姓名：张心顺 学号：23120014029

姓名和学号?	张心顺，23120014029
本实验属于哪门课程?	中国海洋大学25秋《软件工程原理与实践》
实验名称?	实验5：ViT & Swin Transformer
发布地址?	LoongGold/2025FALLSEPP

一、实验内容

- **使用 pytorch 实现 ViT**

按照教程一步步来

```
1. 下载好数据集，代码中默认使用的是花分类数据集，下载地址:
https://storage.googleapis.com/download.tensorflow.org/example_images/flower_photos.tgz
2. 在train.py脚本中将--data-path设置成解压后的flower_photos文件夹绝对路径
3. 下载预训练权重，在vit_model.py文件中每个模型都有提供预训练权重的下载地址，根据自己使用的模型下载对应预训练权重
4. 在train.py脚本中将--weights参数设成下载好的预训练权重路径
5. 设置好数据集的路径--data-path以及预训练权重的路径--weights就能使用train.py脚本开始训练了(训练过程中会自动生成class_indices.json文件)
6.在predict.py脚本中导入和训练脚本中同样的模型，并将model_weight_path设置成训练好的模型权重路径(默认保存在weights文件夹下)
7. 在predict.py脚本中将img_path设置成你自己需要预测的图片绝对路径
8. 设置好权重路径model_weight_path和预测的图片路径img_path就能使用predict.py脚本进行预测了
```

1. 下载并解压数据集
2. 下载预训练权重，选择使用vit_base_patch16_224_in21k模型
3. 训练脚本设置好训练集对应的路径与预训练权重的路径
4. 运行训练集
5. 运行了十个epoch后，找了两张图片进行测试。

