```
# import header files
%matplotlib inline
import torch
import torch.nn as nn
import torchvision
from functools import partial
from dataclasses import dataclass
from collections import OrderedDict
import glob
import os
import random
import tensorflow as tf
from tensorflow import keras
import numpy as np
import seaborn as sn
import pandas as pd
from matplotlib import pyplot as plt
from tqdm import tqdm
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support
import time
import copy
import tqdm
import torch
import random
from PIL import Image
import torch.optim as optim
from torchvision import models
import torch.nn.functional as F
import matplotlib.pyplot as plt
from torch.utils.data import TensorDataset,DataLoader
```

```
# load my google drive
def auth_gdrive():
  from google.colab import drive
  if os.path.exists('content/gdrive/My Drive'): return
  drive.mount('/content/gdrive')
def load_gdrive_dataset():
  loader_assets = 'MyPollen13K.zip'
  auth_gdrive()
```

```
# mount my google drive
from google.colab import drive
drive.mount('/content/gdrive', force_remount=True)
load_gdrive_dataset()
```

```
Mounted at /content/gdrive
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_
```

```
# unzip  dataset
!unzip "/content/gdrive/MyDrive/MyPollen13K.zip"
```

```
Streaming output truncated to the last 5000 lines.
  inflating: MyPollen13K/train/3/20190404111856_OBJ_34_346_175.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_35_136_147.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_36_98_124.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_37_92_79.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_38_261_71.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_39_1097_44.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_3_330_866.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_40_317_606.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_41_160_362.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_5_1185_786.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_8_705_730.png
  inflating: MyPollen13K/train/3/20190404111856_OBJ_9_631_709.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_0_916_870.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_13_1126_429.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_15_978_405.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_16_1070_403.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_19_319_371.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_1_169_850.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_20_616_369.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_21_1191_359.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_24_706_354.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_25_1099_340.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_27_658_300.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_29_640_241.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_30_855_188.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_31_1127_177.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_32_528_174.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_33_341_167.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_34_681_134.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_36_886_102.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_38_1029_77.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_39_251_47.png
```

```
  inflating: MyPollen13K/train/3/20190404111901_OBJ_3_405_784.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_40_1223_542.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_41_1164_520.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_42_683_459.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_43_1081_452.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_44_657_396.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_4_1069_751.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_5_653_688.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_6_1151_679.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_8_235_562.png
  inflating: MyPollen13K/train/3/20190404111901_OBJ_9_850_545.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_0_1198_854.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_12_987_382.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_13_552_347.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_14_119_348.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_16_1000_271.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_17_698_252.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_18_550_205.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_19_85_165.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_1_447_771.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_20_73_112.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_2_416_736.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_6_1200_667.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_7_370_653.png
  inflating: MyPollen13K/train/3/20190404111907_OBJ_8_300_555.png
```

```
# Count the number of samples in the training set and test set
# training set
train_class_1 = os.listdir("/content/MyPollen13K/train/1/")
train_class_1_samples = len(train_class_1)
print("The number of samples in the train_class_1 is:", train_class_1_samples)
train_class_2 = os.listdir("/content/MyPollen13K/train/2/")
train_class_2_samples = len(train_class_2)
print("The number of samples in the train_class_2 is:", train_class_2_samples)
train_class_3 = os.listdir("/content/MyPollen13K/train/3/")
train_class_3_samples = len(train_class_3)
print("The number of samples in the train_class_3 is:", train_class_3_samples)
train_class_4 = os.listdir("/content/MyPollen13K/train/4/")
train_class_4_samples = len(train_class_4)
print("The number of samples in the train_class_4 is:", train_class_4_samples)
number_trainingset = len(train_class_1+train_class_2+train_class_3+train_class_4)
print("The number of samples in the training set is:", number_trainingset)
# test set
test_class_1 = os.listdir("/content/MyPollen13K/test/1/")
test_class_1_samples = len(test_class_1)
print("The number of samples in the test_class_1 is:", test_class_1_samples)
test_class_2 = os.listdir("/content/MyPollen13K/test/2/")
test_class_2_samples = len(test_class_2)
print("The number of samples in the test_class_2 is:", test_class_2_samples)
test_class_3 = os.listdir("/content/MyPollen13K/test/3/")
test_class_3_samples = len(test_class_3)
print("The number of samples in the test_class_3 is:", test_class_3_samples)
test_class_4 = os.listdir("/content/MyPollen13K/test/4/")
test_class_4_samples = len(test_class_4)
print("The number of samples in the test_class_4 is:", test_class_4_samples)
number_testset = len(test_class_1+test_class_2+test_class_3+test_class_4)
print("The number of samples in the test set is:", number_testset)
```

```
The number of samples in the train_class_1 is: 1566
The number of samples in the train_class_2 is: 773
The number of samples in the train_class_3 is: 8216
The number of samples in the train_class_4 is: 724
The number of samples in the training set is: 11279
The number of samples in the test_class_1 is: 277
The number of samples in the test_class_2 is: 136
The number of samples in the test_class_3 is: 1450
The number of samples in the test_class_4 is: 128
The number of samples in the test set is: 1991
```

```
# define transforms
train_transforms = torchvision.transforms.Compose([torchvision.transforms.RandomRotation(30),
                                       torchvision.transforms.Resize((84, 84)),
                                       torchvision.transforms.RandomHorizontalFlip(),
                                       torchvision.transforms.ToTensor(),
                                       torchvision.transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])])
```

