    # Move to gpu and parallelize
    if train_on_gpu:
        model = model.to('cuda')

    if multi_gpu:
        model = nn.DataParallel(model)

    return model
```

In [25]:

```
model = get_pretrained_model('vgg16')
if multi_gpu:
    summary(
        model.module,
        input_size=(3, 224, 224),
        batch_size=batch_size,
        device='cuda')
else:
    summary(
        model, input_size=(3, 224, 224), batch_size=batch_size, device='cuda')
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1        [128, 64, 224, 224]           1,792
              ReLU-2        [128, 64, 224, 224]               0
            Conv2d-3        [128, 64, 224, 224]          36,928
              ReLU-4        [128, 64, 224, 224]               0
         MaxPool2d-5        [128, 64, 112, 112]               0
            Conv2d-6       [128, 128, 112, 112]          73,856
              ReLU-7       [128, 128, 112, 112]               0
            Conv2d-8       [128, 128, 112, 112]         147,584
              ReLU-9       [128, 128, 112, 112]               0
        MaxPool2d-10         [128, 128, 56, 56]               0
           Conv2d-11         [128, 256, 56, 56]         295,168
             ReLU-12         [128, 256, 56, 56]               0
           Conv2d-13         [128, 256, 56, 56]         590,080
             ReLU-14         [128, 256, 56, 56]               0
           Conv2d-15         [128, 256, 56, 56]         590,080
             ReLU-16         [128, 256, 56, 56]               0
        MaxPool2d-17         [128, 256, 28, 28]               0
           Conv2d-18         [128, 512, 28, 28]       1,180,160
             ReLU-19         [128, 512, 28, 28]               0
           Conv2d-20         [128, 512, 28, 28]       2,359,808
             ReLU-21         [128, 512, 28, 28]               0
           Conv2d-22         [128, 512, 28, 28]       2,359,808
             ReLU-23         [128, 512, 28, 28]               0
        MaxPool2d-24         [128, 512, 14, 14]               0
           Conv2d-25         [128, 512, 14, 14]       2,359,808
             ReLU-26         [128, 512, 14, 14]               0
           Conv2d-27         [128, 512, 14, 14]       2,359,808
             ReLU-28         [128, 512, 14, 14]               0
           Conv2d-29         [128, 512, 14, 14]       2,359,808
             ReLU-30         [128, 512, 14, 14]               0
        MaxPool2d-31           [128, 512, 7, 7]               0
           Linear-32                [128, 4096]     102,764,544
             ReLU-33                [128, 4096]               0
          Dropout-34                [128, 4096]               0
           Linear-35                [128, 4096]      16,781,312
             ReLU-36                [128, 4096]               0
          Dropout-37                [128, 4096]               0
           Linear-38                 [128, 256]       1,048,832
             ReLU-39                 [128, 256]               0
          Dropout-40                 [128, 256]               0
           Linear-41                 [128, 100]          25,700
       LogSoftmax-42                 [128, 100]               0
================================================================
Total params: 135,335,076
Trainable params: 1,074,532
Non-trainable params: 134,260,544
----------------------------------------------------------------
Input size (MB): 73.50
Forward/backward pass size (MB): 27979.45
Params size (MB): 516.26
Estimated Total Size (MB): 28569.21
----------------------------------------------------------------
```

In [26]:
```
if multi_gpu:
    print(model.module.classifier[6])
else:
    print(model.classifier[6])
```

```
Sequential(
  (0): Linear(in_features=4096, out_features=256, bias=True)
  (1): ReLU()
  (2): Dropout(p=0.2)
  (3): Linear(in_features=256, out_features=100, bias=True)
  (4): LogSoftmax()
)
```

In [27]:
```
#mapping of classes to indexes

model.class_to_idx = data['train'].class_to_idx
model.idx_to_class = {
    idx: class_
    for class_, idx in model.class_to_idx.items()
}

list(model.idx_to_class.items())[:10]
```

Out[27]:
```
[(0, 'accordion'),
 (1, 'airplanes'),
 (2, 'anchor'),
 (3, 'ant'),
 (4, 'barrel'),
 (5, 'bass'),
 (6, 'beaver'),
 (7, 'binocular'),
 (8, 'bonsai'),
 (9, 'brain')]
```

In [28]:
```
criterion = nn.NLLLoss() #keeps track of the loss itself and the gradients of the loss
optimizer = optim.Adam(model.parameters()) #updates the parameters (weights) with the g
```

In [29]:
```
for p in optimizer.param_groups[0]['params']:
    if p.requires_grad:
        print(p.shape)
```

```
torch.Size([256, 4096])
torch.Size([256])
torch.Size([100, 256])
torch.Size([100])
```

In [30]:

