Q2. Weather Recognition

1. The design of dataloader

First we get the path of all JPG files in the folder, save them in a list which is not only make we easily load all the images but also can be seen as the index for the following operations.

```
# Get the path of all JPG files in the folder
folder_path = '../Q2_data/train_data'
file_list = os.listdir(folder_path)
jpg_files = [file for file in file_list if file.endswith('.jpg')]
print(len(jpg_files))
Executed at 2023.12.15 00:10:11 in 17ms
```

And then, we define a function to resize image and convert to tensor which is aimed to be trained. Using this function we get a tensor of 250*3*224*224.

```
# Define a global transformer to appropriately scale images and subsequently convert them to a
Tensor
img_size = 224
loader = transforms.Compose([
    transforms.Resize(img_size),
    transforms.CenterCrop(img_size),
    transforms.ToTensor(),
])
def load_image(filename):
    image = PILImage.open(filename).convert('RGB')
    image_tensor = loader(image).float()
    image_var = Variable(image_tensor).unsqueeze(0)
    return image_var
Executed at 2023.12.15 00:10:17 in 4ms
```

```
# Convert the images in the folder to a tensor of 3 * 224 * 224
images_list = [load_image(folder_path+'/'+file) for file in jpg_files]
all_img = torch.cat(images_list, dim=0)
print(all_img.shape)
Executed at 2023.12.15 00:10:21 in 2s 284ms

torch.Size([250, 3, 224, 224])

:
```

Next step is converting weather labels into one-hot encoding tensor. We create these two tensors both by looping the list of images' name which we firstly defined, so they are one-to-one correspondence.

```
# Convert weather labels into the form of one-hot encoding
label_list = []
weather_list = ['Cloudy', 'Foggy', 'Rainy', 'Snowy', 'Sunny']
for file in jpg_files:
    label = []
    for weather in weather_list:
        if weather in file:
            label.append(1)
        else:
            label.append(0)
        label_list.append(label)

all_labels = torch.Tensor(label_list)
print(all_labels.shape)
Executed at 2023.12.15 00:10:23 in 15ms

torch.Size([250, 5])

:
```

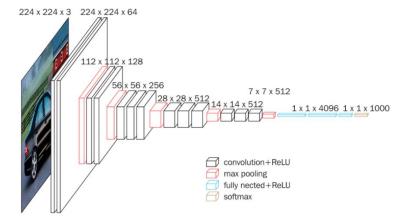
Finally, we use the TensorDataset, a existed Class of dataset in pytorch to encapsulate two tensors. And use Dataloader in pytorch to shuffle it and separate dataset by batch size of 25.

```
# Encapsulate the data
train_dataset = TensorDataset(all_img, all_labels)
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
```

2. Introduction to model

The convolutional part uses the structure of vgg16, and the fully connected layer changes the final output to 5 dimensions.

VGG uses multiple convolutional layers with smaller kernels (3x3) instead of a convolutional layer with a larger kernel. On the one hand, it can reduce parameters, and on the other hand, it is equivalent to performing more nonlinear mapping, which can increase the network's fitting/expression ability.



The following is the model structure:

```
a Construct a class for the model

Class CNMModel(nn.Module):

def __init__(self, nun_classes=5):
    super(CNMModel, self).__init__()

self.conv_layers = nn.Sequential(
    nn.Conv2d(3, 64, sersel_size=3, padding=1),
    nn.BatchNorm2d(64),
    nn.netU(inplase=frue),
    nn.exU(inplase=frue),
    nn.BatchNorm2d(64),
    nn.RetU(inplase=frue),
    nn.ExU(inplase=frue),
    nn.Conv2d(64, 128, kernel_size=3, padding=0),
    nn.BatchNorm2d(128),
    nn.BatchNorm2d(128),
    nn.RetU(inplase=frue),
    nn.Conv2d(128, 128, kernel_size=3, padding=1),
    nn.BatchNorm2d(128),
    nn.RetU(inplase=frue),
    nn.RetU(inplase=frue),
    nn.RetU(inplase=frue),
    nn.BatchNorm2d(280),
    nn.BatchNorm2d(280),
```

```
nn.com/20(100, 312, seroni_lives_, packings_),
nn.stenberod(512),
nn.stell(implex=frue),
nn.com/20(312, 512, seroni_lives_, packings_),
nn.stell(implex=frue),
nn.com/20(312, 512, seroni_lives_, packings_),
nn.stenberod(512),
nn.stell(implex=frue),
nn.com/20(312, 512, seroni_lives_, packings_), ollations_, call=nodesFalse),
nn.tell(implex=frue),
```

```
telf.signoid = nn.Signoid()

def formand(celf.x):
    x = nsil.com.layers(x)
    x = x.vinc(x.size(0), -1)
    x = nsil.fc(2.ayers(x))
    x = nsil.fc(2.ayers(x))
```

3. Accuracy on the training set

Accuracy = 96.4%

```
# Test

# Set the model to evaluation mode
model.eval()
correct = 0
with torch.no_grad():
    train_dataset = TensorDataset(all_img, all_labels)
    train_loader = DataLoader(train_dataset)
    for inputs, labels in train_loader:
    inputs, labels = inputs.to(device), labels.to(device)
    inputs = inputs.double()
    outputs = model(inputs.float())
    predicted = torch.max(outputs, 1)[1]
    label = torch.max(labels, 1)[1]
    correct += (predicted == label).sum()

# Calculate the accuracy
print('acc: %.2f %%' % (100 * correct / 250))
Executed at 2023/12/15 0026.49 in is 39ms
acc: 96.40 %

:
```