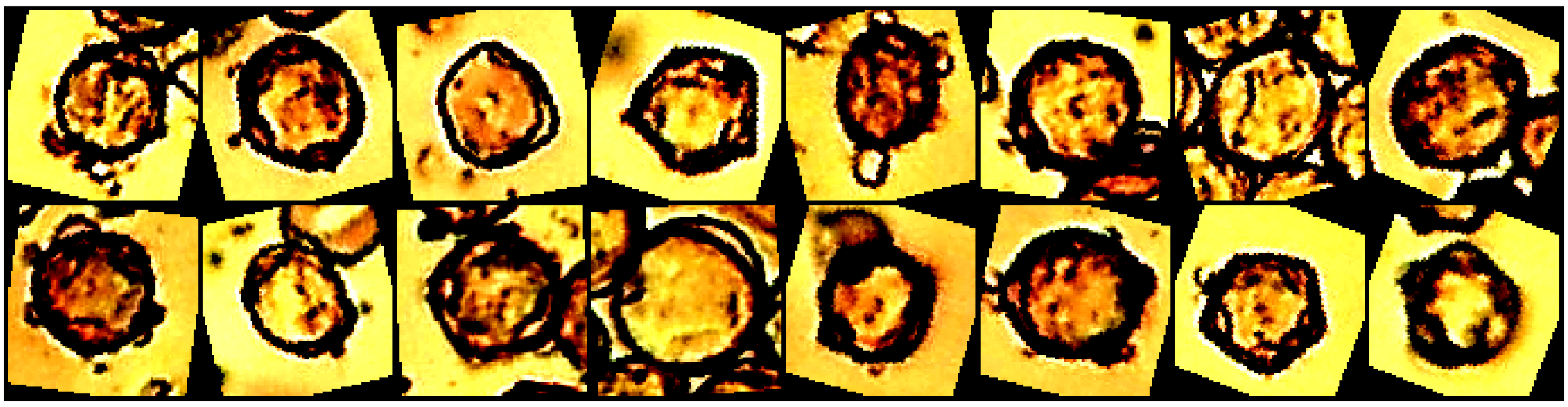
```
# get data
train_data = torchvision.datasets.ImageFolder("/content/MyPollen13K/train/", transform=train_transforms)
test_data = torchvision.datasets.ImageFolder("/content/MyPollen13K/test/", transform=train_transforms)
```

```
# data loader
trainloader = torch.utils.data.DataLoader(train_data, batch_size=16, shuffle=True, num_workers=1, pin_memory=True)
testloader = torch.utils.data.DataLoader(test_data, batch_size=16, shuffle=True, num_workers=1, pin_memory=True)
```

```
# Create a list of our detection classes
classes = ["1", "2", "3", "4"]
```

```
# plot random a batch images
from torchvision.utils import make_grid
def show_batch(dl, classes):
  for data, labels in dl:
    fig, ax = plt.subplots(figsize=(32, 16))
    ax.set_xticks([]); ax.set_yticks([])
    ax.imshow(make_grid(data[:32], nrow=8).squeeze().permute(1, 2, 0).clamp(0,1))
    print('Labels: ', list(map(lambda l: classes[l], labels)))
    break
show_batch(trainloader, classes)
```

```
Labels:  ['3', '3', '2', '3', '3', '3', '3', '3', '1', '3', '3', '1', '3', '3', '3', '3']
```



```
# define PVDAB

class ChannelAttention(nn.Module):
    def __init__(self, in_planes, ratio=16):
        super(ChannelAttention, self).__init__()
        self.avg_pool = nn.AdaptiveAvgPool2d(1)
        self.max_pool = nn.AdaptiveMaxPool2d(1)

        self.fc1   = nn.Conv2d(in_planes, in_planes // 16, 1, bias=False)
        self.relu1 = nn.ReLU()
        self.fc2   = nn.Conv2d(in_planes // 16, in_planes, 1, bias=False)

        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        avg_out = self.fc2(self.relu1(self.fc1(self.avg_pool(x))))
        max_out = self.fc2(self.relu1(self.fc1(self.max_pool(x))))
        out = avg_out + max_out
        return self.sigmoid(out)

class SpatialAttention(nn.Module):
    def __init__(self, kernel_size=3):
        super(SpatialAttention, self).__init__()

        assert kernel_size in (3, 7), 'kernel size must be 3 or 7'
        padding = 3 if kernel_size == 7 else 1

        self.conv1 = nn.Conv2d(2, 1, kernel_size, padding=padding, bias=False)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        avg_out = torch.mean(x, dim=1, keepdim=True)
        max_out, _ = torch.max(x, dim=1, keepdim=True)
        x = torch.cat([avg_out, max_out], dim=1)
        x = self.conv1(x)
        return self.sigmoid(x)

class PVDAB(nn.Module):
    def __init__(self, in_planes):
        super(PVDAB, self).__init__()

        self.ca = ChannelAttention(in_planes)
        self.sa = SpatialAttention()

    def forward(self, x):

        out = x * (self.ca(x))
        out = out * (self.sa(out))

        return out
```

```
# define the model
class BasicBlock(nn.Module):
    expansion = 1

    def __init__(self, in_planes, planes, stride=1):
```

```
    def __init__(self, in_planes, planes, stride=1):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=3, stride=stride, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(planes)
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=1, padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(planes)
        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion*planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion*planes, kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(self.expansion*planes)
            )

        self.pvdab = PVDAB(planes)

    def forward(self, x):
        residual = x
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.bn2(self.conv2(out))
        out = self.pvdab(out)
        out += self.shortcut(residual)
        out = F.relu(out)
        return out


class Bottleneck(nn.Module):
    expansion = 4

    def __init__(self, in_planes, planes, stride=1):
        super(Bottleneck, self).__init__()
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=1, bias=False)
        self.bn1 = nn.BatchNorm2d(planes)
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=stride, padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(planes)
        self.conv3 = nn.Conv2d(planes, self.expansion*planes, kernel_size=1, bias=False)
        self.bn3 = nn.BatchNorm2d(self.expansion*planes)
        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion*planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion*planes, kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(self.expansion*planes)
            )

        self.pvdab = PVDAB(self.expansion*planes)

    def forward(self, x):
        residual = x
        out = F.relu(self.bn1(self.conv1(x)))
        out = F.relu(self.bn2(self.conv2(out)))
        out = self.bn3(self.conv3(out))
        out = self.pvdab(out)
        out += self.shortcut(residual)
        out = F.relu(out)
        return out


class ResNetPVDAB(nn.Module):
    def __init__(self, block, num_blocks, num_classes=4):
        super(ResNetPVDAB, self).__init__()
        self.in_planes = 64

        self.conv1 = nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(64)
        self.layer1 = self._make_layer(block, 64, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 128, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 256, num_blocks[2], stride=2)
        self.layer4 = self._make_layer(block, 512, num_blocks[3], stride=2)
        self.linear = nn.Linear(2048*block.expansion, num_classes)

    def _make_layer(self, block, planes, num_blocks, stride):
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes * block.expansion
        return nn.Sequential(*layers)

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = F.avg_pool2d(out, 4)
        out = out.view(out.size(0), -1)
        out = self.linear(out)
        return out


def ResNet18PVDAB():
    return ResNetPVDAB(BasicBlock, [2,2,2,2])
```

```
def ResNet34PVDAB():
    return ResNetPVDAB(BasicBlock, [3,4,6,3])

def ResNet50PVDAB():
    return ResNetPVDAB(Bottleneck, [3,4,6,3])

def ResNet101PVDAB():
    return ResNetPVDAB(Bottleneck, [3,4,23,3])

def ResNet152PVDAB():
    return ResNetPVDAB(Bottleneck, [3,8,36,3])
```

```
# print the model
import math
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = ResNet18PVDAB()
model.to(device)
```

```
ResNetPVDAB(
  (conv1): Conv2d(3, 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)
  (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)
      (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)
      (shortcut): Sequential()
      (pvdab): PVDAB(
        (ca): ChannelAttention(
          (avg_pool): AdaptiveAvgPool2d(output_size=1)
          (max_pool): AdaptiveMaxPool2d(output_size=1)
          (fc1): Conv2d(64, 4, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (relu1): ReLU()
          (fc2): Conv2d(4, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (sigmoid): Sigmoid()
        )
        (sa): SpatialAttention(
          (conv1): Conv2d(2, 1, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
          (sigmoid): Sigmoid()
        )
      )
    )
    (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)
      (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)
      (shortcut): Sequential()
      (pvdab): PVDAB(
        (ca): ChannelAttention(
          (avg_pool): AdaptiveAvgPool2d(output_size=1)
          (max_pool): AdaptiveMaxPool2d(output_size=1)
          (fc1): Conv2d(64, 4, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (relu1): ReLU()
          (fc2): Conv2d(4, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (sigmoid): Sigmoid()
        )
        (sa): SpatialAttention(
          (conv1): Conv2d(2, 1, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
          (sigmoid): Sigmoid()
        )
      )
    )
  )
  (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)
      (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)
      (shortcut): 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)
      )
      (pvdab): PVDAB(
```

```
# print summary of the model
from torchvision import models
from torchsummary import summary
summary(model, (3, 84, 84))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 64, 84, 84]           1,728
```

```
      BatchNorm2d-2           [-1, 64, 84, 84]             128
           Conv2d-3           [-1, 64, 84, 84]          36,864
      BatchNorm2d-4           [-1, 64, 84, 84]             128
           Conv2d-5           [-1, 64, 84, 84]          36,864
      BatchNorm2d-6           [-1, 64, 84, 84]             128
AdaptiveAvgPool2d-7             [-1, 64, 1, 1]               0
           Conv2d-8              [-1, 4, 1, 1]             256
             ReLU-9              [-1, 4, 1, 1]               0
          Conv2d-10             [-1, 64, 1, 1]             256
AdaptiveMaxPool2d-11            [-1, 64, 1, 1]               0
          Conv2d-12              [-1, 4, 1, 1]             256
            ReLU-13              [-1, 4, 1, 1]               0
          Conv2d-14             [-1, 64, 1, 1]             256
         Sigmoid-15             [-1, 64, 1, 1]               0
ChannelAttention-16             [-1, 64, 1, 1]               0
          Conv2d-17            [-1, 1, 84, 84]              18
         Sigmoid-18            [-1, 1, 84, 84]               0
SpatialAttention-19            [-1, 1, 84, 84]               0
           PVDAB-20           [-1, 64, 84, 84]               0
      BasicBlock-21           [-1, 64, 84, 84]               0
          Conv2d-22           [-1, 64, 84, 84]          36,864
     BatchNorm2d-23           [-1, 64, 84, 84]             128
          Conv2d-24           [-1, 64, 84, 84]          36,864
     BatchNorm2d-25           [-1, 64, 84, 84]             128
AdaptiveAvgPool2d-26            [-1, 64, 1, 1]               0
          Conv2d-27              [-1, 4, 1, 1]             256
            ReLU-28              [-1, 4, 1, 1]               0
          Conv2d-29             [-1, 64, 1, 1]             256
AdaptiveMaxPool2d-30            [-1, 64, 1, 1]               0
          Conv2d-31              [-1, 4, 1, 1]             256
            ReLU-32              [-1, 4, 1, 1]               0
          Conv2d-33             [-1, 64, 1, 1]             256
         Sigmoid-34             [-1, 64, 1, 1]               0
ChannelAttention-35             [-1, 64, 1, 1]               0
          Conv2d-36            [-1, 1, 84, 84]              18
         Sigmoid-37            [-1, 1, 84, 84]               0
SpatialAttention-38            [-1, 1, 84, 84]               0
           PVDAB-39           [-1, 64, 84, 84]               0
      BasicBlock-40           [-1, 64, 84, 84]               0
          Conv2d-41          [-1, 128, 42, 42]          73,728
     BatchNorm2d-42          [-1, 128, 42, 42]             256
          Conv2d-43          [-1, 128, 42, 42]         147,456
     BatchNorm2d-44          [-1, 128, 42, 42]             256
AdaptiveAvgPool2d-45           [-1, 128, 1, 1]               0
          Conv2d-46              [-1, 8, 1, 1]           1,024
            ReLU-47              [-1, 8, 1, 1]               0
          Conv2d-48            [-1, 128, 1, 1]           1,024
AdaptiveMaxPool2d-49           [-1, 128, 1, 1]               0
          Conv2d-50              [-1, 8, 1, 1]           1,024
            ReLU-51              [-1, 8, 1, 1]               0
          Conv2d-52            [-1, 128, 1, 1]           1,024
         Sigmoid-53            [-1, 128, 1, 1]               0
ChannelAttention-54            [-1, 128, 1, 1]               0
          Conv2d-55            [-1, 1, 42, 42]              18
```

```python
# loss function to be used
criterion = torch.nn.CrossEntropyLoss()
# optimizer to be used
optimizer = torch.optim.SGD(model.parameters(), lr=5e-3, momentum=0.9, weight_decay=5e-4)
```

```python
# training process
from torch.utils.tensorboard import SummaryWriter
train_losses = 0.0
train_accuracy = 0
epochs = 50
for epoch in range(epochs):  # loop over the dataset multiple times
    print('Epoch-{0}:'.format(epoch + 1, optimizer.param_groups[0]['lr']))
    for i, data in enumerate(trainloader, 0):
        inputs, labels = data # get the inputs; data is a list of [inputs, labels]
        inputs, labels = inputs.cuda(), labels.cuda() # for using data in GPU
        optimizer.zero_grad() # zero the parameter gradients
        outputs = model(inputs) # forward
        loss = criterion(outputs, labels) # calculate loss
        loss.backward() # backward loss
        optimizer.step() # optimize gradients
        train_losses += loss.item() # save loss
        _, preds = torch.max(outputs, 1) # save prediction
        train_accuracy += torch.sum(preds == labels.data) # save train_accuracy
        if i % 1000 == 999:    # every 1000 mini-batches...
            steps = epoch * len(trainloader) + i # calculate steps
            batch = i*batch_size # calculate batch
            print("Training loss {:.5} Training Accuracy {:.5} Steps: {}".format(train_losses / batch, train_accuracy/batch, steps))
            # Save train_accuracy and loss to Tensorboard
            writer.add_scalar('Training loss by steps', train_losses / batch, steps)
            writer.add_scalar('Training accuracy by steps', train_accuracy / batch, steps)
    print("Training Accuracy: {}/{} ({:.5} %) Training Loss: {:.5}".format(train_accuracy, len(trainloader), 100. * train_accuracy / len(train
    train_losses = 0.0
    train_accuracy = 0
```

```
print('Train is finished...')
```

```
Epoch-1:
Training Accuracy: 5277/542 (60.921 %) Training Loss: 0.076291
Epoch-2:
Training Accuracy: 7288/542 (84.138 %) Training Loss: 0.031611
Epoch-3:
Training Accuracy: 7710/542 (89.009 %) Training Loss: 0.020685
Epoch-4:
Training Accuracy: 8035/542 (92.761 %) Training Loss: 0.01424
Epoch-5:
Training Accuracy: 8185/542 (94.493 %) Training Loss: 0.010308
Epoch-6:
Training Accuracy: 8321/542 (96.063 %) Training Loss: 0.0074665
Epoch-7:
Training Accuracy: 8374/542 (96.675 %) Training Loss: 0.0060973
Epoch-8:
Training Accuracy: 8452/542 (97.576 %) Training Loss: 0.0050023
Epoch-9:
Training Accuracy: 8473/542 (97.818 %) Training Loss: 0.00417
Epoch-10:
Training Accuracy: 8508/542 (98.222 %) Training Loss: 0.0036136
Epoch-11:
Training Accuracy: 8513/542 (98.28 %) Training Loss: 0.0032248
Epoch-12:
Training Accuracy: 8542/542 (98.615 %) Training Loss: 0.0026003
Epoch-13:
Training Accuracy: 8566/542 (98.892 %) Training Loss: 0.0023511
Epoch-14:
Training Accuracy: 8604/542 (99.33 %) Training Loss: 0.0014823
Epoch-15:
Training Accuracy: 8589/542 (99.157 %) Training Loss: 0.0017315
Epoch-16:
Training Accuracy: 8618/542 (99.492 %) Training Loss: 0.0010998
Epoch-17:
Training Accuracy: 8610/542 (99.4 %) Training Loss: 0.0012395
Epoch-18:
Training Accuracy: 8578/542 (99.03 %) Training Loss: 0.0018274
Epoch-19:
Training Accuracy: 8592/542 (99.192 %) Training Loss: 0.0015382
Epoch-20:
Training Accuracy: 8598/542 (99.261 %) Training Loss: 0.0013717
Epoch-21:
Training Accuracy: 8601/542 (99.296 %) Training Loss: 0.0014878
Epoch-22:
Training Accuracy: 8603/542 (99.319 %) Training Loss: 0.0013415
Epoch-23:
Training Accuracy: 8651/542 (99.873 %) Training Loss: 0.00050209
Epoch-24:
Training Accuracy: 8601/542 (99.296 %) Training Loss: 0.0012983
Epoch-25:
Training Accuracy: 8616/542 (99.469 %) Training Loss: 0.0011698
Epoch-26:
Training Accuracy: 8645/542 (99.804 %) Training Loss: 0.00046733
Epoch-27:
Training Accuracy: 8639/542 (99.734 %) Training Loss: 0.00059786
Epoch-28:
Training Accuracy: 8650/542 (99.861 %) Training Loss: 0.00045716
Epoch-29:
Training Accuracy: 8623/542 (99.55 %) Training Loss: 0.00099172
```

```
# test proess
from torch.utils.tensorboard import SummaryWriter
test_losses = 0.0
test_accuracy = 0
epochs = 50
for epoch in range(epochs):  # loop over the dataset multiple times
    print('Epoch-{0}:'.format(epoch + 1, optimizer.param_groups[0]['lr']))
    for i, data in enumerate(testloader, 0):
        inputs, labels = data # get the inputs; data is a list of [inputs, labels]
        inputs, labels = inputs.cuda(), labels.cuda() # for using data in GPU
        optimizer.zero_grad() # zero the parameter gradients
        outputs = model(inputs) # forward
        loss = criterion(outputs, labels) # calculate loss
        loss.backward() # backward loss
        optimizer.step() # optimize gradients
        test_losses += loss.item() # save loss
        _, preds = torch.max(outputs, 1) # save prediction
        test_accuracy += torch.sum(preds == labels.data) # save test_accuracy
        if i % 1000 == 999:    # every 1000 mini-batches...
            steps = epoch * len(testloader) + i # calculate steps
            batch = i*batch_size # calculate batch
            print("Test loss {:.5} Test Accuracy {:.5} Steps: {}".format(test_losses / batch, test_accuracy/batch, steps))
            # Save test_accuracy and loss to Tensorboard
            writer.add_scalar('Test loss by steps', test_losses / batch, steps)
            writer.add_scalar('Test accuracy by steps', test_accuracy / batch, steps)
    print("Test Accuracy: {}/{} ({:.5} %) Test Loss: {:.5}".format(test_accuracy, len(testloader), 100. * test_accuracy / len(testloader.datas
    test_losses = 0.0
    test_accuracy = 0
```