```
#Training

def train(model,
          criterion,
          optimizer,
          train_loader,
          valid_loader,
          save_file_name,
          max_epochs_stop=3,
          n_epochs=20,
          print_every=2):
    """Train a PyTorch Model

    Params
    --------
        model (PyTorch model): cnn to train
        criterion (PyTorch loss): objective to minimize
        optimizer (PyTorch optimizier): optimizer to compute gradients of model paramet
        train_loader (PyTorch dataloader): training dataloader to iterate through
        valid_loader (PyTorch dataloader): validation dataloader used for early stoppin
        save_file_name (str ending in '.pt'): file path to save the model state dict
        max_epochs_stop (int): maximum number of epochs with no improvement in validati
        n_epochs (int): maximum number of training epochs
        print_every (int): frequency of epochs to print training stats

    Returns
    --------
        model (PyTorch model): trained cnn with best weights
        history (DataFrame): history of train and validation loss and accuracy
    """


    # Early stopping intialization
    epochs_no_improve = 0
    valid_loss_min = np.Inf

    valid_max_acc = 0
    history = []

    # Number of epochs already trained (if using loaded in model weights)
    try:
        print(f'Model has been trained for: {model.epochs} epochs.\n')
    except:
        model.epochs = 0
        print(f'Starting Training from Scratch.\n')

    overall_start = timer()

    # Main loop
    for epoch in range(n_epochs):

        # keep track of training and validation loss each epoch
        train_loss = 0.0
        valid_loss = 0.0

        train_acc = 0
        valid_acc = 0

        # Set to training
        model.train()
```

```
start = timer()
```

```
        # Training loop
        for ii, (data, target) in enumerate(train_loader):
            # Tensors to gpu
            if train_on_gpu:
                data, target = data.cuda(), target.cuda()

            # Clear gradients
            optimizer.zero_grad()
            # Predicted outputs are log probabilities
            output = model(data)

            # Loss and backpropagation of gradients
            loss = criterion(output, target)
            loss.backward()

            # Update the parameters
            optimizer.step()

            # Track train loss by multiplying average loss by number of examples in bat
            train_loss += loss.item() * data.size(0)

            # Calculate accuracy by finding max log probability
            _, pred = torch.max(output, dim=1)
            correct_tensor = pred.eq(target.data.view_as(pred))
            # Need to convert correct tensor from int to float to average
            accuracy = torch.mean(correct_tensor.type(torch.FloatTensor))
            # Multiply average accuracy times the number of examples in batch
            train_acc += accuracy.item() * data.size(0)

            # Track training progress
            print(
                f'Epoch: {epoch}\t{100 * (ii + 1) / len(train_loader):.2f}% complete. {
                end='\r')

        # After training loops ends, start validation
        else:
            model.epochs += 1

            # Don't need to keep track of gradients
            with torch.no_grad():
                # Set to evaluation mode
                model.eval()

                # Validation loop
                for data, target in valid_loader:
                    # Tensors to gpu
                    if train_on_gpu:
                        data, target = data.cuda(), target.cuda()

                    # Forward pass
                    output = model(data)

                    # Validation loss
                    loss = criterion(output, target)
                    # Multiply average loss times the number of examples in batch
                    valid_loss += loss.item() * data.size(0)

                    # Calculate validation accuracy
                    _, pred = torch.max(output, dim=1)
                    correct_tensor = pred.eq(target.data.view_as(pred))
                    accuracy = torch.mean(
                        correct_tensor.type(torch.FloatTensor))
```

```
                # Multiply average accuracy times the number of examples
                valid_acc += accuracy.item() * data.size(0)

            # Calculate average losses
            train_loss = train_loss / len(train_loader.dataset)
            valid_loss = valid_loss / len(valid_loader.dataset)

            # Calculate average accuracy
            train_acc = train_acc / len(train_loader.dataset)
            valid_acc = valid_acc / len(valid_loader.dataset)

            history.append([train_loss, valid_loss, train_acc, valid_acc])

            # Print training and validation results
            if (epoch + 1) % print_every == 0:
                print(
                    f'\nEpoch: {epoch} \tTraining Loss: {train_loss:.4f} \tValidati
                )
                print(
                    f'\t\tTraining Accuracy: {100 * train_acc:.2f}%\t Validation Ac
                )

            # Save the model if validation loss decreases
            if valid_loss < valid_loss_min:
                # Save model
                torch.save(model.state_dict(), save_file_name)
                # Track improvement
                epochs_no_improve = 0
                valid_loss_min = valid_loss
                valid_best_acc = valid_acc
                best_epoch = epoch

            # Otherwise increment count of epochs with no improvement
            else:
                epochs_no_improve += 1
                # Trigger early stopping
                if epochs_no_improve >= max_epochs_stop:
                    print(
                        f'\nEarly Stopping! Total epochs: {epoch}. Best epoch: {bes
                    )
                    total_time = timer() - overall_start
                    print(
                        f'{total_time:.2f} total seconds elapsed. {total_time / (ep
                    )

