Lab03 Report

ResNet18 and SEResNet18

In this section of Lab03, ResNet model was implemented on the CIFAR-10 dataset. With the same data set, 2 versions of ResNet were employed namely,

- ResNet18
- ResNet18 with Squeeze and Excitation (SEResNet18)

Firstly, the datasets are transformed to 256x256 scaling and 224x224 cropping for CIFAR as standardized for ImageNet and modified the implementation to use the same convolutions (e.g., initial 7x7). After that,some layers are employed since the given architechture of ResNet was not the same as what can be found on the original paper. The added layers are in the following.

- The input image size
- The modification of the first convolutional layer
- The addition of a maxpool
- The padding
- The kernal size

The two versions were impleneted with the exact same optimizer as well as the loss functions and they are as follows:

- criterion = nn.CrossEntropyLoss()
- optimizer = optim.Adam(model.parameters(), lr=0.01)

The number of trainable parameters of each model are as follows:

- ResNet18 has 11,181,642 trainable parameters
- SEResNet18 has 11,268,682 trainable parameters

The models were both trained for 25 epochs with the batch size of 16 and their performace at the 25th epoch are:

- ResNet18: Train acc = 93.44% , Val acc = 83.98% , Test acc = 85.08%
- SEResNet18: Train acc = 96.44% , Val acc = 82.15% , Test acc = 83.05%

Importing Libraries

In [5]:

```
import torch
import torchvision
from torchvision import datasets, models, transforms
import torch.nn as nn
import torch.optim as optim
import time
import os
from copy import copy
from copy import deepcopy
import numpy as np
from torchvision.transforms.transforms import RandomCrop
```

1.Prepare Dataset

In the below cell, the datasets are transformed to 256x256 scaling and 224x224 cropping for CIFAR as standardized for ImageNet.

In [15]:

```
## Resize to 256
### AUGMENT for train
train_preprocess = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010))])

## Resize to 224
### No AUGMENT for test
eval_preprocess = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010))])

# Download CIFAR-10 and split into training, validation, and test sets.
# The copy of the training dataset after the split allows us to keep
# the same training/validation split of the original training set but
# apply different transforms to the training set and validation set.

full_train_dataset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                                  download=True)

train_dataset, val_dataset = torch.utils.data.random_split(full_train_dataset, [4000
train_dataset.dataset = copy(full_train_dataset)
train_dataset.dataset.transform = train_preprocess
val_dataset.dataset.transform = eval_preprocess

test_dataset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                            download=True, transform=eval_preprocess


# Prepare the data loaders
BATCH_SIZE=16
NUM_WORKERS=2

train_dataloader = torch.utils.data.DataLoader(train_dataset, batch_size=BATCH_SIZE,
                                            shuffle=True, num_workers=NUM_WORKERS)
val_dataloader = torch.utils.data.DataLoader(val_dataset, batch_size=BATCH_SIZE,
                                            shuffle=False, num_workers=NUM_WORKERS)
test_dataloader = torch.utils.data.DataLoader(test_dataset, batch_size=BATCH_SIZE,
                                            shuffle=False, num_workers=NUM_WORKERS)

dataloaders = {'train': train_dataloader, 'val': val_dataloader}
```

```
Files already downloaded and verified
Files already downloaded and verified
```

2.Define Model

In this following Resnet class architecture, the implementation to use 7 for kernel size, 2 for stride and 3 for padding are implemented. The class BottleneckBlock, class BasicBlock and the function ResNet18 are changed nothing so I skip them in this report.

In [10]:

```
class ResNet(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super().__init__()
        self.in_planes = 64
        # Initial convolution
        self.conv1 = nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3, bias=False
        self.bn1 = nn.BatchNorm2d(64)
        self.relu = nn.ReLU(inplace=True)
        self.maxpool = nn.MaxPool2d(kernel_size = 3, stride = 2, padding = 1)
        # Residual blocks
        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)
        # FC layer = 1 layer
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.linear = nn.Linear(512 * 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.maxpool(out)
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = self.avgpool(out)
        out = out.view(out.size(0), -1)
        out = self.linear(out)
        return out
```

3.Define for function evaluation

The class evaluate from the below cell stands for the testing.

