

Build my own CNN

Practice – CNN

- Run “7.2. MyCNN.ipynb”



Build my own CNN model

```
class MyCNN(nn.Module):
    def __init__(self):
        super(MyCNN, self).__init__()
        self.features = nn.Sequential(
            #Assume input image H/W=64
            nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(64+2*1-3)/1+1 = 64
            nn.ReLU(inplace=True),
            nn.MaxPool2d(2, 2, 0), #H/W=(64+2*0-2)/2+1 = 32
            nn.Conv2d(32, 8, 3, 1, 1), #H/W=(32+2*1-3)/1+1 = 32
            nn.ReLU(inplace=True),
            nn.MaxPool2d(2, 2, 0), #H/W=(32+2*0-2)/2+1 = 16
        )
        self.classifier = nn.Sequential(
            nn.Dropout(),
            nn.Linear(8 * 16 * 16, 500),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(500, 100),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(100, 2),
        )

    def forward(self, x):
        x = self.features(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x
```

Suppose input image size = 64 x 64x 3

The MLP used in "4.2. Classification with CE loss"

```
MyNet = nn.Sequential(
    nn.Linear(2, 50),
    nn.ReLU(),
    nn.Linear(50, 100),
    nn.ReLU(),
    nn.Linear(100, 50),
    nn.ReLU(),
    nn.Linear(50, 2),
)
MyNet.to(device)
```

Practice: Draw the structure of MyCNN

```
model = MyCNN().to(device)    Suppose input image size = 64 x 64x 3
print(model)
```

```
MyCNN(
  (features): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(32, 8, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=2048, out_features=500, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=500, out_features=100, bias=True)
    (5): ReLU(inplace=True)
    (6): Dropout(p=0.5, inplace=False)
    (7): Linear(in_features=100, out_features=2, bias=True)
  )
)
```

My own CNN

```
from torchsummary import summary
summary(model, input_size=(3, 64, 64))
```

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 32, 64, 64]	896
ReLU-2	[-1, 32, 64, 64]	0
MaxPool2d-3	[-1, 32, 32, 32]	0
Conv2d-4	[-1, 8, 32, 32]	2,312
ReLU-5	[-1, 8, 32, 32]	0
MaxPool2d-6	[-1, 8, 16, 16]	0
Dropout-7	[-1, 2048]	0
Linear-8	[-1, 500]	1,024,500
ReLU-9	[-1, 500]	0
Dropout-10	[-1, 500]	0
Linear-11	[-1, 100]	50,100
ReLU-12	[-1, 100]	0
Dropout-13	[-1, 100]	0
Linear-14	[-1, 2]	202
Total params: 1,078,010		
Trainable params: 1,078,010		
Non-trainable params: 0		
Input size (MB): 0.05		
Forward/backward pass size (MB): 2.42		
Params size (MB): 4.11		
Estimated Total Size (MB): 6.58		

MLP in "4.2. Classification with CE loss"

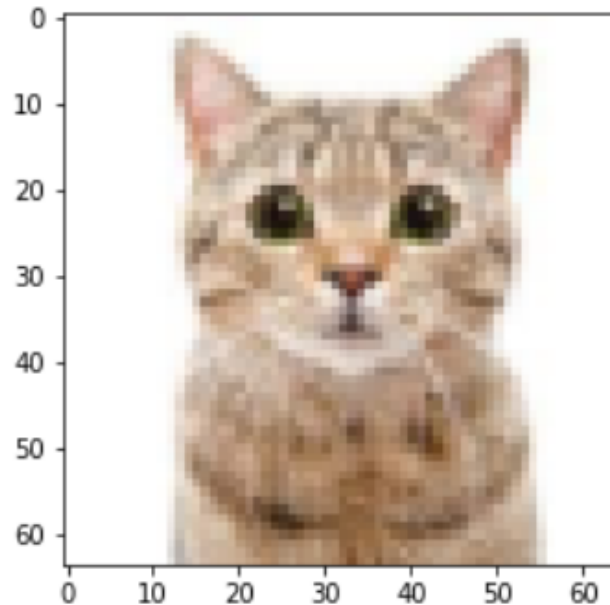
```
BATCH_SIZE = 30
summary(MyNet, input_size=(BATCH_SIZE, 2))
```

Layer (type)	Output Shape	Param #
Linear-1	[-1, 30, 50]	150
ReLU-2	[-1, 30, 50]	0
Linear-3	[-1, 30, 100]	5,100
ReLU-4	[-1, 30, 100]	0
Linear-5	[-1, 30, 50]	5,050
ReLU-6	[-1, 30, 50]	0
Linear-7	[-1, 30, 2]	102
Total params: 10,402		
Trainable params: 10,402		
Non-trainable params: 0		
Input size (MB): 0.00		
Forward/backward pass size (MB): 0.09		
Params size (MB): 0.04		
Estimated Total Size (MB): 0.13		