源码如下：

```
## flops.py
import torch
from fvcore.nn import FlopCountAnalysis

from vit_model import Attention


def main():
    # Self-Attention
    a1 = Attention(dim=512, num_heads=1)
    a1.proj = torch.nn.Identity()  # remove Wo

    # Multi-Head Attention
```

```
    a2 = Attention(dim=512, num_heads=8)

    # [batch_size, num_tokens, total_embed_dim]
    t = (torch.rand(32, 1024, 512),)

    flops1 = FlopCountAnalysis(a1, t)
    print("Self-Attention FLOPs:", flops1.total())

    flops2 = FlopCountAnalysis(a2, t)
    print("Multi-Head Attention FLOPs:", flops2.total())


if __name__ == '__main__':
    main()
```

```
## my_dataset.py
from PIL import Image
import torch
from torch.utils.data import Dataset


class MyDataSet(Dataset):
    """自定义数据集"""

    def __init__(self, images_path: list, images_class: list, transform=None):
        self.images_path = images_path
        self.images_class = images_class
        self.transform = transform

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

    def __getitem__(self, item):
        img = Image.open(self.images_path[item])
        # RGB为彩色图片，L为灰度图片
        if img.mode != 'RGB':
            raise ValueError("image: {} isn't RGB 
mode.".format(self.images_path[item]))
        label = self.images_class[item]

        if self.transform is not None:
            img = self.transform(img)

        return img, label

    @staticmethod
    def collate_fn(batch):
        # 官方实现的default_collate可以参考
        # 
https://github.com/pytorch/pytorch/blob/67b7e751e6b5931a9f45274653f4f653a4e6cdf6/
torch/utils/data/_utils/collate.py
        images, labels = tuple(zip(*batch))
```

```
        images = torch.stack(images, dim=0)
        labels = torch.as_tensor(labels)
        return images, labels
```

```
## predict.py
import os
import json

import torch
from PIL import Image
from torchvision import transforms
import matplotlib.pyplot as plt

from vit_model import vit_base_patch16_224_in21k as create_model


def main():
    device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

    data_transform = transforms.Compose(
        [transforms.Resize(256),
         transforms.CenterCrop(224),
         transforms.ToTensor(),
         transforms.Normalize([0.5, 0.5, 0.5], [0.5, 0.5, 0.5])])

    # load image
    img_path = "../tulip.jpg"
    assert os.path.exists(img_path), "file: '{}' dose not
exist.".format(img_path)
    img = Image.open(img_path)
    plt.imshow(img)
    # [N, C, H, W]
    img = data_transform(img)
    # expand batch dimension
    img = torch.unsqueeze(img, dim=0)

    # read class_indict
    json_path = './class_indices.json'
    assert os.path.exists(json_path), "file: '{}' dose not
exist.".format(json_path)

    with open(json_path, "r") as f:
        class_indict = json.load(f)

    # create model
    model = create_model(num_classes=5, has_logits=False).to(device)
    # load model weights
    model_weight_path = "./weights/model-9.pth"
    model.load_state_dict(torch.load(model_weight_path, map_location=device))
    model.eval()
    with torch.no_grad():
        # predict class
        output = torch.squeeze(model(img.to(device))).cpu()
```

```
        predict = torch.softmax(output, dim=0)
        predict_cla = torch.argmax(predict).numpy()

    print_res = "class: {}   prob: {:.3}".format(class_indict[str(predict_cla)],
                                                 predict[predict_cla].numpy())
    plt.title(print_res)
    for i in range(len(predict)):
        print("class: {:10}   prob: {:.3}".format(class_indict[str(i)],
                                                  predict[i].numpy()))
    plt.show()


if __name__ == '__main__':
    main()
```

```
## train.py
import os
import math
import argparse

import torch
import torch.optim as optim
import torch.optim.lr_scheduler as lr_scheduler
from torch.utils.tensorboard import SummaryWriter
from torchvision import transforms


from my_dataset import MyDataSet
from vit_model import vit_base_patch16_224_in21k as create_model
from utils import read_split_data, train_one_epoch, evaluate


def main(args):
    device = torch.device(args.device if torch.cuda.is_available() else "cpu")

    if os.path.exists("./weights") is False:
        os.makedirs("./weights")

    tb_writer = SummaryWriter()

    train_images_path, train_images_label, val_images_path, val_images_label =
read_split_data(args.data_path)

    data_transform = {
        "train": transforms.Compose([transforms.RandomResizedCrop(224),
                                     transforms.RandomHorizontalFlip(),
                                     transforms.ToTensor(),
                                     transforms.Normalize([0.5, 0.5, 0.5], [0.5,
0.5, 0.5])]),
        "val": transforms.Compose([transforms.Resize(256),
                                   transforms.CenterCrop(224),
                                   transforms.ToTensor(),
```

```
                                   transforms.Normalize([0.5, 0.5, 0.5], [0.5,
0.5, 0.5])])}

    # 实例化训练数据集
    train_dataset = MyDataSet(images_path=train_images_path,
                              images_class=train_images_label,
                              transform=data_transform["train"])

    # 实例化验证数据集
    val_dataset = MyDataSet(images_path=val_images_path,
                            images_class=val_images_label,
                            transform=data_transform["val"])

    batch_size = args.batch_size
    nw = min([os.cpu_count(), batch_size if batch_size > 1 else 0, 8])  # number
of workers
    print('Using {} dataloader workers every process'.format(nw))
    train_loader = torch.utils.data.DataLoader(train_dataset,
                                               batch_size=batch_size,
                                               shuffle=True,
                                               pin_memory=True,
                                               num_workers=nw,

collate_fn=train_dataset.collate_fn)

    val_loader = torch.utils.data.DataLoader(val_dataset,
                                             batch_size=batch_size,
                                             shuffle=False,
                                             pin_memory=True,
                                             num_workers=nw,
                                             collate_fn=val_dataset.collate_fn)

    model = create_model(num_classes=args.num_classes,
has_logits=False).to(device)

    if args.weights != "":
        assert os.path.exists(args.weights), "weights file: '{}' not
exist.".format(args.weights)
        weights_dict = torch.load(args.weights, map_location=device)
        # 删除不需要的权重
