Report of Q2 Weather Recognition

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1. Question Description:

We need to train a five class classification model, with an input of an image and an output of a five dimensional category one hot vector. Therefore, we need to complete the following key steps:

- Building a dataloader
- > Select methods and build models
- ➤ Model Training
- Model Evaluation as Required (On the whole Train set)

2. Building a dataloader

I designed a dataloader to load a dataset for weather recognition tasks. It first converts images into a format acceptable to neural networks, while assigning corresponding category labels to each image. And set the batch size to provide data in batches during training, while shuffling the data before each epoch to increase the randomness of model training.

Figure.1 Dataloader

(1) Data loading and conversion

Data path: using data Dir='Data Q2/train Data 'specifies the data storage path.

Image conversion: using transforms Compose() defines the image conversion process, which includes uniformly adjusting the image to a size of (224, 224) and then converting it to tensor format.

(2) Dataset and label definitions:

Custom Dataset: The WeatherDataset class is used to define the dataset. The __init__ method handles initialization, __len__ method returns the dataset length, and __getitem__ method reads each sample.

Parsing Category Information: In the __getitem__ method, category labels for each image are determined by parsing keywords from the file names. For instance, "Sunny" corresponds to 0, "Snowy" corresponds to 1, "Cloudy" corresponds to 2, "Rainy" corresponds to 3, and "Foggy" corresponds to 4.

(3) Dataloader Configuration:

Batching and Shuffling: A dataloader object is created using torch.utils.data.DataLoader, where the defined WeatherDataset is passed in. It's configured with a batch size of 32, and shuffle=True ensures the data order is randomized before the start of each epoch.

(2) Visualization

Figure.2 Visualization

3. Select methods and build models

I choose to use resnet18 as the backbone network for automatically extracting features from images. The last fully connected layer is replaced with a new linear layer (nn.Linear(num_ftrs, 5)) with an output size of 5, corresponding to the five weather categories.

| layer name | output size | 18-layer | 34-layer | 50-layer | 101-layer | 152-layer |
|------------|-------------|--|--|---|--|--|
| conv1 | 112×112 | | 7×7, 64, stride 2 | | | |
| | | | 3×3 max pool, stride 2 | | | |
| conv2_x | 56×56 | $ \left[\begin{array}{c} 3\times3,64\\3\times3,64 \end{array}\right]\times2 $ | $\left[\begin{array}{c}3\times3,64\\3\times3,64\end{array}\right]\times3$ | $\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$ | $\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$ | $\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$ |
| conv3_x | 28×28 | $\left[\begin{array}{c} 3\times3, 128\\ 3\times3, 128 \end{array}\right] \times 2$ | $\left[\begin{array}{c} 3\times3, 128\\ 3\times3, 128 \end{array}\right] \times 4$ | $\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$ | $\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$ | $\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8$ |
| conv4_x | 14×14 | $\left[\begin{array}{c} 3\times3,256\\ 3\times3,256 \end{array}\right]\times2$ | $\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$ | $\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$ | $\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 23$ | $\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36$ |
| conv5_x | 7×7 | $\left[\begin{array}{c} 3\times3,512\\ 3\times3,512 \end{array}\right]\times2$ | $\left[\begin{array}{c} 3\times3,512\\ 3\times3,512 \end{array}\right]\times3$ | $\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$ | $\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$ | $\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$ |
| | 1×1 | | average pool, 1000-d fc, softmax | | | |
| FLOPs | | 1.8×10^{9} | 3.6×10^{9} | 3.8×10^{9} | 7.6×10^{9} | 11.3×10^9 |

Figure.3 Backbone - Resnet18

4. Model Training

Then I conducted training for 50 epochs using a stochastic gradient descent optimizer with a learning rate of 0.001 and momentum of 0.9, employing cross-entropy loss, iterating through the dataset batches, and updating the model parameters iteratively while monitoring and printing the average loss per epoch.

The Training Process shows as below:

Figure.4 Training Process

5. Model Evaluation as Required (On the whole Train set)

After training the model, I tested the model on ALL the training data and report the accuracy. The Accuracy on the training set shows as below:

```
In [8]: 1 # Model Evaluation On the whole Train set

2 correct = 0
3 total = 0
4 with torch.no_grad():
5 for data in tqdm(dataloader):
6 images, labels = data
7 outputs = model (images)
8 _, predicted = torch.max(outputs.data, 1)
10 total *= labels.size(0)
10 correct *= (predicted == labels).sum().item()
11
12 accuracy = correct / total
13 print(f'Accuracy on training data: (accuracy)')

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Accuracy on training data: 1.0
```

Figure.4 Accuracy on the training set