Deep Learning Lab3

1. Introduction

This lab is to implement ResNet to analysis acute lymphoblastic leukemia. We need to use ResNet to distinguish the different between normal cells and leukemia cells. Same as previous lab, I provide arguments interface to control training easily. Beside training script and plotting, which generates accuracy curve about three models and evaluating interface, which generates test result csv to upload **Kaggle**.

```
├─ train.py
├─ eval.py
└─ plot.py
```

A. How to use

train.py

This script for training. It will store best model weights in ./storage/latest/.

```
-e EPOCHS, --epochs EPOCHS

Number of epochs

-b BATCH_SIZE, --batch_size BATCH_SIZE

Batch size

-o OPTIMIZER, --optimizer OPTIMIZER

Optimizer

-r LEARNING_RATE, --learning_rate LEARNING_RATE

Learning rate

-mm MOMENTUM, --momentum MOMENTUM

Momentum for SGD

-wd WEIGHT_DECAY, --weight_decay WEIGHT_DECAY

Weight dacay for optimizer

example:

python3 train.py -m ResNet18 -e 20 -b 32 -o sgd
```

eval.py

This script will generate test csv to upload kaggle and generate confusion matrix.

```
The architecture for test (test18, test50, test152)
example:
python3 eval.py -a test18 -b 32 -m ...
```

plot.py

This script will generate comparison accuracy curve for three models.

2. Implementation Details

A. The details of your model (ResNet)

There are two major class, BasicBlock and BottleneckBlock for setup ResNet network.

Block Classes

```
class BasicBlock(nn.Module):
    def __init__(
        self,
```

```
in_channels: int,
        out_channels: int,
        stride: int = 1,
        expansion: int = 1,
        down_sample: nn.Module = None,
        activation: nn.modules.activation =
nn.ReLU(inplace=True)
    ) -> None:
        super(BasicBlock, self).__init__()
        self.expansion = expansion
        self.activation = activation
        self.down_sample = down_sample
        # architecture
        self.block = nn.Sequential(
            nn.Conv2d(
                in_channels=in_channels,
                out_channels=out_channels,
                kernel_size=3,
                stride=stride,
                padding=1,
                bias=False
            ),
            nn.BatchNorm2d(out_channels),
            activation,
            nn.Conv2d(
                in_channels=out_channels,
                out_channels=out_channels * self.expansion,
                kernel_size=3,
                padding=1,
```

```
bias=False
    ),
    nn.BatchNorm2d(out_channels * self.expansion)
)

def forward(self, inputs: TensorDataset) -> Tensor:
    outputs = self.block(inputs)

residual = inputs
    if self.down_sample:
        residual = self.down_sample(residual)

outputs = self.activation(outputs + residual)

return outputs
```

```
class BottleneckBlock(nn.Module):
    def __init__(
        self,
        in_channels: int,
        out_channels: int,
        stride: int = 1,
        expansion: int = 4,
        down_sample: nn.Module = None,
        activation: nn.modules.activation =
nn.ReLU(inplace=True)
    ) -> None:
        super(BottleneckBlock, self).__init__()

        self.expansion = expansion
        self.activation = activation
        self.down_sample = down_sample
```

architecture

```
self.block = nn.Sequential(
        nn.Conv2d(
            in_channels=in_channels,
            out_channels=out_channels,
            kernel_size=1,
            bias=False
        ),
        nn.BatchNorm2d(out_channels),
        activation,
        nn.Conv2d(
            in_channels=out_channels,
            out_channels=out_channels,
            kernel_size=3,
            padding=1,
            stride=stride,
            bias=False
        ),
        nn.BatchNorm2d(out_channels),
        activation,
        nn.Conv2d(
            in_channels=out_channels,
            out_channels=out_channels * expansion,
            kernel_size=1,
            bias=False
        ),
        nn.BatchNorm2d(out_channels * expansion)
    )
def forward(self, inputs: TensorDataset) -> Tensor:
```

```
outputs = self.block(inputs)

residual = inputs
if self.down_sample:
    residual = self.down_sample(residual)

outputs = self.activation(outputs + residual)

return outputs
```

■ There is a special arguent in contructor down_sample because I have to ensure input image size and output image size are the same. In ResNet, model contains serveral blocks in series. Therefore, ensuring I/O image size is important.