        del_keys = ['head.weight', 'head.bias'] if model.has_logits \
            else ['pre_logits.fc.weight', 'pre_logits.fc.bias', 'head.weight',
'head.bias']
        for k in del_keys:
            del weights_dict[k]
        print(model.load_state_dict(weights_dict, strict=False))

    if args.freeze_layers:
        for name, para in model.named_parameters():
            # 除head, pre_logits外，其他权重全部冻结
            if "head" not in name and "pre_logits" not in name:
                para.requires_grad_(False)
            else:
                print("training {}".format(name))

    pg = [p for p in model.parameters() if p.requires_grad]
```

```
    optimizer = optim.SGD(pg, lr=args.lr, momentum=0.9, weight_decay=5E-5)
    # Scheduler https://arxiv.org/pdf/1812.01187.pdf
    lf = lambda x: ((1 + math.cos(x * math.pi / args.epochs)) / 2) * (1 -
args.lrf) + args.lrf  # cosine
    scheduler = lr_scheduler.LambdaLR(optimizer, lr_lambda=lf)

    for epoch in range(args.epochs):
        # train
        train_loss, train_acc = train_one_epoch(model=model,
                                                optimizer=optimizer,
                                                data_loader=train_loader,
                                                device=device,
                                                epoch=epoch)

        scheduler.step()

        # validate
        val_loss, val_acc = evaluate(model=model,
                                     data_loader=val_loader,
                                     device=device,
                                     epoch=epoch)

        tags = ["train_loss", "train_acc", "val_loss", "val_acc",
"learning_rate"]
        tb_writer.add_scalar(tags[0], train_loss, epoch)
        tb_writer.add_scalar(tags[1], train_acc, epoch)
        tb_writer.add_scalar(tags[2], val_loss, epoch)
        tb_writer.add_scalar(tags[3], val_acc, epoch)
        tb_writer.add_scalar(tags[4], optimizer.param_groups[0]["lr"], epoch)

        torch.save(model.state_dict(), "./weights/model-{}.pth".format(epoch))


if __name__ == '__main__':
    parser = argparse.ArgumentParser()
    parser.add_argument('--num_classes', type=int, default=5)
    parser.add_argument('--epochs', type=int, default=10)
    parser.add_argument('--batch-size', type=int, default=8)
    parser.add_argument('--lr', type=float, default=0.001)
    parser.add_argument('--lrf', type=float, default=0.01)

    # 数据集所在根目录
    #
https://storage.googleapis.com/download.tensorflow.org/example_images/flower_phot
os.tgz
    parser.add_argument('--data-path', type=str,
                        default="/data/flower_photos")
    parser.add_argument('--model-name', default='', help='create model name')

    # 预训练权重路径，如果不想载入就设置为空字符
    parser.add_argument('--weights', type=str,
default='./vit_base_patch16_224_in21k.pth',
                        help='initial weights path')
    # 是否冻结权重
    parser.add_argument('--freeze-layers', type=bool, default=True)
```

```
    parser.add_argument('--device', default='cuda:0', help='device id (i.e. 0 or 0,1 or cpu)')

    opt = parser.parse_args()

    main(opt)
```

```
## utils.py
import os
import sys
import json
import pickle
import random

import torch
from tqdm import tqdm

import matplotlib.pyplot as plt


def read_split_data(root: str, val_rate: float = 0.2):
    random.seed(0)  # 保证随机结果可复现
    assert os.path.exists(root), "dataset root: {} does not exist.".format(root)

    # 遍历文件夹，一个文件夹对应一个类别
    flower_class = [cla for cla in os.listdir(root) if os.path.isdir(os.path.join(root, cla))]
    # 排序，保证各平台顺序一致
    flower_class.sort()
    # 生成类别名称以及对应的数字索引
    class_indices = dict((k, v) for v, k in enumerate(flower_class))
    json_str = json.dumps(dict((val, key) for key, val in class_indices.items()), indent=4)
    with open('class_indices.json', 'w') as json_file:
        json_file.write(json_str)

    train_images_path = []  # 存储训练集的所有图片路径
    train_images_label = []  # 存储训练集图片对应索引信息
    val_images_path = []  # 存储验证集的所有图片路径
    val_images_label = []  # 存储验证集图片对应索引信息
    every_class_num = []  # 存储每个类别的样本总数
    supported = [".jpg", ".JPG", ".png", ".PNG"]  # 支持的文件后缀类型
    # 遍历每个文件夹下的文件
    for cla in flower_class:
        cla_path = os.path.join(root, cla)
        # 遍历获取supported支持的所有文件路径
        images = [os.path.join(root, cla, i) for i in os.listdir(cla_path)
                  if os.path.splitext(i)[-1] in supported]
        # 排序，保证各平台顺序一致
        images.sort()
        # 获取该类别对应的索引
        image_class = class_indices[cla]
        # 记录该类别的样本数量
```

```
        every_class_num.append(len(images))
        # 按比例随机采样验证样本
        val_path = random.sample(images, k=int(len(images) * val_rate))

        for img_path in images:
            if img_path in val_path:  # 如果该路径在采样的验证集样本中则存入验证集
                val_images_path.append(img_path)
                val_images_label.append(image_class)
            else:  # 否则存入训练集
                train_images_path.append(img_path)
                train_images_label.append(image_class)

    print("{} images were found in the dataset.".format(sum(every_class_num)))
    print("{} images for training.".format(len(train_images_path)))
    print("{} images for validation.".format(len(val_images_path)))
    assert len(train_images_path) > 0, "number of training images must greater
than 0."
    assert len(val_images_path) > 0, "number of validation images must greater
than 0."

    plot_image = False
    if plot_image:
        # 绘制每种类别个数柱状图
        plt.bar(range(len(flower_class)), every_class_num, align='center')
        # 将横坐标0,1,2,3,4替换为相应的类别名称
        plt.xticks(range(len(flower_class)), flower_class)
        # 在柱状图上添加数值标签
        for i, v in enumerate(every_class_num):
            plt.text(x=i, y=v + 5, s=str(v), ha='center')
        # 设置x坐标
        plt.xlabel('image class')
        # 设置y坐标
        plt.ylabel('number of images')
        # 设置柱状图的标题
        plt.title('flower class distribution')
        plt.show()

    return train_images_path, train_images_label, val_images_path,
val_images_label


def plot_data_loader_image(data_loader):
    batch_size = data_loader.batch_size
    plot_num = min(batch_size, 4)

    json_path = './class_indices.json'
    assert os.path.exists(json_path), json_path + " does not exist."
    json_file = open(json_path, 'r')
    class_indices = json.load(json_file)

    for data in data_loader:
        images, labels = data
        for i in range(plot_num):
            # [C, H, W] -> [H, W, C]
            img = images[i].numpy().transpose(1, 2, 0)
            # 反Normalize操作
```

```
            img = (img * [0.229, 0.224, 0.225] + [0.485, 0.456, 0.406]) * 255