                    # Load the best state dict
                    model.load_state_dict(torch.load(save_file_name))
                    # Attach the optimizer
                    model.optimizer = optimizer

                    # Format history
                    history = pd.DataFrame(
                        history,
                        columns=[
                            'train_loss', 'valid_loss', 'train_acc',
                            'valid_acc'
                        ])
                    return model, history

    # Attach the optimizer
    model.optimizer = optimizer
    # Record overall time and print out stats
```

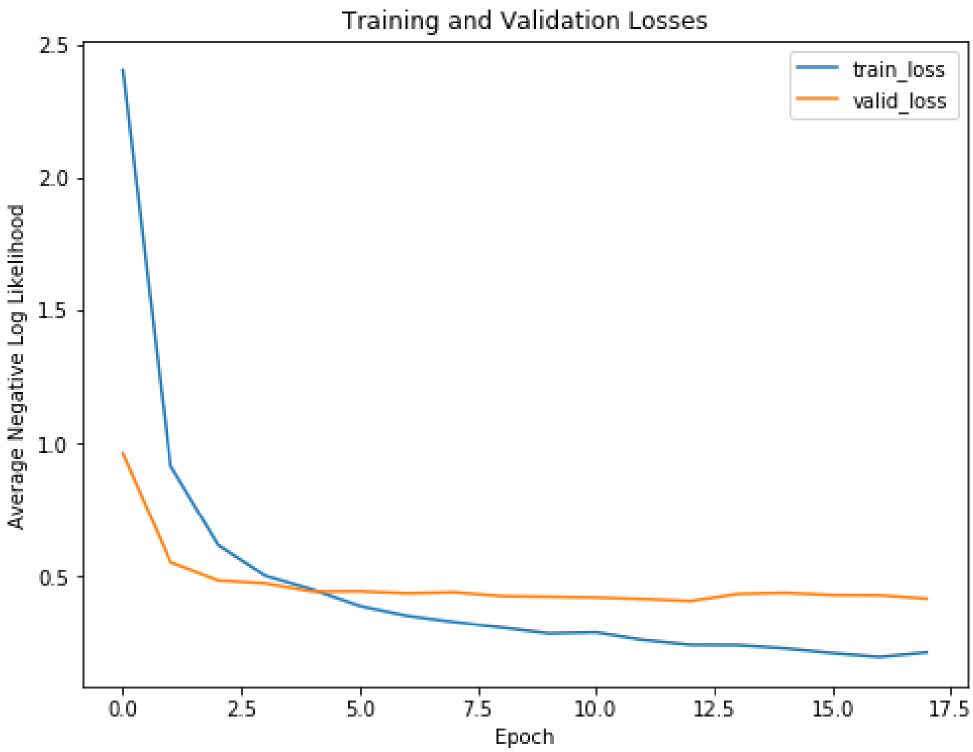
```python
    total_time = timer() - overall_start
    print(
        f'\nBest epoch: {best_epoch} with loss: {valid_loss_min:.2f} and acc: {100 * va
    )
    print(
        f'{total_time:.2f} total seconds elapsed. {total_time / (epoch):.2f} seconds pe
    )
    # Format history
    history = pd.DataFrame(
        history,
        columns=['train_loss', 'valid_loss', 'train_acc', 'valid_acc'])
    return model, history
```

In [31]:
```python
model, history = train(
    model,
    criterion,
    optimizer,
    dataloaders['train'],
    dataloaders['val'],
    save_file_name=save_file_name,
    max_epochs_stop=5,
    n_epochs=30,
    print_every=2)
```

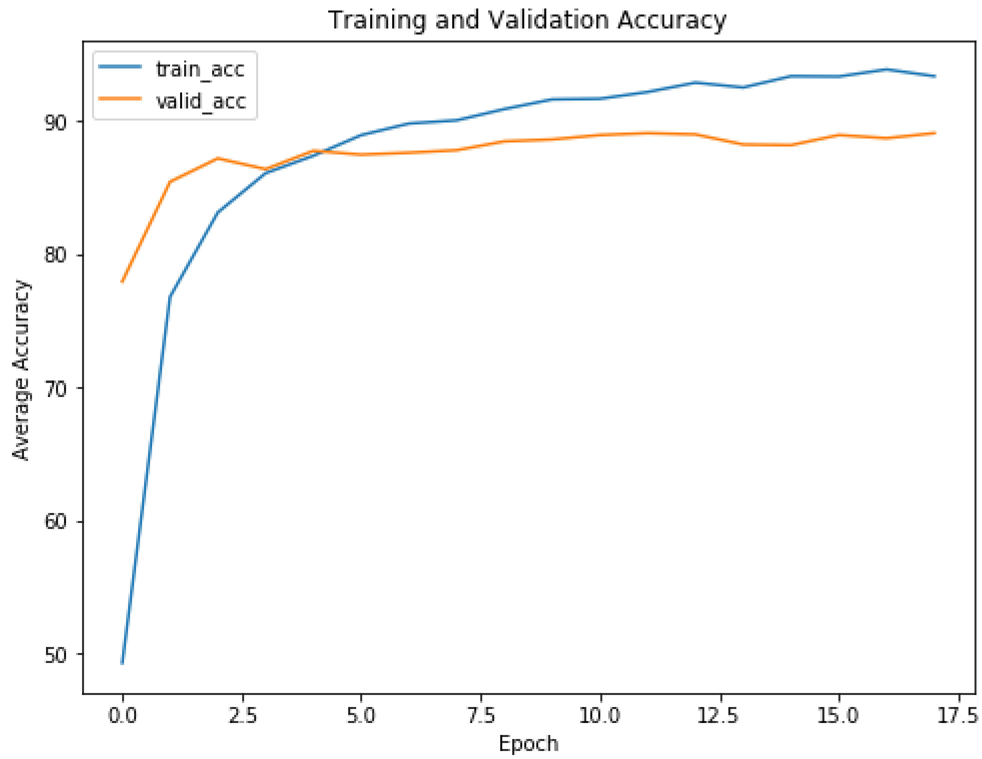
```
Starting Training from Scratch.