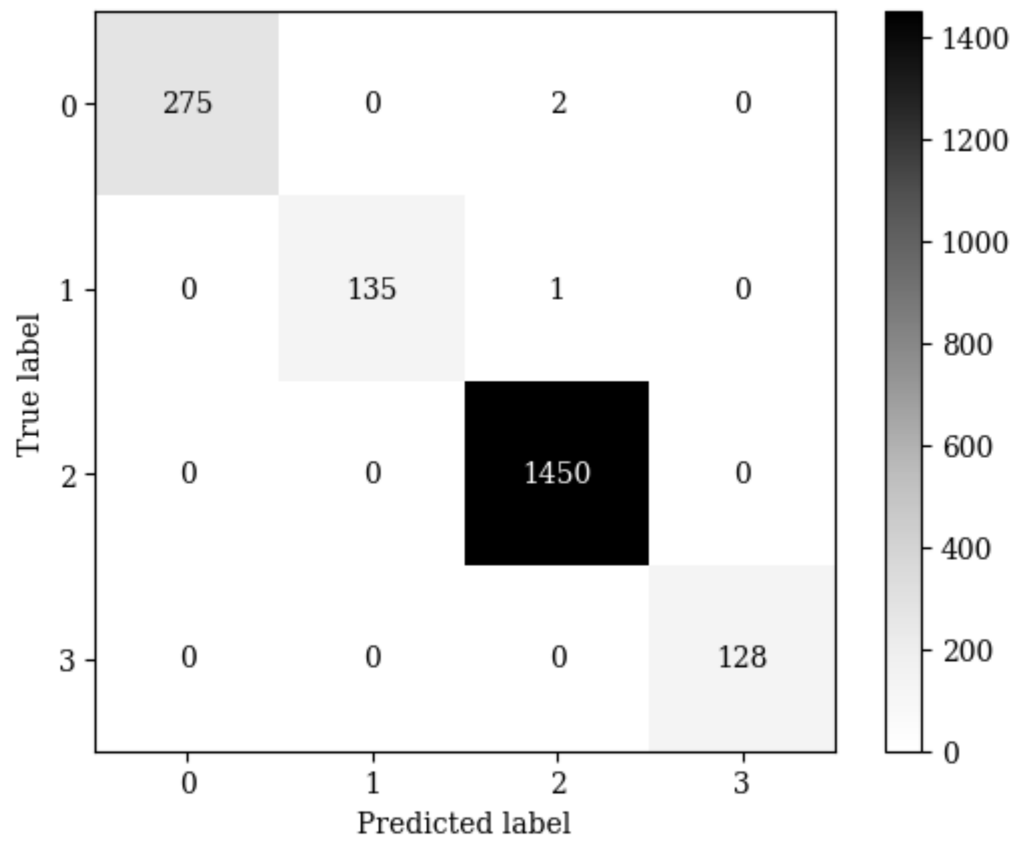
```
print('Test is Finished...')
```

```
Epoch-1:
Test Accuracy: 1775/127 (88.002 %) Test Loss: 0.025296
Epoch-2:
Test Accuracy: 1889/127 (93.654 %) Test Loss: 0.013708
Epoch-3:
Test Accuracy: 1853/127 (91.869 %) Test Loss: 0.01686
Epoch-4:
Test Accuracy: 1889/127 (93.654 %) Test Loss: 0.013393
Epoch-5:
Test Accuracy: 1951/127 (96.728 %) Test Loss: 0.0083648
Epoch-6:
Test Accuracy: 1889/127 (93.654 %) Test Loss: 0.012888
Epoch-7:
Test Accuracy: 1949/127 (96.629 %) Test Loss: 0.0086311
Epoch-8:
Test Accuracy: 1911/127 (94.745 %) Test Loss: 0.0099644
Epoch-9:
Test Accuracy: 1929/127 (95.637 %) Test Loss: 0.0099367
Epoch-10:
Test Accuracy: 1930/127 (95.687 %) Test Loss: 0.0095846
Epoch-11:
Test Accuracy: 1899/127 (94.15 %) Test Loss: 0.011592
Epoch-12:
Test Accuracy: 1968/127 (97.571 %) Test Loss: 0.0047286
Epoch-13:
Test Accuracy: 1974/127 (97.868 %) Test Loss: 0.0048148
Epoch-14:
Test Accuracy: 1937/127 (96.034 %) Test Loss: 0.0087806
Epoch-15:
Test Accuracy: 1925/127 (95.439 %) Test Loss: 0.0094096
Epoch-16:
Test Accuracy: 1971/127 (97.719 %) Test Loss: 0.0048584
Epoch-17:
Test Accuracy: 1961/127 (97.224 %) Test Loss: 0.0054308
Epoch-18:
Test Accuracy: 1977/127 (98.017 %) Test Loss: 0.0043802
Epoch-19:
Test Accuracy: 1958/127 (97.075 %) Test Loss: 0.0057979
Epoch-20:
Test Accuracy: 1984/127 (98.364 %) Test Loss: 0.0031786
Epoch-21:
Test Accuracy: 2009/127 (99.603 %) Test Loss: 0.0016824
Epoch-22:
Test Accuracy: 1993/127 (98.81 %) Test Loss: 0.0027586
Epoch-23:
Test Accuracy: 1973/127 (97.819 %) Test Loss: 0.0048995
Epoch-24:
Test Accuracy: 2003/127 (99.306 %) Test Loss: 0.0012381
Epoch-25:
Test Accuracy: 2003/127 (99.306 %) Test Loss: 0.0014082
Epoch-26:
Test Accuracy: 2003/127 (99.306 %) Test Loss: 0.0016156
Epoch-27:
Test Accuracy: 1999/127 (99.108 %) Test Loss: 0.0014213
Epoch-28:
Test Accuracy: 1996/127 (98.959 %) Test Loss: 0.0029989
Epoch-29:
Test Accuracy: 1949/127 (96.629 %) Test Loss: 0.0062236
```

```
# import Times New Roman font
import matplotlib.font_manager
!wget https://github.com/trishume/OpenTuringCompiler/blob/master/stdlib-sfml/fonts/Times%20New%20Roman.ttf -P /usr/local/lib/python3.6/dist-pa
import matplotlib.pyplot as plt
plt.rcParams['font.family'] = 'serif'
plt.rcParams['font.serif'] = ['Times New Roman'] + plt.rcParams['font.serif']
# test confusion matrix
from sklearn.metrics import confusion_matrix
import seaborn as sns
from sklearn.metrics import ConfusionMatrixDisplay
import seaborn as sn
import pandas as pd
y_pred = []
y_true = []
# iterate over test data
for inputs, labels in testloader:
        inputs, labels = inputs.cuda(), labels.cuda()
        output = model(inputs) # Feed Network
        output = (torch.max(torch.exp(output), 1)[1]).data.cpu().numpy()
        y_pred.extend(output) # Save Prediction
        labels = labels.data.cpu().numpy()
        y_true.extend(labels) # Save Truth
cm = confusion_matrix(y_true, y_pred)
cm_display = ConfusionMatrixDisplay(cm)
cm_display.plot(cmap=plt.cm.Greys)
```