            label = labels[i].item()
            plt.subplot(1, plot_num, i+1)
            plt.xlabel(class_indices[str(label)])
            plt.xticks([])  # 去掉x轴的刻度
            plt.yticks([])  # 去掉y轴的刻度
            plt.imshow(img.astype('uint8'))
        plt.show()


def write_pickle(list_info: list, file_name: str):
    with open(file_name, 'wb') as f:
        pickle.dump(list_info, f)


def read_pickle(file_name: str) -> list:
    with open(file_name, 'rb') as f:
        info_list = pickle.load(f)
        return info_list


def train_one_epoch(model, optimizer, data_loader, device, epoch):
    model.train()
    loss_function = torch.nn.CrossEntropyLoss()
    accu_loss = torch.zeros(1).to(device)  # 累计损失
    accu_num = torch.zeros(1).to(device)   # 累计预测正确的样本数
    optimizer.zero_grad()

    sample_num = 0
    data_loader = tqdm(data_loader, file=sys.stdout)
    for step, data in enumerate(data_loader):
        images, labels = data
        sample_num += images.shape[0]

        pred = model(images.to(device))
        pred_classes = torch.max(pred, dim=1)[1]
        accu_num += torch.eq(pred_classes, labels.to(device)).sum()

        loss = loss_function(pred, labels.to(device))
        loss.backward()
        accu_loss += loss.detach()

        data_loader.desc = "[train epoch {}] loss: {:.3f}, acc:
{:.3f}".format(epoch,

accu_loss.item() / (step + 1),

accu_num.item() / sample_num)

        if not torch.isfinite(loss):
            print('WARNING: non-finite loss, ending training ', loss)
            sys.exit(1)

        optimizer.step()
        optimizer.zero_grad()
```

```
    return accu_loss.item() / (step + 1), accu_num.item() / sample_num


@torch.no_grad()
def evaluate(model, data_loader, device, epoch):
    loss_function = torch.nn.CrossEntropyLoss()

    model.eval()

    accu_num = torch.zeros(1).to(device)   # 累计预测正确的样本数
    accu_loss = torch.zeros(1).to(device)  # 累计损失

    sample_num = 0
    data_loader = tqdm(data_loader, file=sys.stdout)
    for step, data in enumerate(data_loader):
        images, labels = data
        sample_num += images.shape[0]

        pred = model(images.to(device))
        pred_classes = torch.max(pred, dim=1)[1]
        accu_num += torch.eq(pred_classes, labels.to(device)).sum()

        loss = loss_function(pred, labels.to(device))
        accu_loss += loss

        data_loader.desc = "[valid epoch {}] loss: {:.3f}, acc:
{:.3f}".format(epoch,

accu_loss.item() / (step + 1),

accu_num.item() / sample_num)

    return accu_loss.item() / (step + 1), accu_num.item() / sample_num
```

```
## vit_model.py
"""
original code from rwightman:
https://github.com/rwightman/pytorch-image-
models/blob/master/timm/models/vision_transformer.py
"""
from functools import partial
from collections import OrderedDict

import torch
import torch.nn as nn


def drop_path(x, drop_prob: float = 0., training: bool = False):
    """
    Drop paths (Stochastic Depth) per sample (when applied in main path of
residual blocks).
    This is the same as the DropConnect impl I created for EfficientNet, etc
networks, however,
```

```
    the original name is misleading as 'Drop Connect' is a different form of
dropout in a separate paper...
    See discussion: https://github.com/tensorflow/tpu/issues/494#issuecomment-
532968956 ... I've opted for
    changing the layer and argument names to 'drop path' rather than mix
DropConnect as a layer name and use
    'survival rate' as the argument.
    """
    if drop_prob == 0. or not training:
        return x
    keep_prob = 1 - drop_prob
    shape = (x.shape[0],) + (1,) * (x.ndim - 1)  # work with diff dim tensors,
not just 2D ConvNets
    random_tensor = keep_prob + torch.rand(shape, dtype=x.dtype, device=x.device)
    random_tensor.floor_()  # binarize
    output = x.div(keep_prob) * random_tensor
    return output


class DropPath(nn.Module):
    """
    Drop paths (Stochastic Depth) per sample  (when applied in main path of
residual blocks).
    """
    def __init__(self, drop_prob=None):
        super(DropPath, self).__init__()
        self.drop_prob = drop_prob

    def forward(self, x):
        return drop_path(x, self.drop_prob, self.training)


class PatchEmbed(nn.Module):
    """
    2D Image to Patch Embedding
    """
    def __init__(self, img_size=224, patch_size=16, in_c=3, embed_dim=768,
norm_layer=None):
        super().__init__()
        img_size = (img_size, img_size)
        patch_size = (patch_size, patch_size)
        self.img_size = img_size
        self.patch_size = patch_size
        self.grid_size = (img_size[0] // patch_size[0], img_size[1] //
patch_size[1])
        self.num_patches = self.grid_size[0] * self.grid_size[1]

        self.proj = nn.Conv2d(in_c, embed_dim, kernel_size=patch_size,
stride=patch_size)
        self.norm = norm_layer(embed_dim) if norm_layer else nn.Identity()

    def forward(self, x):
        B, C, H, W = x.shape
        assert H == self.img_size[0] and W == self.img_size[1], \
            f"Input image size ({H}*{W}) doesn't match model ({self.img_size[0]}*
{self.img_size[1]})."
```

```
        # flatten: [B, C, H, W] -> [B, C, HW]
        # transpose: [B, C, HW] -> [B, HW, C]
        x = self.proj(x).flatten(2).transpose(1, 2)
        x = self.norm(x)
        return x


class Attention(nn.Module):
    def __init__(self,
                 dim,   # 输入token的dim
                 num_heads=8,
                 qkv_bias=False,
                 qk_scale=None,
                 attn_drop_ratio=0.,
                 proj_drop_ratio=0.):
        super(Attention, self).__init__()
        self.num_heads = num_heads
        head_dim = dim // num_heads
        self.scale = qk_scale or head_dim ** -0.5
        self.qkv = nn.Linear(dim, dim * 3, bias=qkv_bias)
        self.attn_drop = nn.Dropout(attn_drop_ratio)
        self.proj = nn.Linear(dim, dim)
        self.proj_drop = nn.Dropout(proj_drop_ratio)

    def forward(self, x):
        # [batch_size, num_patches + 1, total_embed_dim]
        B, N, C = x.shape

        # qkv(): -> [batch_size, num_patches + 1, 3 * total_embed_dim]
        # reshape: -> [batch_size, num_patches + 1, 3, num_heads,
embed_dim_per_head]
        # permute: -> [3, batch_size, num_heads, num_patches + 1,
embed_dim_per_head]
        qkv = self.qkv(x).reshape(B, N, 3, self.num_heads, C //
self.num_heads).permute(2, 0, 3, 1, 4)
        # [batch_size, num_heads, num_patches + 1, embed_dim_per_head]
        q, k, v = qkv[0], qkv[1], qkv[2]  # make torchscript happy (cannot use
tensor as tuple)

        # transpose: -> [batch_size, num_heads, embed_dim_per_head, num_patches +
1]
