Image Features

Image Feature is a simple image pattern, based on which we can describe what we see in an image.

The main role of features in computer vision is to transform visual information into the vector space.This gives the possibility to perform mathemaatical operations on them.

There are two ways of getting features from image.

1) Image Descriptor(White-box algorithm 2) Neutral Net(Black box algorithm)

In [1]:

```
import torch
import torch.nn as nn
import torchvision.models as models
import torchvision.transforms as transforms
from torch.autograd import Variable
from PIL import Image
```

In [2]:

```
pic_one = str(input("Input first image name\n"))
pic_two = str(input("Input second image name\n"))
```

```
Input first image name
/content/training_set/training_set/cactus/cactus_0028_0.jpg
Input second image name
/content/validation_set/validation_set/cactus/cactus_0181_19.jpg
```

In [3]:

```
# Load the pretrained model
model = models.resnet18(pretrained=True)
# Use the model object to select the desired layer
layer = model._modules.get('avgpool')
```

In [4]:

```
# Set model to evaluation mode
model.eval()
```

Out[4]:

```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
```

```
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=512, out_features=1000, bias=True)
)
```

In [5]:

```
scaler = transforms.Scale((224, 224))
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
to_tensor = transforms.ToTensor()
```

```
/usr/local/lib/python3.7/dist-packages/torchvision/transforms/transforms.py:285: UserWarning: The use of the transforms.Scale transform is deprecated, please use transforms.Resize instead.
  warnings.warn("The use of the transforms.Scale transform is deprecated, " +
```

In [6]:

```
def get_vector(image_name):
    # 1. Load the image with Pillow library
    img = Image.open(image_name)
    # 2. Create a PyTorch Variable with the transformed image
    t_img = Variable(normalize(to_tensor(scaler(img))).unsqueeze(0))
    # 3. Create a vector of zeros that will hold our feature vector
    #    The 'avgpool' layer has an output size of 512
    my_embedding = torch.zeros(1,512,1,1)
    # 4. Define a function that will copy the output of a layer
    def copy_data(m, i, o):
        my_embedding.copy_(o.data)
    # 5. Attach that function to our selected layer
    h = layer.register_forward_hook(copy_data)
    # 6. Run the model on our transformed image
    model(t_img)
    # 7. Detach our copy function from the layer
    h.remove()
    # 8. Return the feature vector
    return my_embedding
```

In [7]:

```
pic_one_vector = get_vector(pic_one)
pic_two_vector = get_vector(pic_two)
```

calculate the cosine similarity between the two vectors:

In [8]:

```
from sklearn.metrics.pairwise import cosine_similarity
image1 = pic_one_vector.reshape(1, -1)
image2 = pic_two_vector.reshape(1, -1)
print(cosine_similarity(image1, image2))
```

```
[[0.5896418]]
```

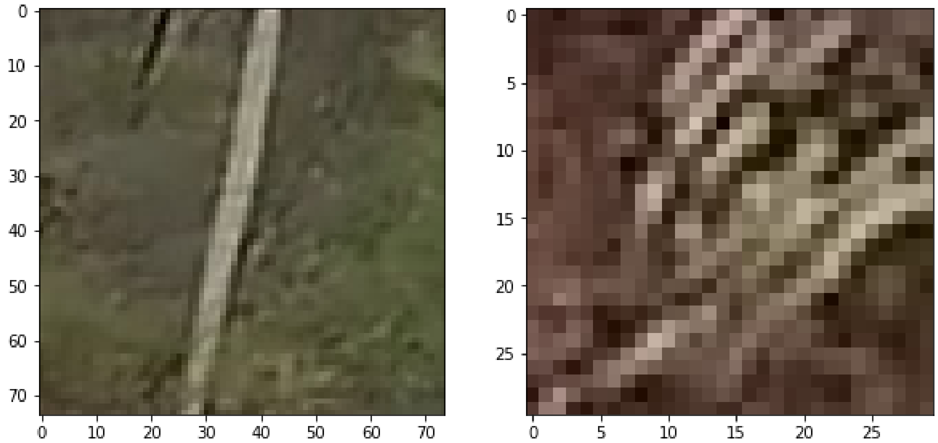
In [9]:

```
import matplotlib.pyplot as plt
plt.figure(figsize=(10,14))

import matplotlib.image as mpimg

plt.subplot(2,2,1),plt.imshow(mpimg.imread(pic_one))
print("similarity:",cosine_similarity(image1,image2))
plt.subplot(2,2,2),plt.imshow(mpimg.imread(pic_two))
plt.show()
```

```
similarity: [[0.5896418]]
```



References:

https://matplotlib.org/stable/tutorials/introductory/images.html

https://www.kaggle.com/pankajgiri/resnet-feature-extraction-pytorch

Dataset :

https://www.kaggle.com/irvingvasquez/cactus-aerial-photos