In [12]:

```
def evaluate(model, iterator, criterion):

    total = 0
    correct = 0
    epoch_loss = 0
    epoch_acc = 0

    predicteds = []
    trues = []

    model.eval()

    with torch.no_grad():

        for batch, labels in iterator:

            #Move tensors to the configured device
            batch = batch.to(device)
            labels = labels.to(device)

            predictions = model(batch.float())

            loss = criterion(predictions, labels.long())

            predictions = nn.functional.softmax(predictions, dim=1)
            _, predicted = torch.max(predictions.data, 1)  #returns max value, indic

            predicteds.append(predicted)
            trues.append(labels)
            total += labels.size(0)  #keep track of total
            correct += (predicted == labels).sum().item()  #.item() give the raw nur
            acc = 100 * (correct / total)

            epoch_loss += loss.item()
            epoch_acc += acc

    return epoch_loss / len(iterator), epoch_acc / len(iterator),predicteds, trues
```

4. Results

4.1 Resnet

For the results, I created new files to save the train losses, val losses and time taken for each 25 epoches and the .txt file is shown in below.

In [42]:

```
resnet18_result = open("output.txt", "r")
print(resnet18_result.read())
```

```
====================== New Run =======================
Epoch 0/24
----------
train Loss: 1.8897 Acc: 0.2865
Epoch time taken: 654.0159502029419
val Loss: 1.6248 Acc: 0.4020
Epoch time taken: 704.2495431900024
Epoch 1/24
----------
train Loss: 1.3662 Acc: 0.5061
Epoch time taken: 656.3922257423401
val Loss: 1.1748 Acc: 0.5833
Epoch time taken: 706.6556115150452
Epoch 2/24
----------
train Loss: 1.0765 Acc: 0.6178
Epoch time taken: 660.3247539997101
val Loss: 0.9954 Acc: 0.6508
Epoch time taken: 712.6144573688507
Epoch 3/24
----------
train Loss: 0.9195 Acc: 0.6766
Epoch time taken: 671.927163362503
val Loss: 0.8655 Acc: 0.6966
Epoch time taken: 730.9818484783173
Epoch 4/24
----------
train Loss: 0.8058 Acc: 0.7195
Epoch time taken: 698.9768545627594
val Loss: 0.7838 Acc: 0.7320
Epoch time taken: 749.3615391254425
Epoch 5/24
----------
train Loss: 0.7232 Acc: 0.7458
Epoch time taken: 652.7142059803009
val Loss: 0.6877 Acc: 0.7610
Epoch time taken: 702.9611570835114
Epoch 6/24
----------
train Loss: 0.6592 Acc: 0.7720
Epoch time taken: 797.6566712856293
val Loss: 0.6585 Acc: 0.7745
Epoch time taken: 866.5435600280762
Epoch 7/24
----------
train Loss: 0.6013 Acc: 0.7920
Epoch time taken: 865.5769665241241
val Loss: 0.8196 Acc: 0.7375
Epoch time taken: 929.0757784843445
Epoch 8/24
----------