        # @: multiply -> [batch_size, num_heads, num_patches + 1, num_patches +
1]
        attn = (q @ k.transpose(-2, -1)) * self.scale
        attn = attn.softmax(dim=-1)
        attn = self.attn_drop(attn)

        # @: multiply -> [batch_size, num_heads, num_patches + 1,
embed_dim_per_head]
        # transpose: -> [batch_size, num_patches + 1, num_heads,
embed_dim_per_head]
        # reshape: -> [batch_size, num_patches + 1, total_embed_dim]
        x = (attn @ v).transpose(1, 2).reshape(B, N, C)
        x = self.proj(x)
        x = self.proj_drop(x)
```

```
        return x


class Mlp(nn.Module):
    """
    MLP as used in Vision Transformer, MLP-Mixer and related networks
    """
    def __init__(self, in_features, hidden_features=None, out_features=None,
act_layer=nn.GELU, drop=0.):
        super().__init__()
        out_features = out_features or in_features
        hidden_features = hidden_features or in_features
        self.fc1 = nn.Linear(in_features, hidden_features)
        self.act = act_layer()
        self.fc2 = nn.Linear(hidden_features, out_features)
        self.drop = nn.Dropout(drop)

    def forward(self, x):
        x = self.fc1(x)
        x = self.act(x)
        x = self.drop(x)
        x = self.fc2(x)
        x = self.drop(x)
        return x


class Block(nn.Module):
    def __init__(self,
                 dim,
                 num_heads,
                 mlp_ratio=4.,
                 qkv_bias=False,
                 qk_scale=None,
                 drop_ratio=0.,
                 attn_drop_ratio=0.,
                 drop_path_ratio=0.,
                 act_layer=nn.GELU,
                 norm_layer=nn.LayerNorm):
        super(Block, self).__init__()
        self.norm1 = norm_layer(dim)
        self.attn = Attention(dim, num_heads=num_heads, qkv_bias=qkv_bias,
qk_scale=qk_scale,
                              attn_drop_ratio=attn_drop_ratio,
proj_drop_ratio=drop_ratio)
        # NOTE: drop path for stochastic depth, we shall see if this is better
than dropout here
        self.drop_path = DropPath(drop_path_ratio) if drop_path_ratio > 0. else
nn.Identity()
        self.norm2 = norm_layer(dim)
        mlp_hidden_dim = int(dim * mlp_ratio)
        self.mlp = Mlp(in_features=dim, hidden_features=mlp_hidden_dim,
act_layer=act_layer, drop=drop_ratio)

    def forward(self, x):
        x = x + self.drop_path(self.attn(self.norm1(x)))
        x = x + self.drop_path(self.mlp(self.norm2(x)))
```

```
        return x


class VisionTransformer(nn.Module):
    def __init__(self, img_size=224, patch_size=16, in_c=3, num_classes=1000,
                 embed_dim=768, depth=12, num_heads=12, mlp_ratio=4.0,
qkv_bias=True,
                 qk_scale=None, representation_size=None, distilled=False,
drop_ratio=0.,
                 attn_drop_ratio=0., drop_path_ratio=0., embed_layer=PatchEmbed,
norm_layer=None,
                 act_layer=None):
        """
        Args:
            img_size (int, tuple): input image size
            patch_size (int, tuple): patch size
            in_c (int): number of input channels
            num_classes (int): number of classes for classification head
            embed_dim (int): embedding dimension
            depth (int): depth of transformer
            num_heads (int): number of attention heads
            mlp_ratio (int): ratio of mlp hidden dim to embedding dim
            qkv_bias (bool): enable bias for qkv if True
            qk_scale (float): override default qk scale of head_dim ** -0.5 if
set
            representation_size (Optional[int]): enable and set representation
layer (pre-logits) to this value if set
            distilled (bool): model includes a distillation token and head as in
DeiT models
            drop_ratio (float): dropout rate
            attn_drop_ratio (float): attention dropout rate
            drop_path_ratio (float): stochastic depth rate
            embed_layer (nn.Module): patch embedding layer
            norm_layer: (nn.Module): normalization layer
        """
        super(VisionTransformer, self).__init__()
        self.num_classes = num_classes
        self.num_features = self.embed_dim = embed_dim  # num_features for
consistency with other models
        self.num_tokens = 2 if distilled else 1
        norm_layer = norm_layer or partial(nn.LayerNorm, eps=1e-6)
        act_layer = act_layer or nn.GELU

        self.patch_embed = embed_layer(img_size=img_size, patch_size=patch_size,
in_c=in_c, embed_dim=embed_dim)
        num_patches = self.patch_embed.num_patches

        self.cls_token = nn.Parameter(torch.zeros(1, 1, embed_dim))
        self.dist_token = nn.Parameter(torch.zeros(1, 1, embed_dim)) if distilled
else None
        self.pos_embed = nn.Parameter(torch.zeros(1, num_patches +
self.num_tokens, embed_dim))
        self.pos_drop = nn.Dropout(p=drop_ratio)

        dpr = [x.item() for x in torch.linspace(0, drop_path_ratio, depth)]  #
stochastic depth decay rule
```

```
        self.blocks = nn.Sequential(*[
            Block(dim=embed_dim, num_heads=num_heads, mlp_ratio=mlp_ratio,
qkv_bias=qkv_bias, qk_scale=qk_scale,
                  drop_ratio=drop_ratio, attn_drop_ratio=attn_drop_ratio,
drop_path_ratio=dpr[i],
                  norm_layer=norm_layer, act_layer=act_layer)
            for i in range(depth)
        ])
        self.norm = norm_layer(embed_dim)

        # Representation layer
        if representation_size and not distilled:
            self.has_logits = True
            self.num_features = representation_size
            self.pre_logits = nn.Sequential(OrderedDict([
                ("fc", nn.Linear(embed_dim, representation_size)),
                ("act", nn.Tanh())
            ]))
        else:
            self.has_logits = False
            self.pre_logits = nn.Identity()

        # Classifier head(s)
        self.head = nn.Linear(self.num_features, num_classes) if num_classes > 0
else nn.Identity()
        self.head_dist = None
        if distilled:
            self.head_dist = nn.Linear(self.embed_dim, self.num_classes) if
num_classes > 0 else nn.Identity()

        # Weight init
        nn.init.trunc_normal_(self.pos_embed, std=0.02)
        if self.dist_token is not None:
            nn.init.trunc_normal_(self.dist_token, std=0.02)

        nn.init.trunc_normal_(self.cls_token, std=0.02)
        self.apply(_init_vit_weights)

    def forward_features(self, x):
        # [B, C, H, W] -> [B, num_patches, embed_dim]
        x = self.patch_embed(x)  # [B, 196, 768]
        # [1, 1, 768] -> [B, 1, 768]
        cls_token = self.cls_token.expand(x.shape[0], -1, -1)
        if self.dist_token is None:
            x = torch.cat((cls_token, x), dim=1)  # [B, 197, 768]
        else:
            x = torch.cat((cls_token, self.dist_token.expand(x.shape[0], -1, -1),
x), dim=1)

        x = self.pos_drop(x + self.pos_embed)
        x = self.blocks(x)
        x = self.norm(x)
        if self.dist_token is None:
            return self.pre_logits(x[:, 0])
        else:
            return x[:, 0], x[:, 1]
```

```
    def forward(self, x):
        x = self.forward_features(x)
        if self.head_dist is not None:
            x, x_dist = self.head(x[0]), self.head_dist(x[1])
            if self.training and not torch.jit.is_scripting():
                # during inference, return the average of both classifier
predictions
                return x, x_dist
            else:
                return (x + x_dist) / 2
        else:
            x = self.head(x)
        return x


def _init_vit_weights(m):
    """
    ViT weight initialization
    :param m: module
    """
    if isinstance(m, nn.Linear):
        nn.init.trunc_normal_(m.weight, std=.01)
        if m.bias is not None:
            nn.init.zeros_(m.bias)
    elif isinstance(m, nn.Conv2d):
        nn.init.kaiming_normal_(m.weight, mode="fan_out")
        if m.bias is not None:
            nn.init.zeros_(m.bias)
    elif isinstance(m, nn.LayerNorm):
        nn.init.zeros_(m.bias)
        nn.init.ones_(m.weight)


def vit_base_patch16_224(num_classes: int = 1000):
    """
    ViT-Base model (ViT-B/16) from original paper
(https://arxiv.org/abs/2010.11929).
    ImageNet-1k weights @ 224x224, source https://github.com/google-
research/vision_transformer.
    weights ported from official Google JAX impl:
    链接: https://pan.baidu.com/s/1zqb08naP0RPqqfSXfkB2EA  密码: eu9f
    """
    model = VisionTransformer(img_size=224,
                              patch_size=16,
                              embed_dim=768,
                              depth=12,
                              num_heads=12,
                              representation_size=None,
                              num_classes=num_classes)
    return model


def vit_base_patch16_224_in21k(num_classes: int = 21843, has_logits: bool =
True):
    """
```

```
    ViT-Base model (ViT-B/16) from original paper
(https://arxiv.org/abs/2010.11929).
    ImageNet-21k weights @ 224x224, source https://github.com/google-
research/vision_transformer.
    weights ported from official Google JAX impl:
    https://github.com/rwightman/pytorch-image-models/releases/download/v0.1-
vitjx/jx_vit_base_patch16_224_in21k-e5005f0a.pth
    """
    model = VisionTransformer(img_size=224,
                              patch_size=16,
                              embed_dim=768,
                              depth=12,
                              num_heads=12,
                              representation_size=768 if has_logits else None,
                              num_classes=num_classes)
    return model


def vit_base_patch32_224(num_classes: int = 1000):
    """
    ViT-Base model (ViT-B/32) from original paper
(https://arxiv.org/abs/2010.11929).
    ImageNet-1k weights @ 224x224, source https://github.com/google-
research/vision_transformer.
    weights ported from official Google JAX impl:
    链接: https://pan.baidu.com/s/1hCv0U8pQomwAtHBYc4hmZg  密码: s5hl
    """
    model = VisionTransformer(img_size=224,
                              patch_size=32,
                              embed_dim=768,
                              depth=12,
                              num_heads=12,
                              representation_size=None,
                              num_classes=num_classes)
    return model


def vit_base_patch32_224_in21k(num_classes: int = 21843, has_logits: bool =
True):
    """
    ViT-Base model (ViT-B/32) from original paper
(https://arxiv.org/abs/2010.11929).
    ImageNet-21k weights @ 224x224, source https://github.com/google-
research/vision_transformer.
    weights ported from official Google JAX impl:
    https://github.com/rwightman/pytorch-image-models/releases/download/v0.1-
vitjx/jx_vit_base_patch32_224_in21k-8db57226.pth
    """
    model = VisionTransformer(img_size=224,
                              patch_size=32,
                              embed_dim=768,
                              depth=12,
                              num_heads=12,
                              representation_size=768 if has_logits else None,
                              num_classes=num_classes)
    return model
```

```
def vit_large_patch16_224(num_classes: int = 1000):
    """
    ViT-Large model (ViT-L/16) from original paper
(https://arxiv.org/abs/2010.11929).
    ImageNet-1k weights @ 224x224, source https://github.com/google-
research/vision_transformer.
    weights ported from official Google JAX impl:
    链接: https://pan.baidu.com/s/1cxBgZJJ6qUWPSBNcE4TdRQ  密码: qqt8
    """
    model = VisionTransformer(img_size=224,
                              patch_size=16,
                              embed_dim=1024,
                              depth=24,
                              num_heads=16,
                              representation_size=None,
                              num_classes=num_classes)
    return model


def vit_large_patch16_224_in21k(num_classes: int = 21843, has_logits: bool =
True):
    """
    ViT-Large model (ViT-L/16) from original paper
(https://arxiv.org/abs/2010.11929).
    ImageNet-21k weights @ 224x224, source https://github.com/google-
research/vision_transformer.
    weights ported from official Google JAX impl:
    https://github.com/rwightman/pytorch-image-models/releases/download/v0.1-
vitjx/jx_vit_large_patch16_224_in21k-606da67d.pth
    """
    model = VisionTransformer(img_size=224,
                              patch_size=16,
                              embed_dim=1024,
                              depth=24,
                              num_heads=16,
                              representation_size=1024 if has_logits else None,
                              num_classes=num_classes)
    return model


def vit_large_patch32_224_in21k(num_classes: int = 21843, has_logits: bool =
True):
    """
    ViT-Large model (ViT-L/32) from original paper
(https://arxiv.org/abs/2010.11929).
    ImageNet-21k weights @ 224x224, source https://github.com/google-
research/vision_transformer.
    weights ported from official Google JAX impl:
    https://github.com/rwightman/pytorch-image-models/releases/download/v0.1-
vitjx/jx_vit_large_patch32_224_in21k-9046d2e7.pth
    """
    model = VisionTransformer(img_size=224,
                              patch_size=32,
                              embed_dim=1024,
```