Epoch: 1        100.00% complete. 35.76 seconds elapsed in epoch.
Epoch: 1        Training Loss: 0.9153   Validation Loss: 0.5520
                Training Accuracy: 76.76%       Validation Accuracy: 85.42%
Epoch: 3        100.00% complete. 35.77 seconds elapsed in epoch.
Epoch: 3        Training Loss: 0.5012   Validation Loss: 0.4724
                Training Accuracy: 86.06%       Validation Accuracy: 86.37%
Epoch: 5        100.00% complete. 32.21 seconds elapsed in epoch.
Epoch: 5        Training Loss: 0.3876   Validation Loss: 0.4425
                Training Accuracy: 88.92%       Validation Accuracy: 87.46%
Epoch: 7        100.00% complete. 37.51 seconds elapsed in epoch.
Epoch: 7        Training Loss: 0.3271   Validation Loss: 0.4389
                Training Accuracy: 90.04%       Validation Accuracy: 87.79%
Epoch: 9        100.00% complete. 33.26 seconds elapsed in epoch.
Epoch: 9        Training Loss: 0.2837   Validation Loss: 0.4220
                Training Accuracy: 91.61%       Validation Accuracy: 88.60%
Epoch: 11       100.00% complete. 33.16 seconds elapsed in epoch.
Epoch: 11       Training Loss: 0.2590   Validation Loss: 0.4135
                Training Accuracy: 92.17%       Validation Accuracy: 89.07%
Epoch: 13       100.00% complete. 31.84 seconds elapsed in epoch.
Epoch: 13       Training Loss: 0.2397   Validation Loss: 0.4326
                Training Accuracy: 92.51%       Validation Accuracy: 88.22%
Epoch: 15       100.00% complete. 36.79 seconds elapsed in epoch.
Epoch: 15       Training Loss: 0.2101   Validation Loss: 0.4284
                Training Accuracy: 93.33%       Validation Accuracy: 88.93%
Epoch: 17       100.00% complete. 30.47 seconds elapsed in epoch.
Epoch: 17       Training Loss: 0.2127   Validation Loss: 0.4152
                Training Accuracy: 93.36%       Validation Accuracy: 89.07%

Early Stopping! Total epochs: 17. Best epoch: 12 with loss: 0.41 and acc: 89.07%
931.73 total seconds elapsed. 51.76 seconds per epoch.
```

In [32]:

```python
#Training results shown graphically

plt.figure(figsize=(8, 6))
for c in ['train_loss', 'valid_loss']:
    plt.plot(
        history[c], label=c)
plt.legend()
plt.xlabel('Epoch')
plt.ylabel('Average Negative Log Likelihood')
plt.title('Training and Validation Losses')
```



In [33]:
```
plt.figure(figsize=(8, 6))
for c in ['train_acc', 'valid_acc']:
    plt.plot(
        100 * history[c], label=c)
plt.legend()
plt.xlabel('Epoch')
plt.ylabel('Average Accuracy')
plt.title('Training and Validation Accuracy')
```



In [ ]:
```
#The accuracy cones out to be >80%
```

In [40]:
```python
'''This function processes an image path into a PyTorch tensor for predictions. It appl

def process_image(image_path):
    """Process an image path into a PyTorch tensor"""

    image = Image.open(image_path)
    # Resize
    img = image.resize((256, 256))

