## Q1 Augmentation Implementation 2 分數

Implement augmentation by finishing train\_tfm in the code with image size of your choice. Copy your train\_tfm code here, for example :

```
train_tfm = transforms.Compose([

# Resize the image into a fixed shape (height = width = 128)

transforms.Resize((128, 128)),

# You need to add some transforms here.

transforms.ToTensor(),
])

policies = [transforms.AutoAugmentPolicy.CIFAR10,

transforms.AutoAugmentPolicy.IMAGENET]

augmenters = [transforms.AutoAugment(policy) for policy in policies]

train_tfm = transforms.Compose([

transforms.Resize((128, 128)),

*augmenters,

transforms.ToTensor(),

transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])
```

## Q2 Residual\_Model Implementation 2 分數

Implement Residual Connections in the Residual\_Model, following the graph in the slides.

Copy your Residual Model code and paste it here, for example:

```
from torch import nn
class Residual_Network(nn.Module):
    def __init__(self):
        super(Residual_Network, self).__init__()

    self.cnn_layer1 = nn.Sequential(
        nn.Conv2d(3, 64, 3, 1, 1),
        nn.BatchNorm2d(64),
    )

    self.cnn_layer2 = nn.Sequential(
        nn.Conv2d(64, 64, 3, 1, 1),
        nn.BatchNorm2d(64),
    )
```

```
self.cnn_layer3 = nn.Sequential(
    nn.Conv2d(64, 128, 3, 2, 1),
    nn.BatchNorm2d(128),
  )
  self.cnn_layer4 = nn.Sequential(
    nn.Conv2d(128, 128, 3, 1, 1),
    nn.BatchNorm2d(128),
  )
  self.cnn_layer5 = nn.Sequential(
    nn.Conv2d(128, 256, 3, 2, 1),
    nn.BatchNorm2d(256),
  )
  self.cnn layer6 = nn.Sequential(
    nn.Conv2d(256, 256, 3, 1, 1),
    nn.BatchNorm2d(256),
  )
  self.fc_layer = nn.Sequential(
    nn.Linear(256* 32* 32, 256),
    nn.ReLU(),
    nn.Linear(256, 11)
  )
  self.relu = nn.ReLU()
def forward(self, x):
  # input (x): [batch size, 3, 128, 128]
  # output: [batch_size, 11]
  # Extract features by convolutional layers.
  x1 = self.cnn layer1(x)
  x1 = self.relu(x1)
  x2 = self.cnn layer2(x1)
  x2 = self.relu(x2)
  x3 = self.cnn layer3(x2)
  x3 = self.relu(x3)
  x4 = self.cnn layer4(x3)
  x4 = self.relu(x4)
  x5 = self.cnn_layer5(x4)
  x5 = self.relu(x5)
  x6 = self.cnn_layer6(x5)
  x6 = self.relu(x6)
```

```
xout = x6.flatten(1)
     xout = self.fc_layer(xout)
     return xout
from torch import nn
class Residual Network(nn.Module):
  def init (self, input dim, output dim, prob=0.2):
     super(Residual_Network, self).__init__()
     self.cnn layer1 = nn.Sequential(
       nn.Conv2d(3, 64, 3, 1, 1),
       nn.BatchNorm2d(64),
    )
    self.cnn layer2 = nn.Sequential(
       nn.Conv2d(64, 64, 3, 1, 1),
       nn.BatchNorm2d(64),
    )
     self.cnn layer3 = nn.Sequential(
       nn.Conv2d(64, 128, 3, 2, 1),
       nn.BatchNorm2d(128),
    )
     self.cnn layer4 = nn.Sequential(
       nn.Conv2d(128, 128, 3, 1, 1),
       nn.BatchNorm2d(128),
    )
     self.cnn layer5 = nn.Sequential(
       nn.Conv2d(128, 256, 3, 2, 1),
       nn.BatchNorm2d(256),
    )
    self.cnn layer6 = nn.Sequential(
       nn.Conv2d(256, 256, 3, 1, 1),
       nn.BatchNorm2d(256),
    )
    self.fc layer = nn.Sequential(
       nn.Linear(256 * 32 * 32, 256),
       nn.ReLU(),
       nn.Linear(256, 11)
    )
     self.relu = nn.ReLU()
  def forward(self, x):
    x1 = self.cnn_layer1(x)
```

x1 = self.relu(x1)

 $x2 = self.cnn_layer2(x1)$ 

x2 += x1

x2 = self.relu(x2)

 $x3 = self.cnn_layer3(x2)$ 

x3 = self.relu(x3)

 $x4 = self.cnn_layer4(x3)$ 

x4 += x3

x4 = self.relu(x4)

 $x5 = self.cnn_layer5(x4)$ 

x5 = self.relu(x5)

 $x6 = self.cnn_layer6(x5)$ 

x6 += x5

x6 = self.relu(x6)

xout = x6.flatten(1)

xout = self.fc\_layer(xout)

return xout

總分	
4 / 4 pts 問題 1	
Augmentation Implementation	2 / 2 pts
問題 2	
Residual_Model Implementation	2 / 2 pts