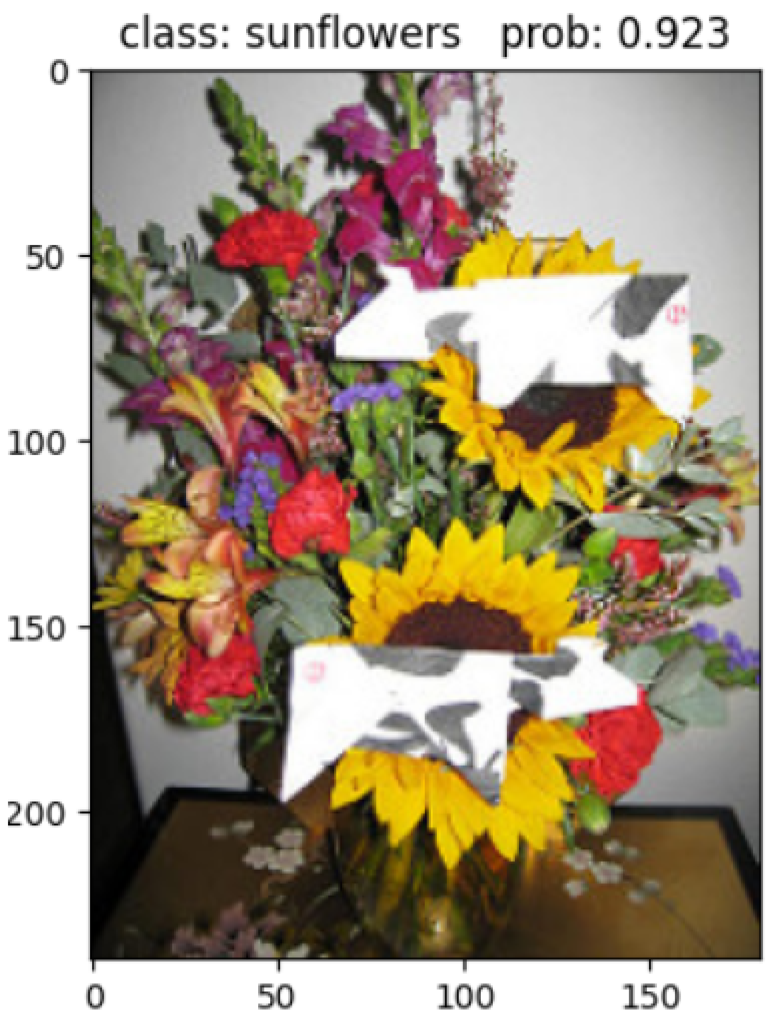
```
                                depth=24,
                                num_heads=16,
                                representation_size=1024 if has_logits else None,
                                num_classes=num_classes)
    return model


def vit_huge_patch14_224_in21k(num_classes: int = 21843, has_logits: bool =
True):
    """
    ViT-Huge model (ViT-H/14) from original paper
(https://arxiv.org/abs/2010.11929).
    ImageNet-21k weights @ 224x224, source https://github.com/google-
research/vision_transformer.
    NOTE: converted weights not currently available, too large for github release
hosting.
    """
    model = VisionTransformer(img_size=224,
                                patch_size=14,
                                embed_dim=1280,
                                depth=32,
                                num_heads=16,
                                representation_size=1280 if has_logits else None,
                                num_classes=num_classes)
    return model
```