    # Center crop
    width = 256
    height = 256
    new_width = 224
    new_height = 224

    left = (width - new_width) / 2
    top = (height - new_height) / 2
    right = (width + new_width) / 2
    bottom = (height + new_height) / 2
    img = img.crop((left, top, right, bottom))

    # Convert to numpy, transpose color dimension and normalize
    img = np.array(img).transpose((2, 0, 1)) / 256

    # Standardization
    means = np.array([0.485, 0.456, 0.406]).reshape((3, 1, 1))
    stds = np.array([0.229, 0.224, 0.225]).reshape((3, 1, 1))

    img = img - means
    img = img / stds

    img_tensor = torch.Tensor(img)

    return img_tensor
```

In [41]:
```python
x = process_image(testdir + 'dragonfly/image_0015.jpg')
x.shape
```

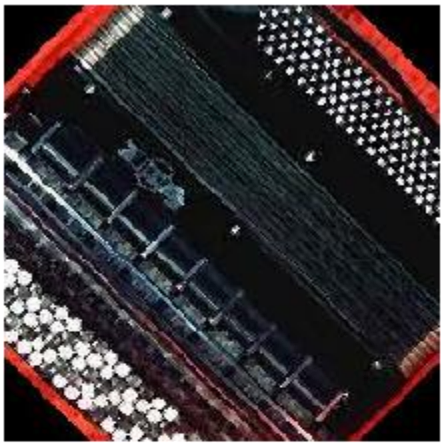
Out[41]:
```
torch.Size([3, 224, 224])
```

In [42]:
```python
ax, image = imshow_tensor(x)
```

In [43]:
```
ax, image = imshow_tensor(process_image(testdir + 'dalmatian/image_0053.jpg'))
```

In [44]:
```
#Fucntion to make predictions

def predict(image_path, model, topk=5):
    """Make a prediction for an image using a trained model

    Params
    --------
        image_path (str): filename of the image
        model (PyTorch model): trained model for inference
        topk (int): number of top predictions to return

    Returns

    """
    real_class = image_path.split('/')[-2]

    # Convert to pytorch tensor
    img_tensor = process_image(image_path)

    # Resize
    if train_on_gpu:
        img_tensor = img_tensor.view(1, 3, 224, 224).cuda()
    else:
        img_tensor = img_tensor.view(1, 3, 224, 224)

    # Set to evaluation
    with torch.no_grad():
        model.eval()
        # Model outputs log probabilities
        out = model(img_tensor)
        ps = torch.exp(out)

        # Find the topk predictions
        topk, topclass = ps.topk(topk, dim=1)

        # Extract the actual classes and probabilities
        top_classes = [
            model.idx_to_class[class_] for class_ in topclass.cpu().numpy()[0]
        ]
        top_p = topk.cpu().numpy()[0]

        return img_tensor.cpu().squeeze(), top_p, top_classes, real_class
```

In [45]:
```
np.random.seed = 100


def random_test_image():
    """Pick a random test image from the test directory"""
    c = np.random.choice(cat_df['category'])
    root = testdir + c + '/'
    img_path = root + np.random.choice(os.listdir(root))
    return img_path


_ = imshow_tensor(process_image(random_test_image()))
```



In [46]:
```
img, top_p, top_classes, real_class = predict(random_test_image(), model)
img.shape
```

Out[46]:
```
torch.Size([3, 224, 224])
```

In [47]:
```
top_p, top_classes, real_class
```

Out[47]:
```
(array([0.615789  , 0.35459077, 0.01252878, 0.00679292, 0.00269399],
       dtype=float32),
 ['ceiling_fan', 'gramophone', 'anchor', 'chair', 'octopus'],
 'ceiling_fan')
```

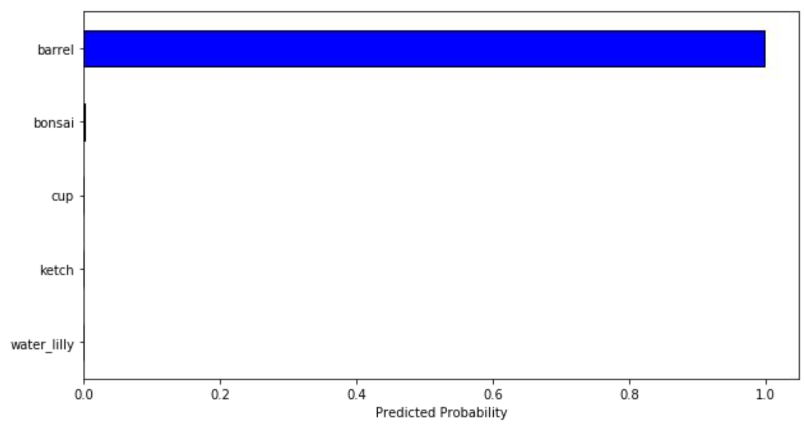
In [48]:
```
img, top_p, top_classes, real_class = predict(random_test_image(), model)
top_p, top_classes, real_class
```

Out[48]:
```
(array([9.9574465e-01, 9.7864203e-04, 9.5386576e-04, 6.3906156e-04,
        6.0763489e-04], dtype=float32),
 ['pizza', 'brain', 'lobster', 'garfield', 'nautilus'],
 'pizza')
```

In [49]:
```
#function to display predictions. some predicted classes are shown but title seems to b

def display_prediction(image_path, model, topk):
    """Display image and preditions from model"""