train Loss: 0.5611 Acc: 0.8058
Epoch time taken: 867.2764942646027
val Loss: 0.6653 Acc: 0.7760
Epoch time taken: 936.1533434391022
Epoch 9/24
```

```
----------
train Loss: 0.5264 Acc: 0.8171
Epoch time taken: 860.0926620960236
val Loss: 0.6110 Acc: 0.7934
Epoch time taken: 929.0617113113403
Epoch 10/24
----------
train Loss: 0.4923 Acc: 0.8300
Epoch time taken: 873.0831277370453
val Loss: 0.5592 Acc: 0.8111
Epoch time taken: 936.1327166557312
Epoch 11/24
----------
train Loss: 0.4579 Acc: 0.8417
Epoch time taken: 869.6140451431274
val Loss: 0.5615 Acc: 0.8144
Epoch time taken: 939.1863374710083
Epoch 12/24
----------
train Loss: 0.4265 Acc: 0.8522
Epoch time taken: 861.1319098472595
val Loss: 0.5387 Acc: 0.8266
Epoch time taken: 929.6519300937653
Epoch 13/24
----------
train Loss: 0.3979 Acc: 0.8633
Epoch time taken: 867.0516841411591
val Loss: 0.5626 Acc: 0.8214
Epoch time taken: 930.129467010498
Epoch 14/24
----------
train Loss: 0.3708 Acc: 0.8719
Epoch time taken: 773.7603902816772
val Loss: 0.5746 Acc: 0.8116
Epoch time taken: 826.9446794986725
Epoch 15/24
----------
train Loss: 0.3481 Acc: 0.8785
Epoch time taken: 656.0127289295197
val Loss: 0.5574 Acc: 0.8100
Epoch time taken: 706.5103137493134
Epoch 16/24
----------
train Loss: 0.3228 Acc: 0.8873
Epoch time taken: 654.3113939762115
val Loss: 0.5417 Acc: 0.8348
Epoch time taken: 705.3092188835144
Epoch 17/24
----------
train Loss: 0.3005 Acc: 0.8951
Epoch time taken: 749.7369577884674
val Loss: 0.5496 Acc: 0.8251
Epoch time taken: 839.1684982776642
Epoch 18/24
----------
train Loss: 0.2825 Acc: 0.9012
Epoch time taken: 1109.7353236675262
val Loss: 0.4948 Acc: 0.8448
Epoch time taken: 1197.5072758197784
Epoch 19/24
----------
```

```
train Loss: 0.2635 Acc: 0.9077
Epoch time taken: 1105.310772895813
val Loss: 0.5242 Acc: 0.8372
Epoch time taken: 1185.3529224395752
Epoch 20/24
----------
train Loss: 0.2415 Acc: 0.9170
Epoch time taken: 1079.9227287769318
val Loss: 0.5600 Acc: 0.8292
Epoch time taken: 1168.5465817451477
Epoch 21/24
----------
train Loss: 0.2292 Acc: 0.9201
Epoch time taken: 884.4250338077545
val Loss: 0.6390 Acc: 0.8205
Epoch time taken: 940.6406226158142
Epoch 22/24
----------
train Loss: 0.2136 Acc: 0.9253
Epoch time taken: 955.9319491386414
val Loss: 0.5219 Acc: 0.8409
Epoch time taken: 1036.6956267356873
Epoch 23/24
----------
train Loss: 0.1942 Acc: 0.9313
Epoch time taken: 1137.2763874530792
val Loss: 0.5761 Acc: 0.8383
Epoch time taken: 1222.1849756240845
Epoch 24/24
----------
train Loss: 0.1851 Acc: 0.9344
Epoch time taken: 1159.1404569149017
val Loss: 0.5503 Acc: 0.8398
Epoch time taken: 1244.049742937088
```