ResNet

```
class ResNet(nn.Module):
    def __init__(
        self,
        block: Type[Union[BasicBlock, BottleneckBlock]],
        layer_blocks: List[int],
        expansion: int,
        num_classes: int
) -> None:
        super(ResNet, self).__init__()

        self.current_channels = 64
        self.expansion = expansion

# architecture
```

```
self.conv_1 = nn.Sequential(
    nn.Conv2d(
        in_channels=3,
        out_channels=64,
        kernel_size=7,
        stride=2,
        padding=3,
        bias=False
    ),
    nn.BatchNorm2d(64),
    nn.ReLU(inplace=True),
    nn.MaxPool2d(
        kernel_size=3,
        stride=2,
        padding=1
    )
)
self.conv_2 = self.__make_layer(
    block=block,
    num_of_blocks=layer_blocks[0],
    in_channels=64
self.conv_3 = self.__make_layer(
    block=block,
    num_of_blocks=layer_blocks[1],
    in_channels=128,
    stride=2
)
self.conv_4 = self.__make_layer(
```

```
block=block,
            num_of_blocks=layer_blocks[2],
            in_channels=256,
            stride=2
        )
        self.conv_5 = self.__make_layer(
            block=block,
            num_of_blocks=layer_blocks[3],
            in_channels=512,
            stride=2
        )
        self.classify = nn.Sequential(
            nn.AdaptiveAvqPool2d((1, 1)),
            nn.Flatten(),
            nn.Linear(512 * self.expansion, num_classes)
        )
    def forward(self, inputs: TensorDataset) -> Tensor:
        partial_result = inputs
        for i in range(1, 6):
            partial_result = getattr(self, f'conv_{i}')
(partial_result)
        return self.classify(partial_result)
    def __make_layer(
        self,
        block: Type[Union[BasicBlock, BottleneckBlock]],
        num_of_blocks: int,
        in_channels: int,
        stride: int = 1
```

```
) -> nn.Sequential:
        Make a layer with given block module
        :param block: block module to be used
        :param num_of_blocks: number of block layers
        :param in_channels: number od block input channels
        :param stride: stride
        down_sample = None
        out_channels = in_channels * self.expansion
        if stride != 1 or self.current channels !=
out_channels:
            down_sample = nn.Sequential(
                nn.Conv2d(
                    in_channels=self.current_channels,
                    out_channels=out_channels,
                    kernel_size=1,
                    stride=stride,
                    bias=False
                ),
                nn.BatchNorm2d(out_channels)
            )
        layers = [
            block(
                in_channels=self.current_channels,
                out_channels=in_channels,
                stride=stride,
                down_sample=down_sample
            )
```

- ResNet class supports using different blocks and the number of blocks in each layer to implement different architecture of ResNet.
- Private classmethod self.__make_layer is to build one layer for model. In method, I need to control whether using down_sample or not for builing blocks.Apart from first block in each layer, the other blocks I/O image size are the same, so it does not use down_sample.

B. The details of your DataLoader

```
class LeukemiaLoader(data.Dataset):
    def __init__(
       self,
       mode: str,
```

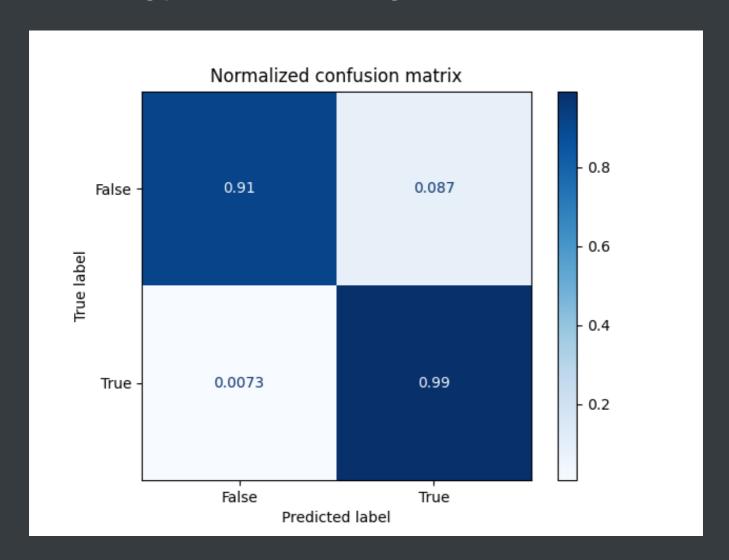
```
root_path: str = './new_dataset'
) -> None:
    :param mode: which mode dataset (train, valid, test)
    :param root_path: root path for dataset
    super(LeukemiaLoader, self).__init__()
    self.mode = mode
    self.root_path = root_path
    self.img_path_list, self.label_list = self.__get_data()
    self.transform = transforms.RandomOrder([
        transforms.RandomRotation(degrees=20),
        transforms.RandomHorizontalFlip(p=0.5),
        transforms.RandomVerticalFlip(p=0.5)
   ])
    self.to_tensor = transforms.Compose([
        transforms.CenterCrop(350),
        transforms.Resize([350, 350]),
        transforms.ToTensor(),
    ])
def __len__(self) -> int:
    return len(self.img_path_list)
def __getitem__(self, index: int) -> Tuple[Tensor, int]:
    label = self.label_list[index]
    img = Image.open(self.img_path_list[index])
    if self.mode == 'train':
```

```
img = self.transform(img)
        img_data = self.to_tensor(img)
        return img_data, label
    def __qet_data(self) -> Tuple[List[str]]:
        if self.mode == 'train':
            df = pd.read_csv(f'{self.root_path}/train.csv')
        elif self.mode == 'valid':
            df = pd.read_csv(f'{self.root_path}/valid.csv')
        elif self.mode == 'test18':
            df =
pd.read_csv(f'{self.root_path}/resnet_18_test.csv')
        elif self.mode == 'test50':
            df =
pd.read_csv(f'{self.root_path}/resnet_50_test.csv')
        elif self.mode == 'test152':
            df =
pd.read_csv(f'{self.root_path}/resnet_152_test.csv')
        else:
            raise ValueError(f'Does not support {self.mode}')
        img_path_list = df['Path'].to_list()
        try:
            label_list = df['label'].to_list()
        except:
            label_list = [0 for _ in range(len(img_path_list))]
        return img_path_list, label_list
```

- constructor: define transformations and load data from csv.
- len: return dataset length.