    # Get predictions
    img, ps, classes, y_obs = predict(image_path, model, topk)
    # Convert results to dataframe for plotting
    result = pd.DataFrame({'p': ps}, index=classes)

    # Show the image
    plt.figure(figsize=(16, 5))
    ax = plt.subplot(1, 2, 1)
    ax, img = imshow_tensor(img, ax=ax)

    # Set title to be the actual class
    ax.set_title(y_obs, size=20)

    ax = plt.subplot(1, 2, 2)
    # Plot a bar plot of predictions
    result.sort_values('p')['p'].plot.barh(color='blue', edgecolor='k', ax=ax)
    plt.xlabel('Predicted Probability')
    plt.tight_layout()
```

In [52]:
```
display_prediction(random_test_image(), model, topk=5)
```

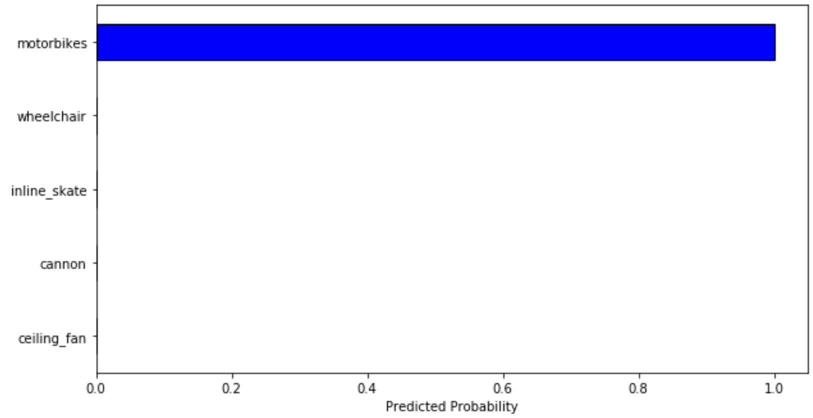
23 training images for barrel.



In [53]:
```python
display_prediction(random_test_image(), model, topk=5)
```

398 training images for motorbikes.

motorbikes

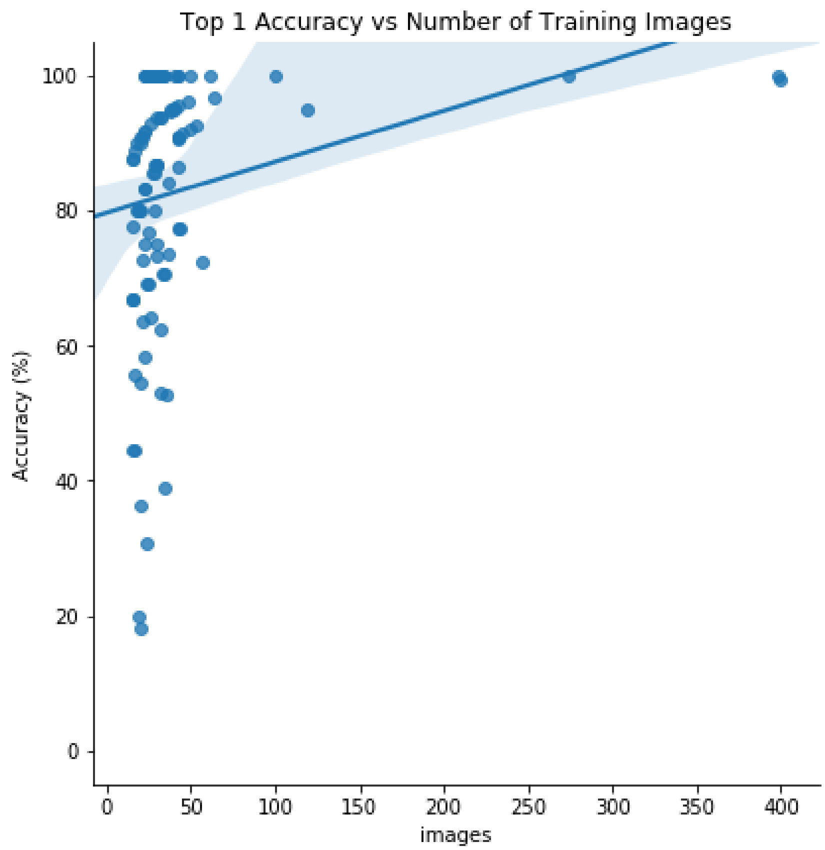


In [54]:
```python
#Testing the accuracy
def accuracy(output, target, topk=(1, )):
    """Compute the topk accuracy(s)"""
    if train_on_gpu:
        output = output.to('cuda')
        target = target.to('cuda')

    with torch.no_grad():
        maxk = max(topk)
        batch_size = target.size(0)