测试与结果:

```
class: daisy         prob: 0.00723
class: dandelion     prob: 0.00571
class: roses         prob: 0.962
class: sunflowers    prob: 0.00677
class: tulips        prob: 0.0185
```

换一个难点的




```
class: daisy         prob: 0.0201
class: dandelion     prob: 0.0055
class: roses         prob: 0.0398
class: sunflowers    prob: 0.923
class: tulips        prob: 0.0113
```

得到完美结果

二、问题总结与体会

- **在ViT中要降低 Attention的计算量，有哪些方法？（提示：Swin的 Window attention，PVT的 attention）**

  方法：

Swin 引入了窗口注意力（Window Attention），将全局注意力计算限制在局部窗口内，使计算复杂度从图像块数量的二次方降低到线性，再通过移位窗口机制实现跨窗口信息交互。

PVT（Pyramidal Vision Transformer）采用空间缩减注意力，通过下采样键和值来减少序列长度，并结合金字塔结构构建多尺度特征。

局部敏感哈希（LSH）通过哈希桶近似全局注意力，以及标记选择（Token Selection）动态筛选重要标记，降低计算量。

- **Swin体现了一种什么思路？对后来工作有哪些启发？（提示：先局部再整体）**

  Swin 体现了一种“先局部再整体”的分层渐进思路，即先通过窗口注意力捕捉局部特征，再通过移位窗口和层级结构（如Patch Merging）逐步融合信息，形成多尺度特征金字塔，最终实现全局建模。

  这一思路对后来工作产生了深远启发：它推动了分层Transformer架构的普及，使模型能更高效地处理多尺度视觉任务；

  同时，其局部-全局注意力范式成为许多高效Transformer模型（如CSWin、PVTv2）的基础，证明了不必在所有层都进行全局计算；

  此外，Swin的成功还促进了CNN与Transformer的融合探索，启发后续研究更注重结合局部归纳偏置与全局关系建模。

- **有些网络将CNN和Transformer结合，为什么一般把 CNN block放在面前，Transformer block放在后面？**

  CNN擅长通过卷积核提取局部低级特征（如边缘和纹理），并利用平移不变性等归纳偏置高效处理高分辨率输入，为后续模块奠定基础；

  而Transformer则通过自注意力机制捕捉长距离依赖和全局上下文，但计算复杂度较高，因此放在后端可以处理经CNN下采样后的特征，减少序列长度，从而平衡计算负担。这种顺序符合视觉任务从局部细节到整体结构的认知规律，同时优化了模型性能与效率。

- **阅读并了解Restormer，思考：Transformer的基本结构为 attention+ FFN，这个工作分别做了哪些改进？**

  在注意力模块中，它用多头转置注意力（MDTA）替代标准注意力，在通道维度计算全局依赖而非空间维度，显著降低计算复杂度，并引入深度卷积增强局部上下文；

  在前馈网络（FFN）部分，它设计了门控前馈网络（GDFN），通过门控机制控制信息流，并结合深度卷积进一步强化局部特征提取。