- __getitem__: define operation about get image data according index.
- get_data: according csv load data and transform to list.

C. Describing your evaluation through the confusion matrix



After serveral times training, the accuracy of distinguishing leukemmia cells is about to 100%, but the accuracy of distinguishing normal cells is lower. Therefore, I will use accuracy of distinguishing normal cells to evaluate model is good or bad.

3. Data Preprocessing

A. How you prepocessed your data?

```
# define transformation in contructor
    self.transform = transforms.RandomOrder(Γ
        transforms.RandomRotation(degrees=20),
        transforms.RandomHorizontalFlip(p=0.5),
        transforms.RandomVerticalFlip(p=0.5)
    ])
    self.to_tensor = transforms.Compose([
        transforms.CenterCrop(350),
        transforms.Resize([350, 350]),
        transforms.ToTensor(),
    7)
    # end define
def __getitem__(self, index: int) -> Tuple[Tensor, int]:
    label = self.label_list[index]
    img = Image.open(self.img_path_list[index])
    if self.mode == 'train':
        img = self.transform(img)
    img_data = self.to_tensor(img)
    return img_data, label
```

- Transform is for data preprocessing in training. The major way to increase data strength are rotation, flip.
- To_tensor is two steps transformation. First is to crop cells and enlarge cell ratio about image. Second is to transform (H, W, C) to (C, H, W).

B. What makes your method special?

In my opinion, the most special method is CenterCrop, because it increases the ratio of cell in image easily. In other words, it enlarges the cell image resolution.

Other students will use rotation and flip to increase image strength. The different part between me and others is CenterCrop.

4. Experimental results

A. The highest testing accuracy

ResNet18	\odot	312553004_resnet18.csv Complete · 1d ago	Score: 0.9775
ResNet50	\bigcirc	312553004_resnet50.csv Complete · 2d ago	Score: 0.95407
ResNet152	\bigcirc	312553004_resnet152.csv Complete · 2d ago	Score: 0.92033

Above is my best accuracy in each Kaggle competition. The best accuracy is **ResNet18**.

• epochs: 120

batch size: 32

optimizer: SGD

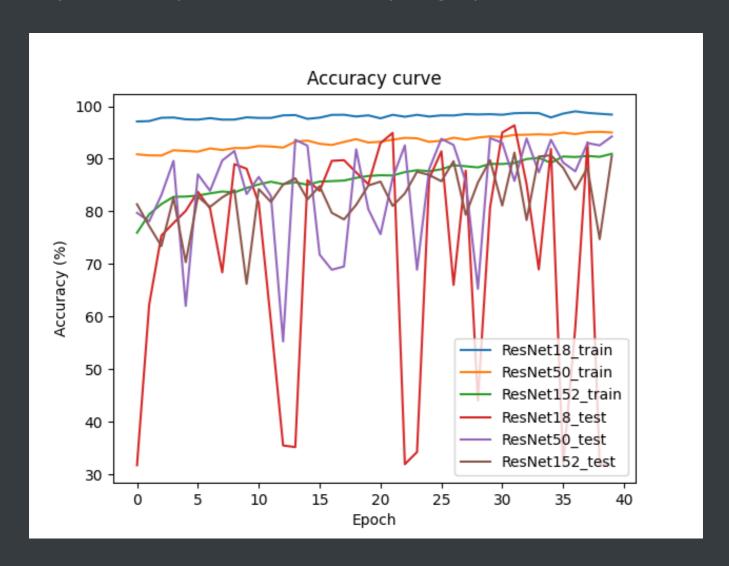
■ learning rate: 0.001

■ Momentum: 0.9

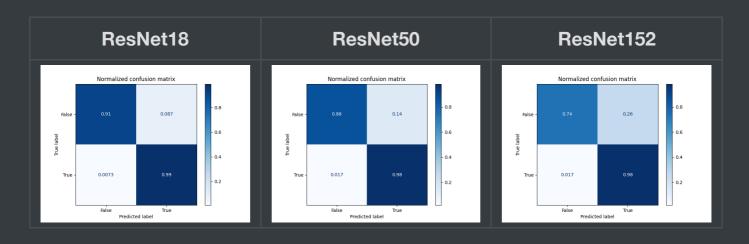
• weight decay: 0.00001

B. Comparison figures

This is accuracy curve with three models. Because of three models with different epochs, I only show last 40 epochs limit by ResNet152 (epochs 40). Valid test always oscillates up and down, but accuracy will go up.



This is confusion matrix about three models. The distinguishing leukemia part has better accuracy. The complete accuracy is limited by distinguishing normal cells.



5. Disscussion