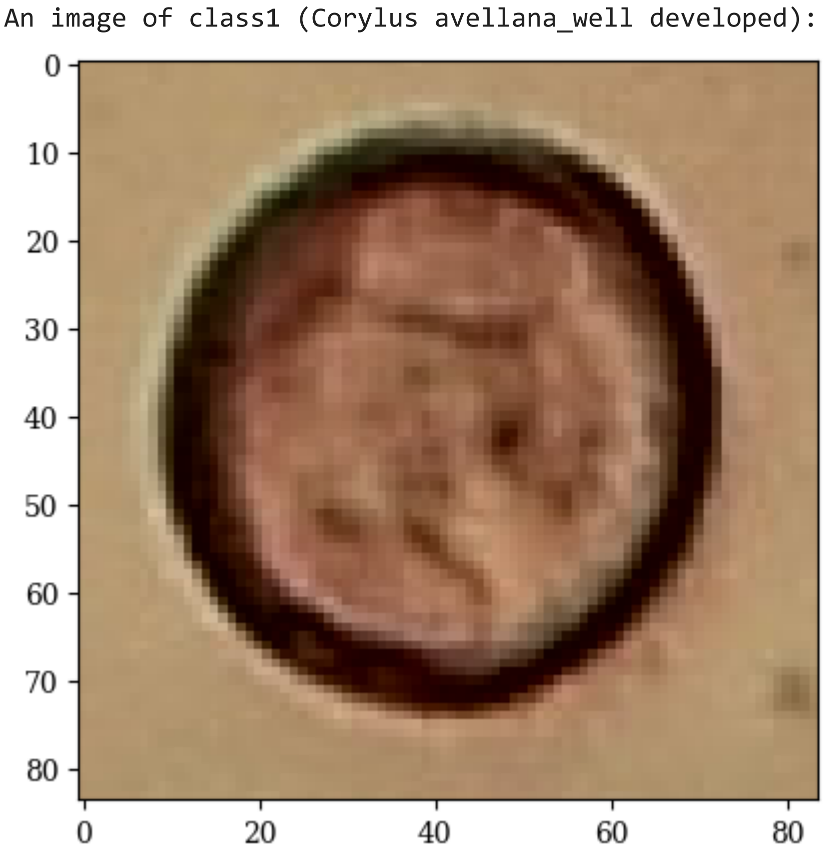
```
--2023-10-07 06:04:36--  https://github.com/trishume/OpenTuringCompiler/blob/master/stdlib-sfml/fonts/Times%20New%20
```

```
--2023-10-07 06:04:36--  https://github.com/trishume/OpenTuringCompiler/blob/master/stdlib-sfml/fonts/Times%20New%20
Resolving github.com (github.com)... 140.82.113.3
Connecting to github.com (github.com)|140.82.113.3|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 5676 (5.5K) [text/plain]
Saving to: ‘/usr/local/lib/python3.6/dist-packages/matplotlib/mpl-data/fonts/ttf/Times New Roman.ttf’

Times New Roman.ttf 100%[===================>]   5.54K  --.-KB/s    in 0s

2023-10-07 06:04:37 (79.4 MB/s) - ‘/usr/local/lib/python3.6/dist-packages/matplotlib/mpl-data/fonts/ttf/Times New Ro

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7882b1dcbc40>
```




```
import tensorflow
from tensorflow.keras.utils import load_img
from tensorflow.keras.utils import img_to_array
image = load_img('/content/MyPollen13K/train/1/20190402165648_OBJ_0_1099_759.png')
data = img_to_array(image)
samples = np.expand_dims(data, 0)
print('An image of class1 (Corylus avellana_well developed):')
plt.imshow(image)
plt.show()
```

```
An image of class1 (Corylus avellana_well developed):
```




```
from torchvision import models, transforms, utils
transform = transforms.Compose([
    transforms.Resize((84, 84)),
    transforms.ToTensor(),
    transforms.Normalize(mean=0., std=1.)
])
# we will save the conv layer weights in this list
model_weights =[]
# we will save the 49 conv layers in this list
conv_layers = []
# get all the model children as list
model_children = list(model.children())
# counter to keep count of the conv layers
```

```
counter = 0
# append all the conv layers and their respective wights to the list
for i in range(len(model_children)):
    if type(model_children[i]) == nn.Conv2d:
        counter+=1
        model_weights.append(model_children[i].weight)
        conv_layers.append(model_children[i])
    elif type(model_children[i]) == nn.Sequential:
        for j in range(len(model_children[i])):
            for child in model_children[i][j].children():
                if type(child) == nn.Conv2d:
                    counter+=1
                    model_weights.append(child.weight)
                    conv_layers.append(child)
print(f"Total convolution layers: {counter}")
print("conv_layers")
```

```
Total convolution layers: 17
conv_layers
```

```
from torch.autograd import Variable
import matplotlib.pyplot as plt
import scipy.misc
from PIL import Image
import json
%matplotlib inline
image = transform(image)
print(f"Image shape before: {image.shape}")
image = image.unsqueeze(0)
print(f"Image shape after: {image.shape}")
image = image.to(device)
```

```
Image shape before: torch.Size([3, 84, 84])
Image shape after: torch.Size([1, 3, 84, 84])
```

```
outputs = []
names = []
for layer in conv_layers[0:]:
    image = layer(image)
    outputs.append(image)
    names.append(str(layer))
print(len(outputs))
# print feature_maps
for feature_map in outputs:
    print(feature_map.shape)
```