4.2 SEResnet

In [14]:

```
SEresnet18_result = open("outputSE.txt", "r")
print(SEresnet18_result.read())
```

```
====================== New Run =======================
Epoch 0/24
----------
train Loss: 1.7253 Acc: 0.3661
Epoch time taken: 181.560795545578
val Loss: 1.5392 Acc: 0.4544
Epoch time taken: 202.71159482002258
Epoch 1/24
----------
train Loss: 1.2321 Acc: 0.5574
Epoch time taken: 183.8565845489502
val Loss: 1.0812 Acc: 0.6207
Epoch time taken: 205.04378199577332
Epoch 2/24
----------
train Loss: 0.9731 Acc: 0.6599
Epoch time taken: 183.80808281898499
val Loss: 0.8443 Acc: 0.7060
Epoch time taken: 204.99090814590454
Epoch 3/24
----------
train Loss: 0.7826 Acc: 0.7259
Epoch time taken: 183.35695719718933
val Loss: 0.7339 Acc: 0.7484
Epoch time taken: 204.3735625743866
Epoch 4/24
----------
train Loss: 0.6607 Acc: 0.7679
Epoch time taken: 182.95550084114075
val Loss: 0.6557 Acc: 0.7761
Epoch time taken: 204.1663293838501
Epoch 5/24
----------
train Loss: 0.5753 Acc: 0.7980
Epoch time taken: 182.6628623008728
val Loss: 0.6570 Acc: 0.7790
Epoch time taken: 203.77781987190247
Epoch 6/24
----------
train Loss: 0.5051 Acc: 0.8232
Epoch time taken: 182.38938331604004
val Loss: 0.5742 Acc: 0.8061
Epoch time taken: 203.43639945983887
Epoch 7/24
----------
train Loss: 0.4367 Acc: 0.8481
Epoch time taken: 181.8331093788147
val Loss: 0.5669 Acc: 0.8119
Epoch time taken: 202.70471000671387
Epoch 8/24
----------
train Loss: 0.3884 Acc: 0.8649
Epoch time taken: 181.6044681072235
val Loss: 0.6221 Acc: 0.8003
Epoch time taken: 202.50563144683838
Epoch 9/24
```

```
----------
train Loss: 0.3423 Acc: 0.8798
Epoch time taken: 181.58322024345398
val Loss: 0.5584 Acc: 0.8167
Epoch time taken: 202.29446983337402
Epoch 10/24
----------
train Loss: 0.3064 Acc: 0.8925
Epoch time taken: 181.46194410324097
val Loss: 0.5762 Acc: 0.8208
Epoch time taken: 202.36961483955383
Epoch 11/24
----------
train Loss: 0.2686 Acc: 0.9049
Epoch time taken: 181.59209394454956
val Loss: 0.5871 Acc: 0.8214
Epoch time taken: 202.54343128204346
Epoch 12/24
----------
train Loss: 0.2406 Acc: 0.9174
Epoch time taken: 181.41520881652832
val Loss: 0.6254 Acc: 0.8236
Epoch time taken: 202.44427871704102
Epoch 13/24
----------
train Loss: 0.2119 Acc: 0.9258
Epoch time taken: 181.35414242744446
val Loss: 0.6346 Acc: 0.8231
Epoch time taken: 202.36792182922363
Epoch 14/24
----------
train Loss: 0.1989 Acc: 0.9308
Epoch time taken: 181.09195852279663
val Loss: 0.6385 Acc: 0.8250
Epoch time taken: 201.9873070716858
Epoch 15/24
----------
train Loss: 0.1817 Acc: 0.9353
Epoch time taken: 180.81857681274414
val Loss: 0.6073 Acc: 0.8311
Epoch time taken: 201.62484526634216
Epoch 16/24
----------
train Loss: 0.1613 Acc: 0.9437
Epoch time taken: 181.25544786453247
val Loss: 0.6694 Acc: 0.8268
Epoch time taken: 202.1974811553955
Epoch 17/24
----------
train Loss: 0.1482 Acc: 0.9481
Epoch time taken: 180.74844360351562
val Loss: 0.7519 Acc: 0.8173
Epoch time taken: 201.4949085712433
Epoch 18/24
----------
train Loss: 0.1410 Acc: 0.9516
Epoch time taken: 180.70662879943848
val Loss: 0.7258 Acc: 0.8241
Epoch time taken: 201.44750905036926
Epoch 19/24
----------
```

```
train Loss: 0.1338 Acc: 0.9538
Epoch time taken: 180.8685336112976
val Loss: 0.7284 Acc: 0.8252
Epoch time taken: 201.48338890075684
Epoch 20/24
----------
train Loss: 0.1210 Acc: 0.9584
Epoch time taken: 181.23830699920654
val Loss: 0.7191 Acc: 0.8290
Epoch time taken: 202.22886180877686
Epoch 21/24
----------
train Loss: 0.1116 Acc: 0.9610
Epoch time taken: 181.02049493789673
val Loss: 0.7206 Acc: 0.8321
Epoch time taken: 202.04218292236328
Epoch 22/24
----------
train Loss: 0.1083 Acc: 0.9630
Epoch time taken: 181.08765625953674
val Loss: 0.7813 Acc: 0.8242
Epoch time taken: 202.06452298164368
Epoch 23/24
----------
train Loss: 0.1069 Acc: 0.9636
Epoch time taken: 183.45331382751465
val Loss: 0.7739 Acc: 0.8285
Epoch time taken: 205.85710620880127
Epoch 24/24
----------
train Loss: 0.1027 Acc: 0.9644
Epoch time taken: 183.69805264472961
val Loss: 0.7732 Acc: 0.8215
Epoch time taken: 206.04672050476074
```

5. Check avilability of the GPU

In [31]:

```
from chosen_gpu import get_free_gpu

device = torch.device(get_free_gpu()) if torch.cuda.is_available() else torch.device
print("Configured device: ", device)
```