        # Find the predicted classes and transpose
        _, pred = output.topk(k=maxk, dim=1, largest=True, sorted=True)
        pred = pred.t()

        # Determine predictions equal to the targets
        correct = pred.eq(target.view(1, -1).expand_as(pred))

        res = []

        # For each k, find the percentage of correct
        for k in topk:
            correct_k = correct[:k].view(-1).float().sum(0, keepdim=True)
            res.append(correct_k.mul_(100.0 / batch_size).item())
        return res
```

In [55]:
```python
testiter = iter(dataloaders['test'])
# Get a batch of testing images and labels
features, targets = next(testiter)

if train_on_gpu:
    accuracy(model(features.to('cuda')), targets, topk=(1, 5))
else:
    accuracy(model(features), targets, topk=(1, 5))
```

Out[55]: [89.84375, 99.21875]

In [58]:
```
#visualising results

results = results.merge(cat_df, left_on='class', right_on='category').\
    drop(columns=['category'])

# Plot using seaborn
sns.lmplot(
    y='top1', x='n_train', data=results, height=6)
plt.xlabel('images')
plt.ylabel('Accuracy (%)')
plt.title('Top 1 Accuracy vs Number of Training Images')
plt.ylim(-5, 105)
```



In [59]:
```
print('Category with minimum accuracy.')
results.loc[results['top1'].idxmin]

print('Category with minimum images.')
results.loc[results['n_train'].idxmin]
```

```
Category with minimum accuracy.
```

Out[59]:
```
class       anchor
top1       18.1818
top5       63.6364
loss       2.89586
n_train         20
n_valid         11
n_test          11
Name: 2, dtype: object
```

```
Category with minimum images.
```

Out[59]:
```
class      inline_skate
top1               87.5
top5                100
loss           0.221262
n_train              15
n_valid               8
n_test                8
Name: 49, dtype: object
```

In [60]:
```
sns.lmplot(
    y='top5', x='n_train', data=results, height=6)
plt.xlabel('images')
plt.ylabel('Accuracy (%)')
plt.title('Top 5 Accuracy vs Number of Training Images')
plt.ylim(-5, 105)
```

In [61]:
```
# Weighted column of test images
results['weighted'] = results['n_test'] / results['n_test'].sum()

# Create weighted accuracies
for i in (1, 5):
    results[f'weighted_top{i}'] = results['weighted'] * results[f'top{i}']

# Find final accuracy accounting for frequencies
top1_weighted = results['weighted_top1'].sum()
top5_weighted = results['weighted_top5'].sum()
loss_weighted = (results['weighted'] * results['loss']).sum()

print(f'Final test cross entropy per image = {loss_weighted:.4f}.')
print(f'Final test top 1 weighted accuracy = {top1_weighted:.2f}%')
print(f'Final test top 5 weighted accuracy = {top5_weighted:.2f}%')
```

```
Final test cross entropy per image = 0.3772.
Final test top 1 weighted accuracy = 88.65%
Final test top 5 weighted accuracy = 98.00%
```

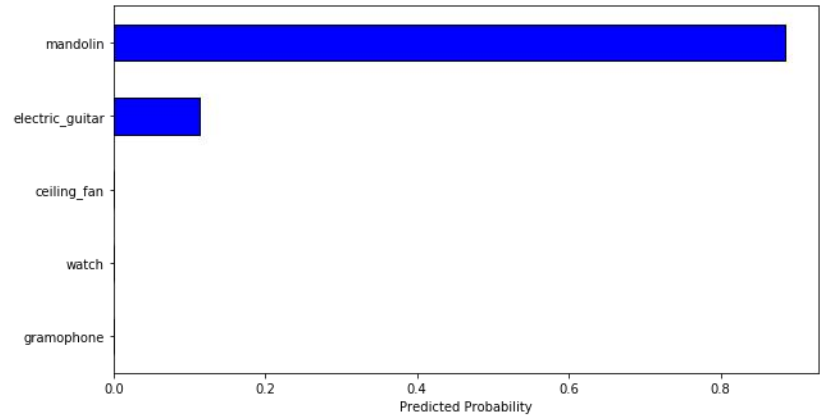
In [70]:

```
#fucntion to display the predictions for an image

def display_category(model, category, n=4):
    """Display predictions for a category
    """
    category_results = results.loc[results['class'] == category]
    print(category_results.iloc[:, :6], '/n')

    images = np.random.choice(
        os.listdir(testdir + category + '/'), size=4, replace=False)

    for img in images:
        display_prediction(testdir + category + '/' + img, model, 5)
```

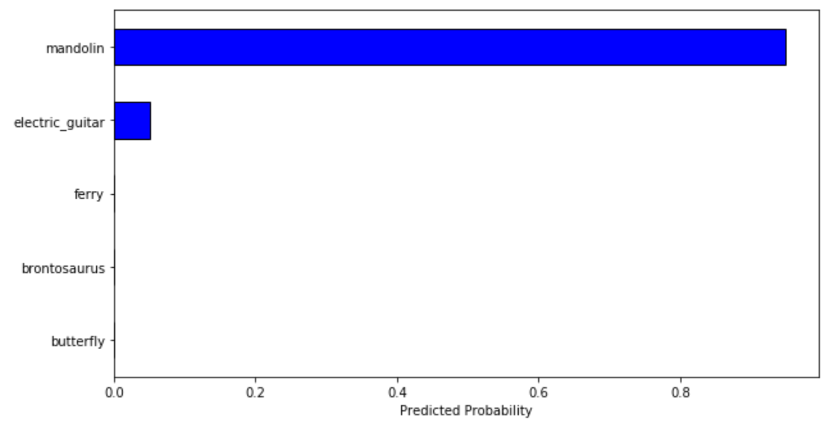
```
In [73]: display_category(model, 'mandolin')
```

```
       class       top1    top5      loss  n_train  n_valid
59  mandolin  90.909091  100.0  0.420903       21       11 /n
21 training images for mandolin.
21 training images for mandolin.
21 training images for mandolin.
21 training images for mandolin.
```

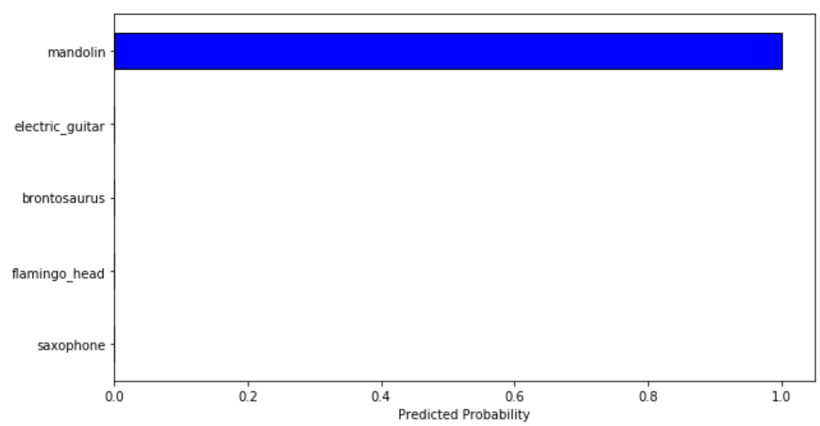
mandolin

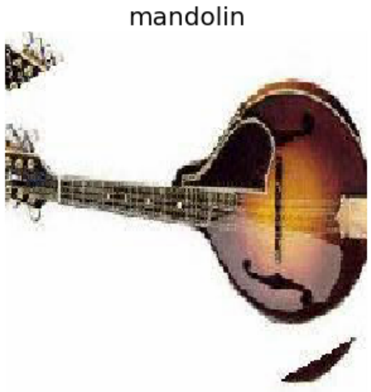


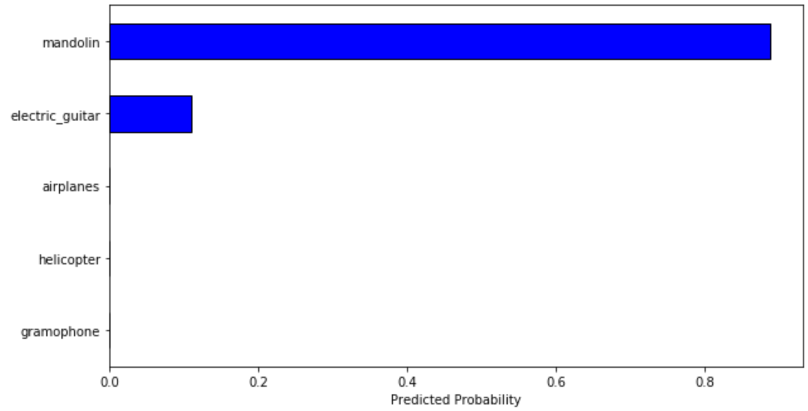
mandolin



mandolin




mandolin


mandolin
electric_guitar
airplanes
helicopter
gramophone
0.0
0.2
0.4
0.6
0.8
Predicted Probability