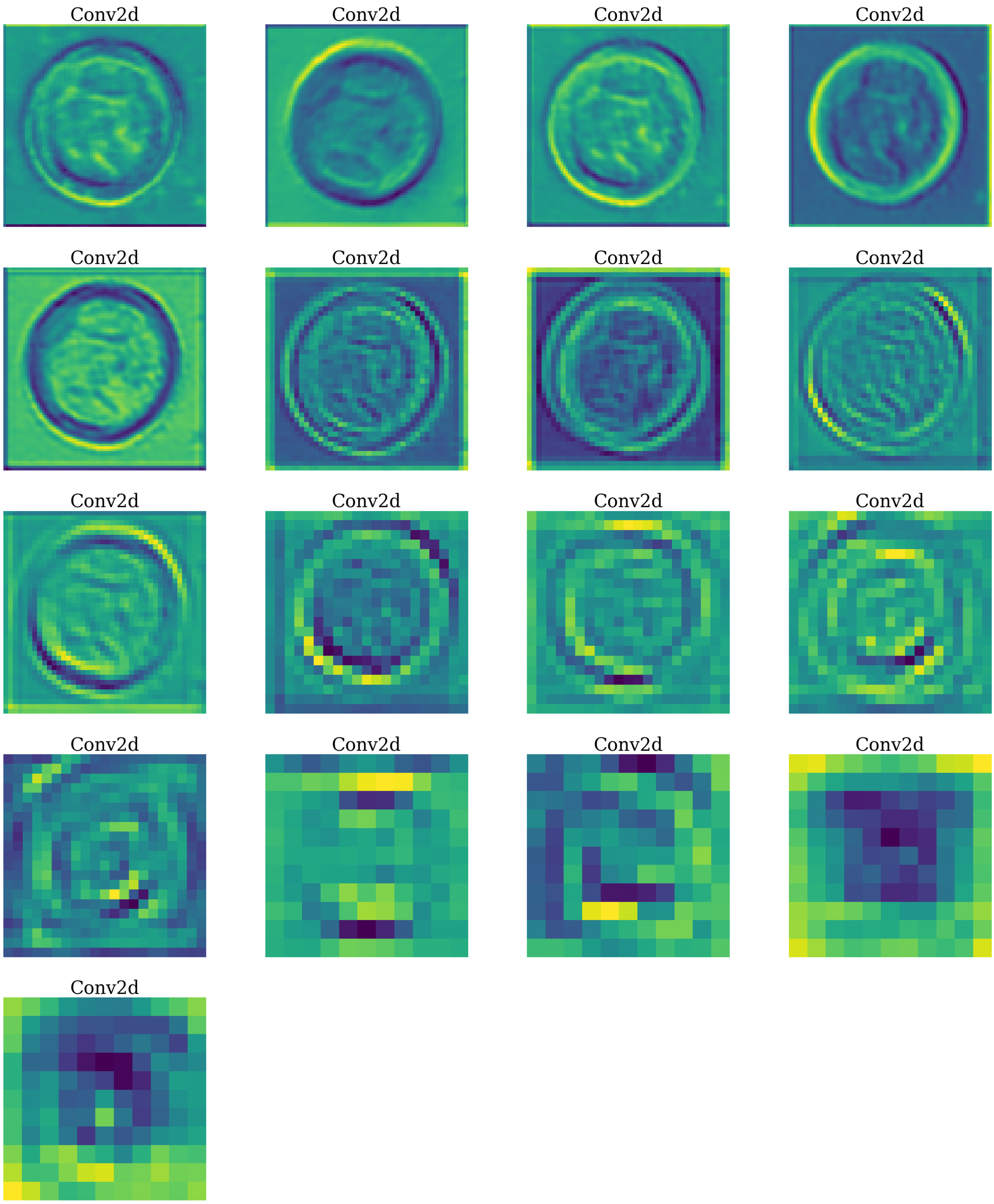
```
17
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
```

```
processed = []
for feature_map in outputs:
    feature_map = feature_map.squeeze(0)
    gray_scale = torch.sum(feature_map,0)
    gray_scale = gray_scale / feature_map.shape[0]
    processed.append(gray_scale.data.cpu().numpy())
for fm in processed:
    print(fm.shape)
```

```
(84, 84)
(84, 84)
(84, 84)
(84, 84)
(84, 84)
(42, 42)
(42, 42)
(42, 42)
(42, 42)
(21, 21)
(21, 21)
(21, 21)
(21, 21)
```

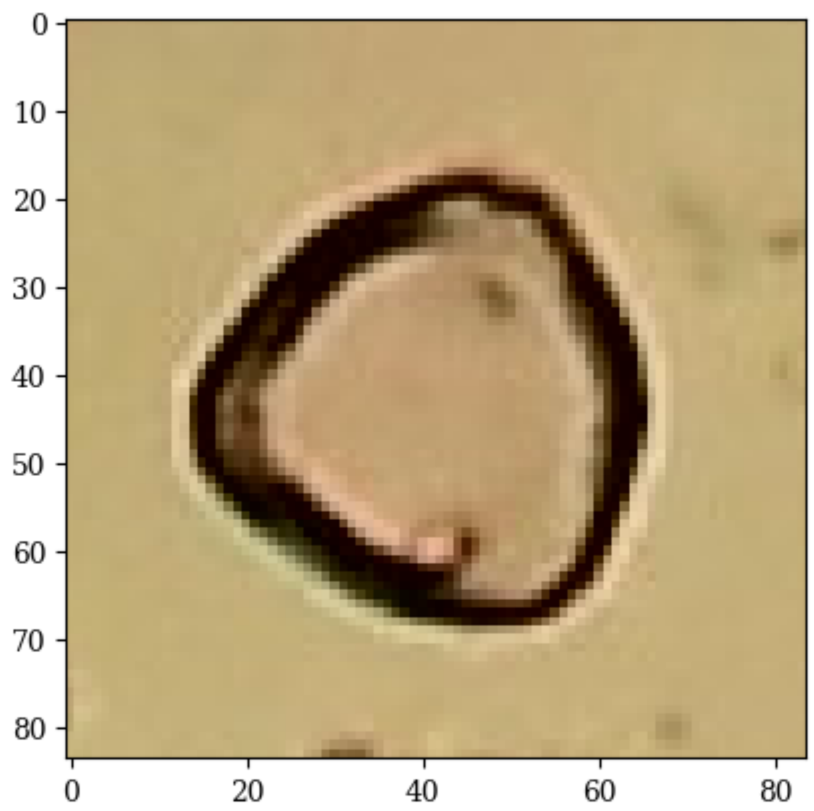
```
(11, 11)
(11, 11)
(11, 11)
(11, 11)
```

```
# print Corylus avellana_well developed feature maps
fig = plt.figure(figsize=(30, 50))
for i in range(len(processed)):
    a = fig.add_subplot(7, 4, i+1)
    imgplot = plt.imshow(processed[i])
    a.axis("off")
    a.set_title(names[i].split('(')[0], fontsize=30)
```



```
from tensorflow.keras.utils import load_img
from tensorflow.keras.utils import img_to_array
image = load_img('/content/MyPollen13K/train/2/20190404110723_OBJ_42_791_49.png')
data = img_to_array(image)
samples = np.expand_dims(data, 0)
print('An image of class2 (Corylus avellana_anomalous):')
plt.imshow(image)
plt.show()
```

```
An image of class2 (Corylus avellana_anomalous):
```




```
from torchvision import models, transforms, utils
transform = transforms.Compose([
    transforms.Resize((84, 84)),
    transforms.ToTensor(),
    transforms.Normalize(mean=0., std=1.)
])
```

```
# we will save the conv layer weights in this list
model_weights =[]
#we will save the 49 conv layers in this list
conv_layers = []
# get all the model children as list
model_children = list(model.children())
# counter to keep count of the conv layers
counter = 0
# append all the conv layers and their respective wights to the list
for i in range(len(model_children)):
    if type(model_children[i]) == nn.Conv2d:
        counter+=1
        model_weights.append(model_children[i].weight)
        conv_layers.append(model_children[i])
    elif type(model_children[i]) == nn.Sequential:
        for j in range(len(model_children[i])):
            for child in model_children[i][j].children():
                if type(child) == nn.Conv2d:
                    counter+=1
                    model_weights.append(child.weight)
                    conv_layers.append(child)
print(f"Total convolution layers: {counter}")
print("conv_layers")
```

```
Total convolution layers: 17
conv_layers
```

```
from torch.autograd import Variable
import matplotlib.pyplot as plt
import scipy.misc
from PIL import Image
import json
%matplotlib inline
image = transform(image)
print(f"Image shape before: {image.shape}")
image = image.unsqueeze(0)
print(f"Image shape after: {image.shape}")
image = image.to(device)
```

```
Image shape before: torch.Size([3, 84, 84])
Image shape after: torch.Size([1, 3, 84, 84])
```

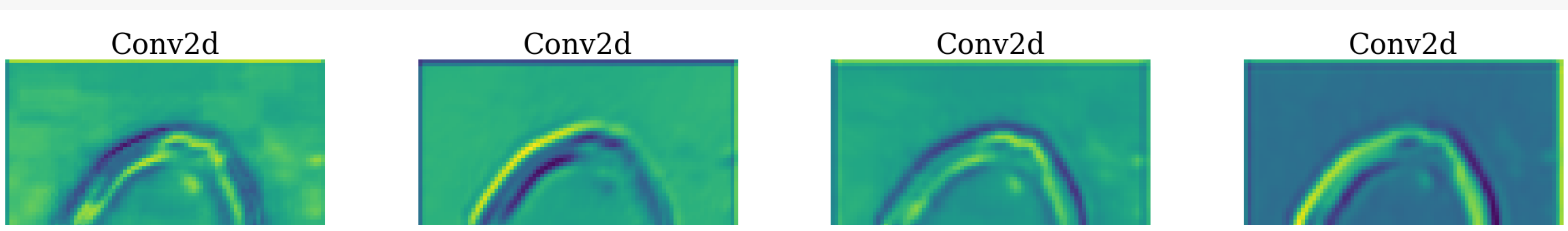
```
outputs = []
names = []
for layer in conv_layers[0:]:
    image = layer(image)
    outputs.append(image)
    names.append(str(layer))
print(len(outputs))
# print feature_maps
for feature_map in outputs:
    print(feature_map.shape)
```