6. Evaluation

In [72]:

```
from resnet import ResNet18
from SEbasicblock import ResSENet18

model_resnet = ResNet18()
model_SEresnet = ResSENet18()

model  = model_resnet.to(device)
model_SE = model_SEresnet.to(device)

criterion = nn.CrossEntropyLoss()
criterion = criterion.to(device)


model_resnet.load_state_dict(torch.load('resnet18_bestsofar.pth',
                                        map_location=torch.device('cpu')))
model_SEresnet.load_state_dict(torch.load('SEresnet18_bestsofar.pth',
                                          map_location=torch.device('cpu')))



# model_resnet = torch.load('resnet18_bestsofar.pth', map_location=torch.device('cpu
# model_SEresnet = torch.load('SEresnet18_bestsofar.pth', map_location=torch.device(


resnet_test_loss,resnet_test_acc,
resnet_test_pred_label,resnet_test_true_label=evaluate(model_resnet,
                                                       test_dataloader,
                                                       criterion)
SEresnet_test_loss, SEresnet_test_acc,
SEresnet_test_pred_label,SEresnet_test_true_label=evaluate(model_SEresnet,
                                                           test_dataloader,
                                                           criterion)
print('...................ResNet18...................',
      file = open("test_resnet_seresnet.txt", "a"))
print(f'Test Loss: {resnet_test_loss:.3f} | Test Acc: {resnet_test_acc:.2f}%',
      file = open("test_resnet_seresnet.txt", "a"))
print('...................SEResNet18 ...................',
      file = open("test_resnet_seresnet.txt", "a"))
print(f'Test Loss: {SEresnet_test_loss:.3f} | Test Acc: {SEresnet_test_acc:.2f}%',
      file = open("test_resnet_seresnet.txt", "a"))
```

The following is the test and loss result of the resnet and SEresnet.

In [54]:

```
test_result = open("test_resnet_seresnet.txt", "r")
print(test_result.read())
```

```
...................ResNet18...................
Test Loss: 0.653 | Test Acc: 85.08%
...................SEResNet18 ...................
Test Loss: 0.703| Test Acc: 83.05%
```

7. Plotting

In [69]:

```
import torch
import matplotlib.pyplot as plt

resnet_loss = torch.load('reset-18-cifar-10-loss-acc.pth',
                         map_location=torch.device('cpu'))
seresnet_loss = torch.load('se-reset-18-cifar-10-loss-acc.pth',
                           map_location=torch.device('cpu'))

resnet_val_acc = torch.load('reset-18-cifar-10-val-acc.pth',
                            map_location=torch.device('cpu'))
seresnet_val_acc = torch.load('reset-18-cifar-10-loss-acc.pth',
                              map_location=torch.device('cpu'))


plt.plot(resnet_loss, label = 'ResNet18')
plt.plot(seresnet_loss, label = 'ResSENet18')
plt.title('Training loss over time')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.savefig('loss-cifar-10.png', bbox_inches = 'tight')


plt.plot(resnet_val_acc, label = 'ResNet18')
plt.plot(seresnet_val_acc, label = 'ResSENet18')
plt.title('Validation accuracy over time')
plt.xlabel('Epoch')
plt.ylabel('Acc')
plt.savefig('acc-cifar-10.png', bbox_inches = 'tight')
```

Chihuahua or Muffin

In this section of Lab03, taken the trained SE_ResNet model from the previous section, the model was fine-tuned by adjusting the hyper-paremeters during the 8-fold cross validation.

Since SE_ResNet was initially trained for a 10-class classification problem, The last layer of the output must be modified. In our case, the last layer was changed from 10 to 2.

In [ ]:

```
def ResSENet18(num_classes = 2):
    return ResNet(ResidualSEBasicBlock, [2, 2, 2, 2], num_classes)
```

The 8 variations (8-fold cross validation) were impleneted with Adam optimizer and crossentropy loss functions and they are as follows:

criterion = nn.CrossEntropyLoss() optimizer = optim.Adam() which starts lr = 0.05 and increases by 0.05 every model.

The model was trained for 25 epochs with the batch size of 4 and their performace at the 25th epoch are:

- With optimizer0: Avg acc = 0.9275000000000001
- With optimizer1: Avg acc = 0.915

- With optimizer2: Avg acc = 0.835
- With optimizer3: Avg acc = 0.8200000000000001
- With optimizer4: Avg acc = 0.7725
- With optimizer5: Avg acc = 0.83
- With optimizer6: Avg acc = 0.8049999999999999
- With optimizer7: Avg acc = 0.78

As for the evalution, optimizer2 was chosen due to its high accuracy as well as relatively less time taken to train which results in 92.75%.