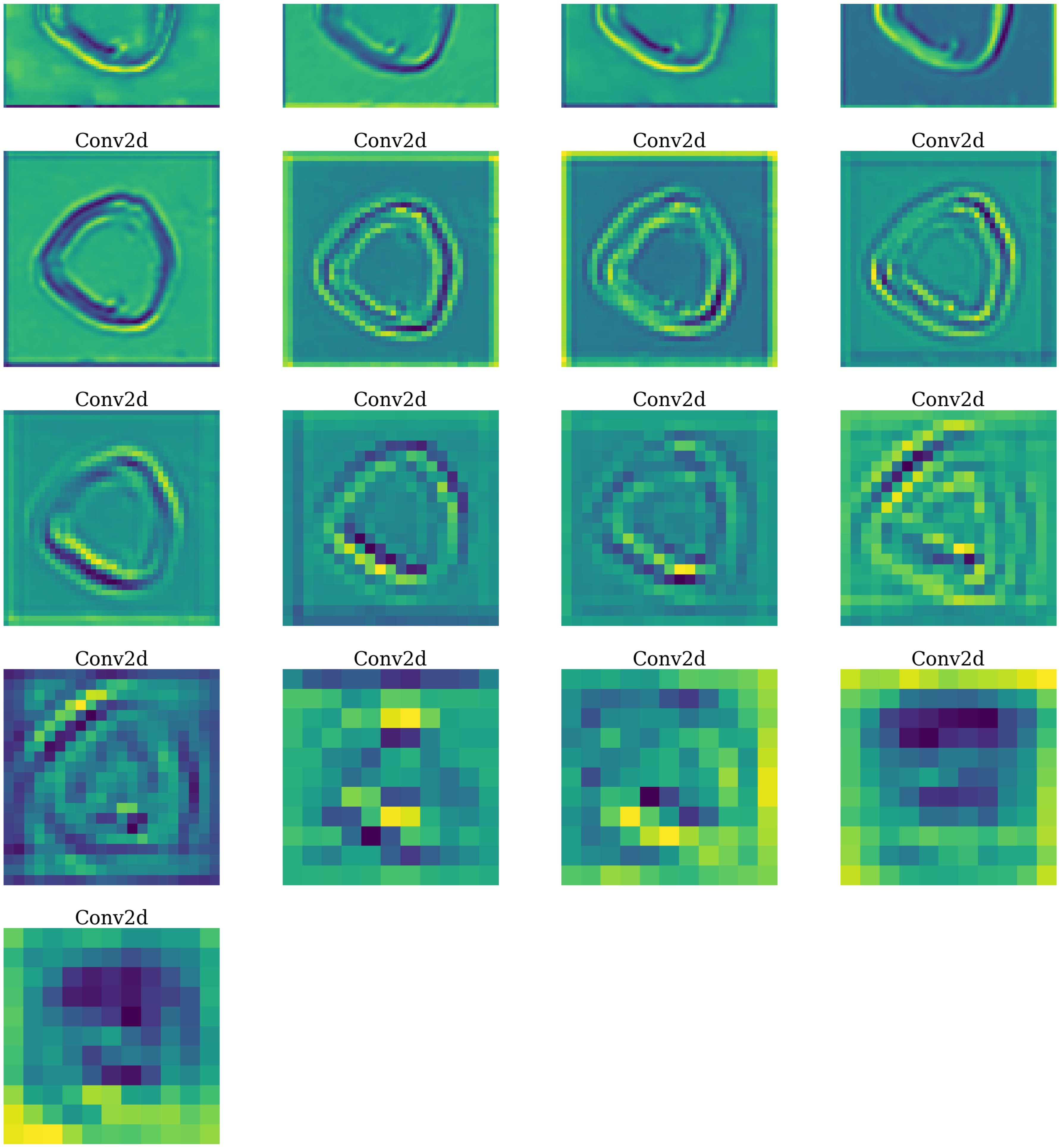
```
17
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
```

```
processed = []
for feature_map in outputs:
    feature_map = feature_map.squeeze(0)
    gray_scale = torch.sum(feature_map,0)
    gray_scale = gray_scale / feature_map.shape[0]
    processed.append(gray_scale.data.cpu().numpy())
for fm in processed:
    print(fm.shape)
```

```
(84, 84)
(84, 84)
(84, 84)
(84, 84)
(84, 84)
(42, 42)
(42, 42)
(42, 42)
(42, 42)
(21, 21)
(21, 21)
(21, 21)
(21, 21)
(11, 11)
(11, 11)
(11, 11)
(11, 11)
```

```
# print Corylus avellana_anomalous feature maps
fig = plt.figure(figsize=(30, 50))
for i in range(len(processed)):
    a = fig.add_subplot(7, 4, i+1)
    imgplot = plt.imshow(processed[i])
    a.axis("off")
    a.set_title(names[i].split('(')[0], fontsize=30)
```

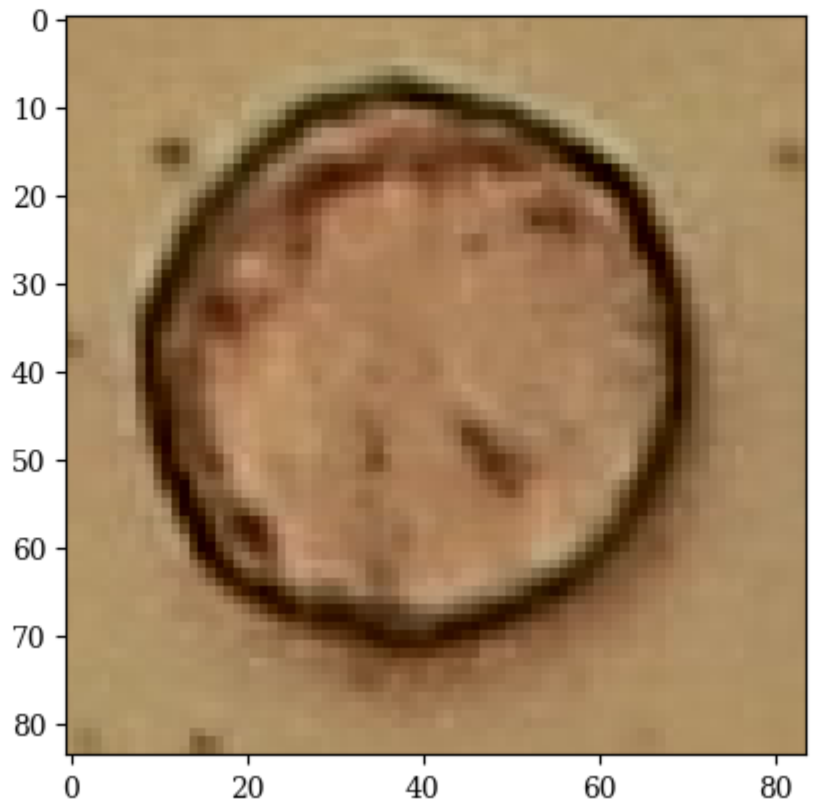





```
import tensorflow
from tensorflow.keras.utils import load_img
from tensorflow.keras.utils import img_to_array
```

```
image = load_img('/content/MyPollen13K/train/3/20190404105005_OBJ_0_933_905.png')
data = img_to_array(image)
samples = np.expand_dims(data, 0)
print('An image of class3 (Alnus__well developed):')
plt.imshow(image)
plt.show()
```

```
An image of class3 (Alnus__well developed):
```




```
from torchvision import models, transforms, utils
transform = transforms.Compose([
    transforms.Resize((84, 84)),
    transforms.ToTensor(),
    transforms.Normalize(mean=0., std=1.)
])
```

```
# we will save the conv layer weights in this list
model_weights =[]
# we will save the 49 conv layers in this list
conv_layers = []
# get all the model children as list
model_children = list(model.children())
# counter to keep count of the conv layers
counter = 0
# append all the conv layers and their respective wights to the list
for i in range(len(model_children)):
    if type(model_children[i]) == nn.Conv2d:
        counter+=1
        model_weights.append(model_children[i].weight)
        conv_layers.append(model_children[i])
    elif type(model_children[i]) == nn.Sequential:
        for j in range(len(model_children[i])):
            for child in model_children[i][j].children():
                if type(child) == nn.Conv2d:
                    counter+=1
                    model_weights.append(child.weight)
                    conv_layers.append(child)
print(f"Total convolution layers: {counter}")
print("conv_layers")
```

```
Total convolution layers: 17
conv_layers
```

```
from torch.autograd import Variable
import matplotlib.pyplot as plt
import scipy.misc
from PIL import Image
import json
%matplotlib inline
image = transform(image)
print(f"Image shape before: {image.shape}")
image = image.unsqueeze(0)
print(f"Image shape after: {image.shape}")
image = image.to(device)
```

```
Image shape before: torch.Size([3, 84, 84])
Image shape after: torch.Size([1, 3, 84, 84])
```

```
outputs = []
names = []
for layer in conv_layers[0:]:
    image = layer(image)
```

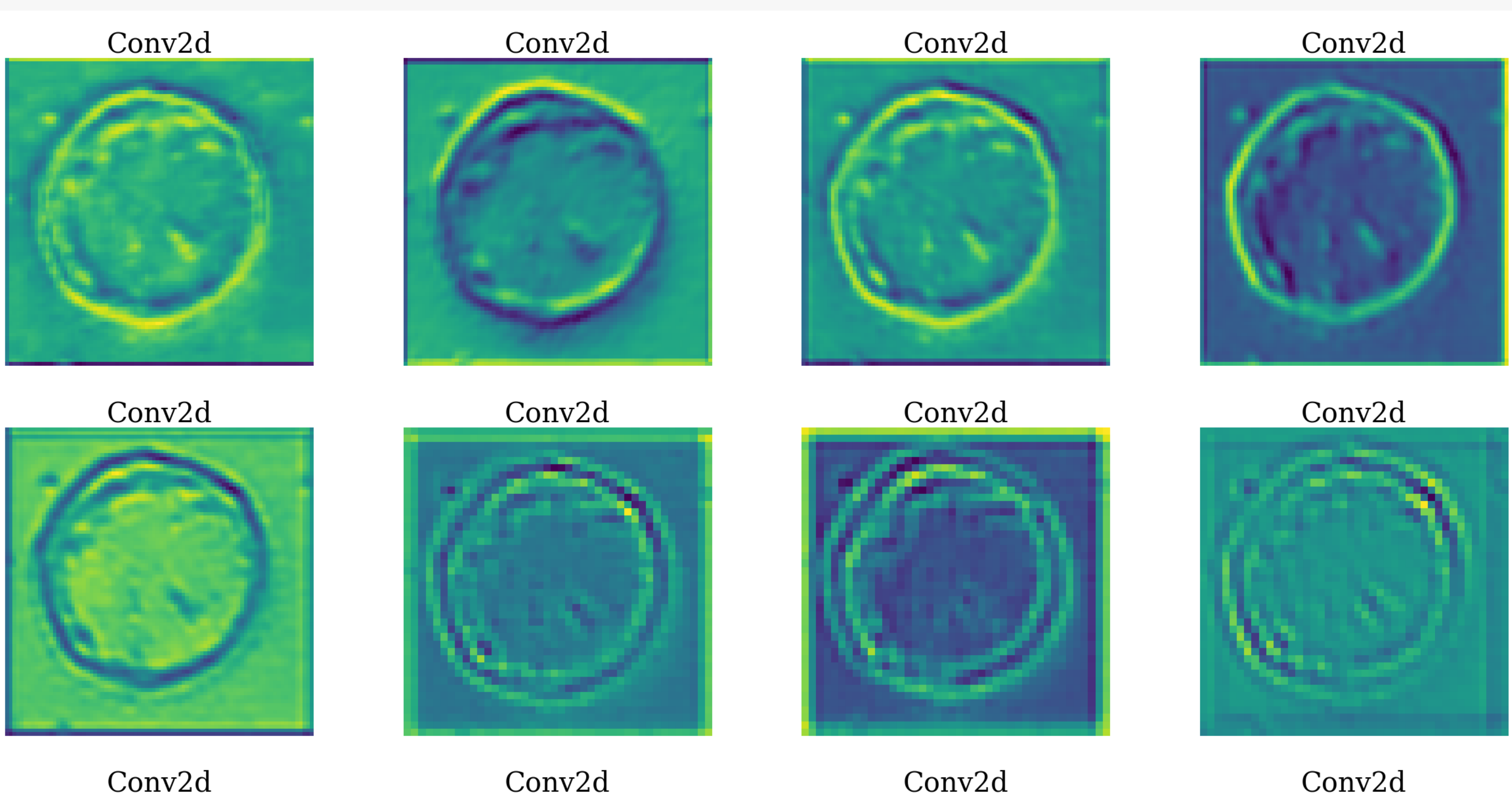
```
    outputs.append(image)
    names.append(str(layer))
print(len(outputs))
# print feature_maps
for feature_map in outputs:
    print(feature_map.shape)
```

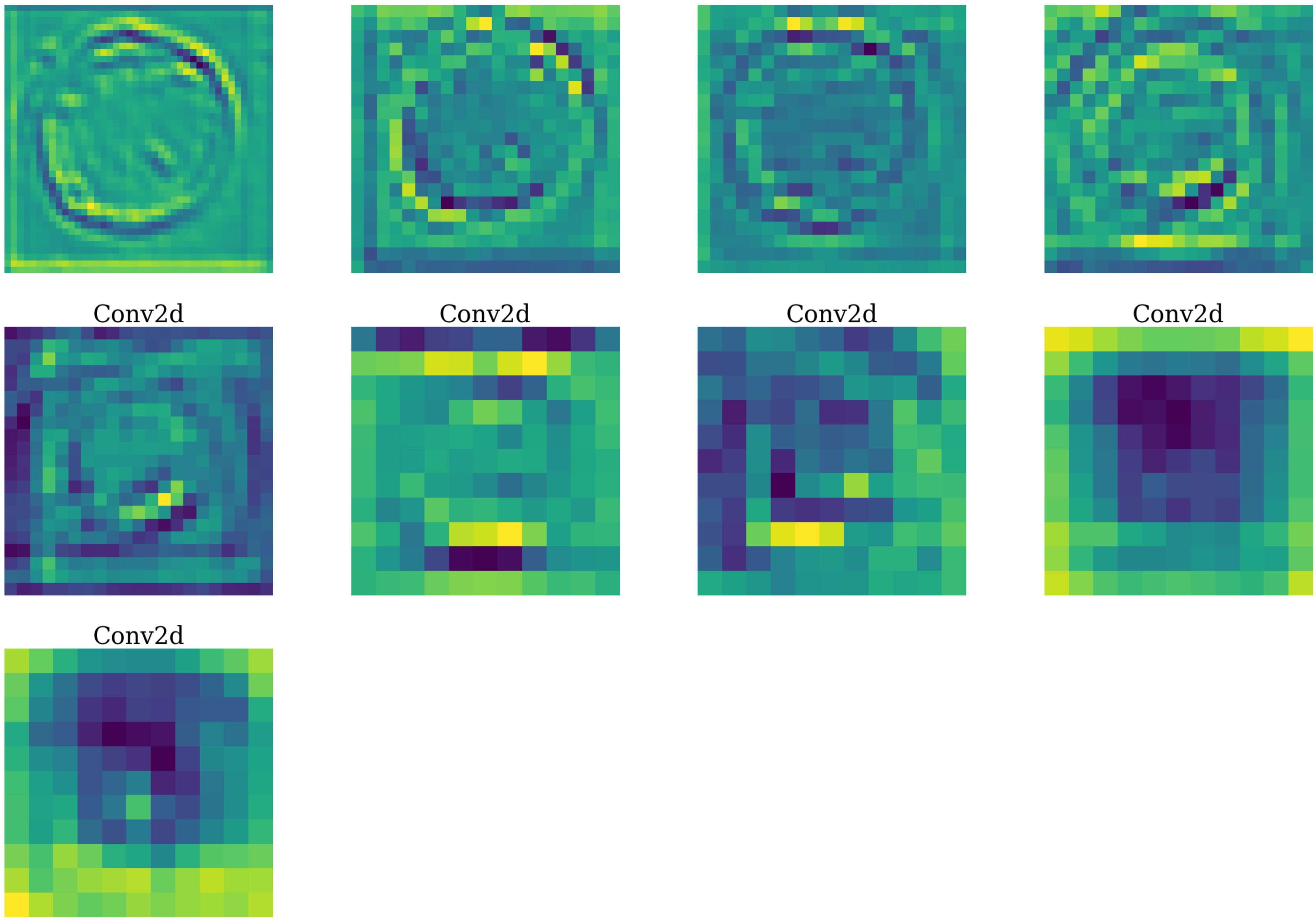
```
17
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 64, 84, 84])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 128, 42, 42])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 256, 21, 21])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
torch.Size([1, 512, 11, 11])
```

```
processed = []
for feature_map in outputs:
    feature_map = feature_map.squeeze(0)
    gray_scale = torch.sum(feature_map,0)
    gray_scale = gray_scale / feature_map.shape[0]
    processed.append(gray_scale.data.cpu().numpy())
for fm in processed:
    print(fm.shape)
```

```
(84, 84)
(84, 84)
(84, 84)
(84, 84)
(84, 84)
(42, 42)
(42, 42)
(42, 42)
(42, 42)
(21, 21)
(21, 21)
(21, 21)
(21, 21)
(11, 11)
(11, 11)
(11, 11)
(11, 11)
```

```
# print Alnus__well developed feature maps
fig = plt.figure(figsize=(30, 50))
for i in range(len(processed)):
    a = fig.add_subplot(7, 4, i+1)
    imgplot = plt.imshow(processed[i])
    a.axis("off")
    a.set_title(names[i].split('(')[0], fontsize=30)
```






```
!pip install git+https://github.com/jacobgil/pytorch-grad-cam.git
```

```
Collecting git+https://github.com/jacobgil/pytorch-grad-cam.git
  Cloning https://github.com/jacobgil/pytorch-grad-cam.git to /tmp/pip-req-build-tsqtmlns
  Running command git clone --filter=blob:none --quiet https://github.com/jacobgil/pytorch-grad-cam.git /tmp/pip-req
  Resolved https://github.com/jacobgil/pytorch-grad-cam.git to commit 09ac162e8f609eed02a8e35a370ef5bf30de19a1
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from grad-cam==1.4.8) (1.23.5)
Requirement already satisfied: Pillow in /usr/local/lib/python3.10/dist-packages (from grad-cam==1.4.8) (9.4.0)
Requirement already satisfied: torch>=1.7.1 in /usr/local/lib/python3.10/dist-packages (from grad-cam==1.4.8) (2.0.1
Requirement already satisfied: torchvision>=0.8.2 in /usr/local/lib/python3.10/dist-packages (from grad-cam==1.4.8)
Collecting ttach (from grad-cam==1.4.8)
  Downloading ttach-0.0.3-py3-none-any.whl (9.8 kB)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from grad-cam==1.4.8) (4.66.1)
Requirement already satisfied: opencv-python in /usr/local/lib/python3.10/dist-packages (from grad-cam==1.4.8) (4.8.
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from grad-cam==1.4.8) (3.7.1)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (from grad-cam==1.4.8) (1.2.2
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch>=1.7.1->grad-cam==1.4
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-packages (from torch>=1.7.1->grad
Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch>=1.7.1->grad-cam==1.4.8)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch>=1.7.1->grad-cam==1.4
```

```
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch>=1.7.1->grad-cam==1.4
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch>=1.7.1->grad-cam==1.4.8
Requirement already satisfied: triton==2.0.0 in /usr/local/lib/python3.10/dist-packages (from torch>=1.7.1->grad-cam
Requirement already satisfied: cmake in /usr/local/lib/python3.10/dist-packages (from triton==2.0.0->torch>=1.7.1->g
Requirement already satisfied: lit in /usr/local/lib/python3.10/dist-packages (from triton==2.0.0->torch>=1.7.1->gra
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from torchvision>=0.8.2->grad-ca
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->grad-ca
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->grad-cam==1
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->grad-c
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->grad-c
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->grad-cam
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->grad-ca
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->gra
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->grad-cam=
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->grad-cam
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->g
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matpl
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch>=1.7.1
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->t
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->torchvision>=
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->torchvi
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->torchvi
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/dist-packages (from sympy->torch>=1.7.1->gr
Building wheels for collected packages: grad-cam
  Building wheel for grad-cam (pyproject.toml) ... done
  Created wheel for grad-cam: filename=grad_cam-1.4.8-py3-none-any.whl size=37447 sha256=17b6e3fc14c81d4e22867f95ec1
  Stored in directory: /tmp/pip-ephem-wheel-cache-lsj7bnu9/wheels/23/11/66/71a38b0c29ba4ec5f62105a2145278613855bc9c9
Successfully built grad-cam
Installing collected packages: ttach, grad-cam
Successfully installed grad-cam-1.4.8 ttach-0.0.3
```

```
import copy
from pytorch_grad_cam import GradCAM, ScoreCAM, GradCAMPlusPlus, AblationCAM, XGradCAM, EigenCAM, FullGrad
from pytorch_grad_cam.utils.model_targets import ClassifierOutputTarget
from pytorch_grad_cam.utils.image import show_cam_on_image
from torchvision.models import resnet18
import numpy as np
from PIL import Image
import torch
import torch.nn as nn
import torchvision
```

```
# Pick up layers for visualization
target_layers = [model.layer4[-1]]
```

```
path1 = ('/content/MyPollen13K/train/1/20190402165648_OBJ_0_1099_759.png')
print('Corylus avellana_well developed:')
Image.open(path1).convert('RGB')
```