1. Import the dataset

In [39]:

```
import torchvision.datasets as dset
import torchvision.utils as vutils
from torch.utils.data import TensorDataset
from sklearn.model_selection import StratifiedKFold
import matplotlib.pyplot as plt

dataset = dset.ImageFolder('/root/Lab03/chi_muf',
                           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)),
                           ]))
```

2.Define Train function

In [67]:

```
def train_model(model, dataloaders, criterion,
                optimizer, num_epochs=25,
                weights_name='weight_save',
                is_inception=False):
    print('====================== New Run =======================',
          file=open(f"{weights_name}.txt", "a"))

    since = time.time()

    val_acc_history = []
    loss_acc_history = []

    best_model_wts = deepcopy(model.state_dict())
    best_acc = 0.0

    for epoch in range(num_epochs):
        epoch_start = time.time()
        print('Epoch {}/{}'.format(epoch, num_epochs - 1),
              file=open(f"{weights_name}.txt", "a"))
        print('-' * 10, file=open(f"{weights_name}.txt", "a"))

        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
            else:
                model.eval()

            running_loss = 0.0
            running_corrects = 0

            for inputs, labels in dataloaders[phase]:

                inputs = inputs.to(device)
                labels = labels.to(device)

                optimizer.zero_grad()

                with torch.set_grad_enabled(phase == 'train'):

                    if is_inception and phase == 'train':
                        outputs, aux_outputs = model(inputs)

                        loss1 = criterion(outputs, labels)
                        loss2 = criterion(aux_outputs, labels)
                        loss = loss1 + 0.4*loss2
                    else:
                        outputs = model(inputs)
                        loss = criterion(outputs, labels)

                    _, preds = torch.max(outputs, 1)

                    if phase == 'train':
                        loss.backward()
                        optimizer.step()

                running_loss += loss.item() * inputs.size(0)
                running_corrects += torch.sum(preds == labels.data)

            epoch_loss = running_loss / len(dataloaders[phase].dataset)
```

```
            epoch_acc = running_corrects.double() / len(dataloaders[phase].dataset)
            epoch_end = time.time()

            elapsed_epoch = epoch_end - epoch_start

            print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss, epoch_acc)
                  file=open(f"{weights_name}.txt", "a"))
            print(f"Epoch time taken: {elapsed_epoch}",
                  file=open(f"{weights_name}.txt", "a"))

            # deep copy the model
            if phase == 'val' and epoch_acc > best_acc:
                best_acc = epoch_acc
                best_model_wts = deepcopy(model.state_dict())
                torch.save(model.state_dict(), weights_name + ".pth")
            if phase == 'val':
                val_acc_history.append(epoch_acc)
            if phase == 'train':
                loss_acc_history.append(epoch_loss)

    time_elapsed = time.time() - since
    print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60,
                                                         time_elapsed % 60),
          file=open(f"{weights_name}.txt", "a"))
    print('Best val Acc: {:4f}'.format(best_acc),
          file=open(f"{weights_name}.txt", "a"))

    return  val_acc_history, loss_acc_history
```

3. Perform 8-Fold Cross Validation

In [74]:

```
folds = 8
skf = StratifiedKFold(n_splits=folds, shuffle=True)


from modules import ResSENet18
models = []
def make_model(ResSENet18):
    model = ResSENet18()
    model.load_state_dict(torch.load('SEresnet18_bestsofar.pth'))
    model.linear = nn.Linear(512,2)
    model.eval()
    return model

n_models = 8

for i in np.arange(n_models):
    fig,ax = plt.subplots(1,2,sharex=True,figsize=(20,5))
    model_acc = 0
    for fold, (train_index, val_index) in enumerate(skf.split(dataset,
                                                              dataset.targets)):
        print('******************** Fold {}/{} ******************** '.format(fold,
              file=open(f"SE_muff_chi_model{i}.txt", "a"))
        batch_size = 4
        train = torch.utils.data.Subset(dataset, train_index)
        val = torch.utils.data.Subset(dataset, val_index)

        train_loader = torch.utils.data.DataLoader(train, batch_size=batch_size,
                                                   shuffle=True, num_workers=0,
                                                   pin_memory=False)
        val_loader = torch.utils.data.DataLoader(val, batch_size=batch_size,
                                                 shuffle=True, num_workers=0,
                                                 pin_memory=False)

        dataloaders = {'train': train_loader, 'val': val_loader}

        model  = make_model(ResSENet18)
        model.to(device)
        dataloaders = {'train': train_loader, 'val': val_loader}
        criterion = nn.CrossEntropyLoss().to(device)
        optimizer =  optim.Adam(model.parameters(), lr = 0.005 + 0.005*i)

        val_acc_history, loss_acc_history = train_model(model, dataloaders,
                                                        criterion, optimizer,
                                                        25, f'SE_muff_chi_model{i}')
        #print(len(val_acc_history))
        #print(sum(val_acc_history))
        model_acc = model_acc + sum(val_acc_history)/len(val_acc_history)

    plt.show()
    print(f'Average accuracy of model{i}: {model_acc/8}')
```

After the implementaion 8-fold cross-validation 8 times to train 8 models, the average accuracy are save in .txt file which is shown in the below cell.

In [41]:

```
chi_muf_acc = open("muf_chi_Average_acc.txt", "r")
print(chi_muf_acc.read())
```

```
Average accuracy of model0: 0.9275000000000001
Average accuracy of model1: 0.915
Average accuracy of model2: 0.835
Average accuracy of model3: 0.8200000000000001
Average accuracy of model4: 0.7725
Average accuracy of model5: 0.83
Average accuracy of model6: 0.8049999999999999
Average accuracy of model7: 0.78
```

The below cell shown the implementation of 8-fold cross-validation 8 times to train 8 models to find the best hyperparameters.(e.g.,optimizer0 which has the highest average accuracy).

In [50]:

```
optimizer_0= open("SE_muff_chi_model0.txt", "r")
print(optimizer_0.read())
```

```
******************** Fold 0/7 ********************
===================== New Run ======================
Epoch 0/24
----------
train Loss: 0.6779 Acc: 0.6429
Epoch time taken: 0.34758782386779785
val Loss: 0.6522 Acc: 0.5000
Epoch time taken: 0.36956000328063965
Epoch 1/24
----------
train Loss: 0.6347 Acc: 0.5714
Epoch time taken: 0.31200361251831055
val Loss: 0.6098 Acc: 1.0000
Epoch time taken: 0.3371620178222656
Epoch 2/24
----------
train Loss: 0.6120 Acc: 0.8571
Epoch time taken: 0.3169143199920654З
val Loss: 0.5787 Acc: 1.0000
```

4. Train with Optimizer2

I trained with Optimizer2 was chosen due to its highest in average accuracy

Optimizer2 = optim.Adam(model.parameters(), lr = 0.015)

After training the test accuracy is 83.75%

5. Evaluation

In [76]:

```
dataset_test = dset.ImageFolder('/root/Lab03/chi_muff_test',
                           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)
                           ]))
test_dataloader = torch.utils.data.DataLoader(dataset_test,
                                              batch_size = 16,shuffle = True)



model_test = ResSENet18()
model_test.linear = nn.Linear(512,2)
model_test.eval()
model_test.to(device)
model_test.load_state_dict(torch.load(f'Train_SE_muff_chi_model.pth'))
criterion = nn.CrossEntropyLoss()
test_loss,test_acc,test_pred_label,test_true_label=evaluate(model_test,
                                                            test_dataloader,
                                                            criterion)

print('...................Result...................',
      file = open("test_chi_muff.txt", "a"))
print(f'Test Loss: {test_loss:.3f} | Test Acc: {test_acc:.2f}%',
      file = open("test_chi_muff.txt", "a") )
```