Corylus avellana_well developed:

```
rgb_img = Image.open(path1).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!
# Construct the CAM object once, and then re-use it on many images:
cam = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
# cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=False)
# cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=False)
# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...
# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None
# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam = cam(input_tensor=input_tensor)
# In this example grayscale_cam has only one image in the batch:
grayscale_cam = grayscale_cam[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam, use_rgb=True)
```

```
# plot Corylus avellana_well developed GradCAM
print('Corylus avellana_well developed GradCAM:')
```

```
Image.fromarray(visualization, 'RGB')
```

Corylus avellana_well developed GradCAM:

```
rgb_img = Image.open(path1).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!
# Construct the CAM object once, and then re-use it on many images:
#cam = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=True)
# cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=False)
# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...
# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None
# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam = cam(input_tensor=input_tensor)
# In this example grayscale_cam has only one image in the batch:
grayscale_cam = grayscale_cam[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam, use_rgb=True)
```

```
# plot Corylus avellana_well developed GradCAMPlusPlus
print('Corylus avellana_well developed GradCAMPlusPlus')
Image.fromarray(visualization, 'RGB')
```

Corylus avellana_well developed GradCAMPlusPlus

```
rgb_img = Image.open(path1).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!
# Construct the CAM object once, and then re-use it on many images:
#cam = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
#cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=True)
cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=True)
# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...
# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None
# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam = cam(input_tensor=input_tensor)
# In this example grayscale_cam has only one image in the batch:
grayscale_cam = grayscale_cam[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam, use_rgb=True)
```

```
100%|██████████| 32/32 [00:01<00:00, 30.68it/s]
```

```
# plot Corylus avellana_well developed ScoreCAM
print('Corylus avellana_well developed ScoreCAM:')
Image.fromarray(visualization, 'RGB')
```

Corylus avellana_well developed ScoreCAM:

```
path2 = ('/content/MyPollen13K/train/2/20190404110723_OBJ_42_791_49.png')
print('Corylus avellana_anomalous:')
Image.open(path2).convert('RGB')
```

Corylus avellana_anomalous:

```
rgb_img = Image.open(path2).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!

# Construct the CAM object once, and then re-use it on many images:
cam1 = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
#cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=True)
# cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=False)

# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...

# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None

# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam1 = cam1(input_tensor=input_tensor)

# In this example grayscale_cam1 has only one image in the batch:
grayscale_cam1 = grayscale_cam1[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam1, use_rgb=True)
```

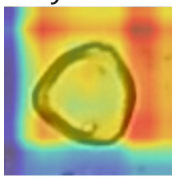
```
# plot Corylus avellana_anomalous GradCAM
print('Corylus avellana_anomalous GradCAM:')
Image.fromarray(visualization, 'RGB')
```

Corylus avellana_anomalous GradCAM:

```
rgb_img = Image.open(path2).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!
# Construct the CAM object once, and then re-use it on many images:
#cam = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=True)
# cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=False)
# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...
# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None
# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam = cam(input_tensor=input_tensor)
# In this example grayscale_cam has only one image in the batch:
grayscale_cam = grayscale_cam[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam, use_rgb=True)
```

```
# plot Corylus avellana_anomalous GradCAMPlusPlus
print('Corylus avellana_anomalous GradCAMPlusPlus')
Image.fromarray(visualization, 'RGB')
```

Corylus avellana_anomalous GradCAMPlusPlus



```
rgb_img = Image.open(path2).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!
# Construct the CAM object once, and then re-use it on many images:
#cam = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
#cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=True)
cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=True)
# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...
# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None
# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam = cam(input_tensor=input_tensor)
# In this example grayscale_cam has only one image in the batch:
grayscale_cam = grayscale_cam[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam, use_rgb=True)
```

```
100%|██████████| 32/32 [00:01<00:00, 29.60it/s]
```

```
# plot Corylus avellana_anomalous ScoreCAM
print('Corylus avellana_anomalous ScoreCAM:')
Image.fromarray(visualization, 'RGB')
```

Corylus avellana_anomalous ScoreCAM:

```
path3 = ('/content/MyPollen13K/train/3/20190404105005_OBJ_0_933_905.png')
print('Alnus__well developed:')
Image.open(path3).convert('RGB')
```

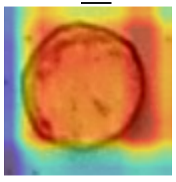
Alnus__well developed:

```
rgb_img = Image.open(path3).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!

# Construct the CAM object once, and then re-use it on many images:
cam1 = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
#cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=True)
# cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=False)

# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...

# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
```

```
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None

# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam1 = cam1(input_tensor=input_tensor)

# In this example grayscale_cam1 has only one image in the batch:
grayscale_cam1 = grayscale_cam1[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam1, use_rgb=True)
```

```
# plot Alnus__well developed GradCAM
print('Alnus__well developed GradCAM:')
Image.fromarray(visualization, 'RGB')
```

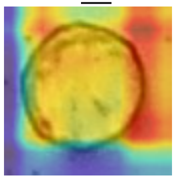
Alnus__well developed GradCAM:



```
rgb_img = Image.open(path3).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!
# Construct the CAM object once, and then re-use it on many images:
#cam = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=True)
# cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=False)
# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...
# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None
# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam = cam(input_tensor=input_tensor)
# In this example grayscale_cam has only one image in the batch:
grayscale_cam = grayscale_cam[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam, use_rgb=True)
```

```
# plot Alnus__well developed GradCAMPlusPlus
print('Alnus__well developed GradCAMPlusPlus')
Image.fromarray(visualization, 'RGB')
```

Alnus__well developed GradCAMPlusPlus



```
rgb_img = Image.open(path3).convert('RGB')
# Max min normalization
rgb_img = (rgb_img - np.min(rgb_img)) / (np.max(rgb_img) - np.min(rgb_img))
# Create an input tensor image for your model
input_tensor = torchvision.transforms.functional.to_tensor(rgb_img).unsqueeze(0).float()
# Note: input_tensor can be a batch tensor with several images!
# Construct the CAM object once, and then re-use it on many images:
#cam = GradCAM(model=model, target_layers=target_layers, use_cuda=True)
#cam = GradCAMPlusPlus(model=model, target_layers=target_layers, use_cuda=True)
cam = ScoreCAM(model=model, target_layers=target_layers, use_cuda=True)
# You can also use it within a with statement, to make sure it is freed,
# In case you need to re-create it inside an outer loop:
# with GradCAM(model=model, target_layers=target_layers, use_cuda=args.use_cuda) as cam:
#   ...
# We have to specify the target we want to generate
# the Class Activation Maps for.
# If targets is None, the highest scoring category
# will be used for every image in the batch.
# Here we use ClassifierOutputTarget, but you can define your own custom targets
# That are, for example, combinations of categories, or specific outputs in a non standard model.
# targets = [e.g ClassifierOutputTarget(281)]
# target_category = None
# You can also pass aug_smooth=True and eigen_smooth=True, to apply smoothing.
grayscale_cam = cam(input_tensor=input_tensor)
# In this example grayscale_cam has only one image in the batch:
grayscale_cam = grayscale_cam[0, :]
visualization = show_cam_on_image(rgb_img, grayscale_cam, use_rgb=True)
```

```
100%|██████████| 32/32 [00:00<00:00, 33.05it/s]
```

```
# plot Alnus__well developed ScoreCAM
print('Alnus__well developed ScoreCAM:')
Image.fromarray(visualization, 'RGB')
```

```
Alnus__well developed ScoreCAM:
```