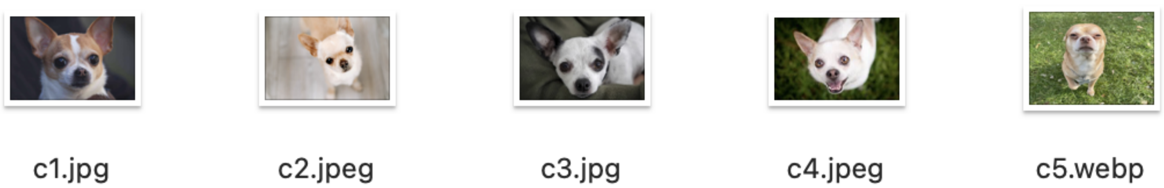
In [63]:

```
chi_muf_result= open("test_chi_muff.txt", "r")
print(chi_muf_result.read())
```

```
...................Result...................
Test Loss: 0.649 | Test Acc: 83.75%
```

In [3]:

```
from IPython.display import display
from PIL import Image
display(Image.open("chi_test.png"))
```



In [5]:

```
display(Image.open("muf_test.png"))
```

6. Conclusion

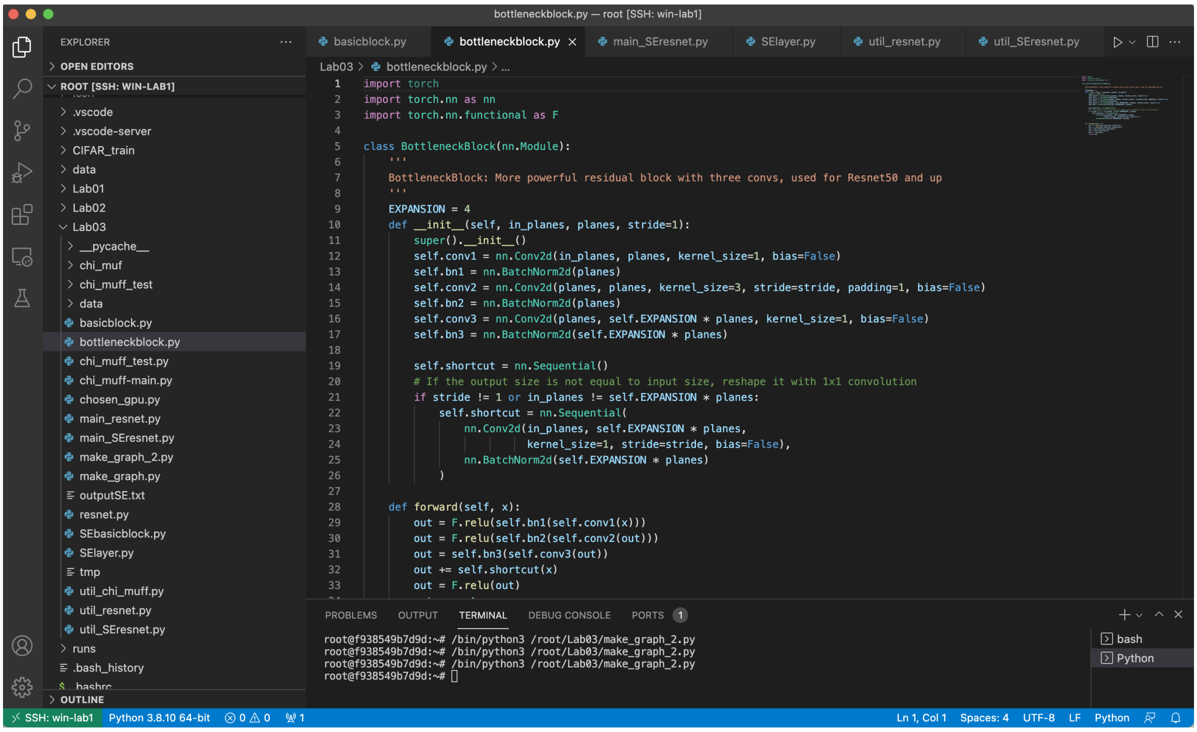
Since the test accuracy for chihuahua_or_muffun is 83.75% and test loss is 0.649, it seems quite good. The transfer learning in this lab was employed increaseing the size of training and validation data, modifying the model artchitecture to output 2 classes, some data augmentation or exploring more hyperparameters of the optimizer.

Moreover, I learned about the components of oridinary ResNet and Squeeze and Excite networks and more about implementing k-fold and cross-validation to find the best hyperparameters.

Evidance of my Docker container running on the GPU server and get VSCode

In [3]:

```
from IPython.display import display
from PIL import Image
display(Image.open("screenshot.png"))
```



In [ ]:

```

```