Input image after pre-processing

```
In [13]: #visualize the image after pre-processing
# Tensor is channel first, to plot, we need to convert to channel last
import numpy as np
PILImgArray = np.zeros((PILImg.shape[1], PILImg.shape[2], 3))
PILImgArray[:, :, 0] = PILImg[0, :, :]
PILImgArray[:, :, 1] = PILImg[1, :, :]
PILImgArray[:, :, 2] = PILImg[2, :, :]
PILImgArray = PILImgArray*0.5+0.5 # change  $N(0, 1)$  to  $[0, 1]$ 
print(PILImgArray.shape, PILImgArray.min(), PILImgArray.max())
plt.imshow(PILImgArray)
plt.show()
```

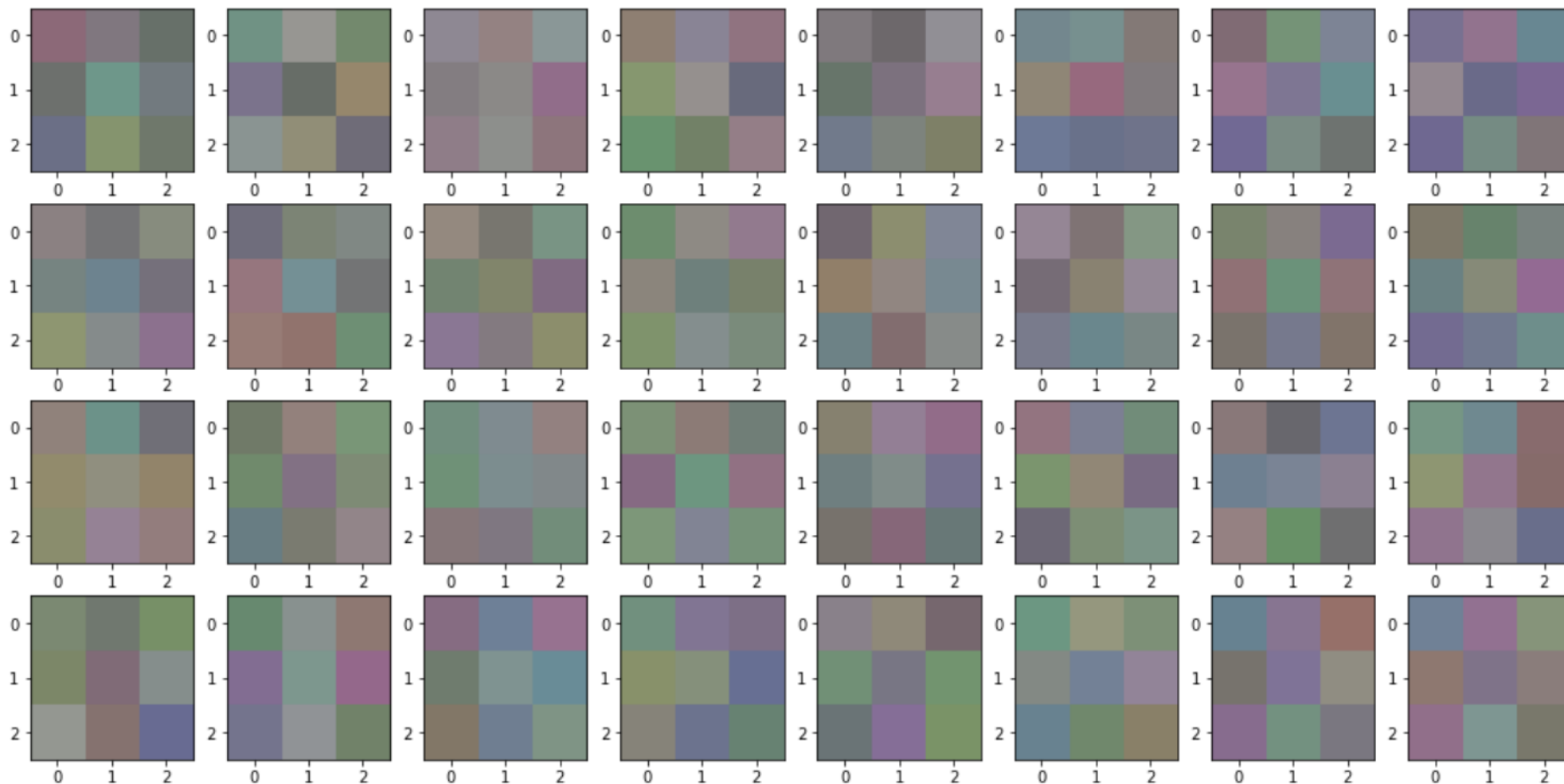
(64, 64, 3) 0.027450978755950928 1.0



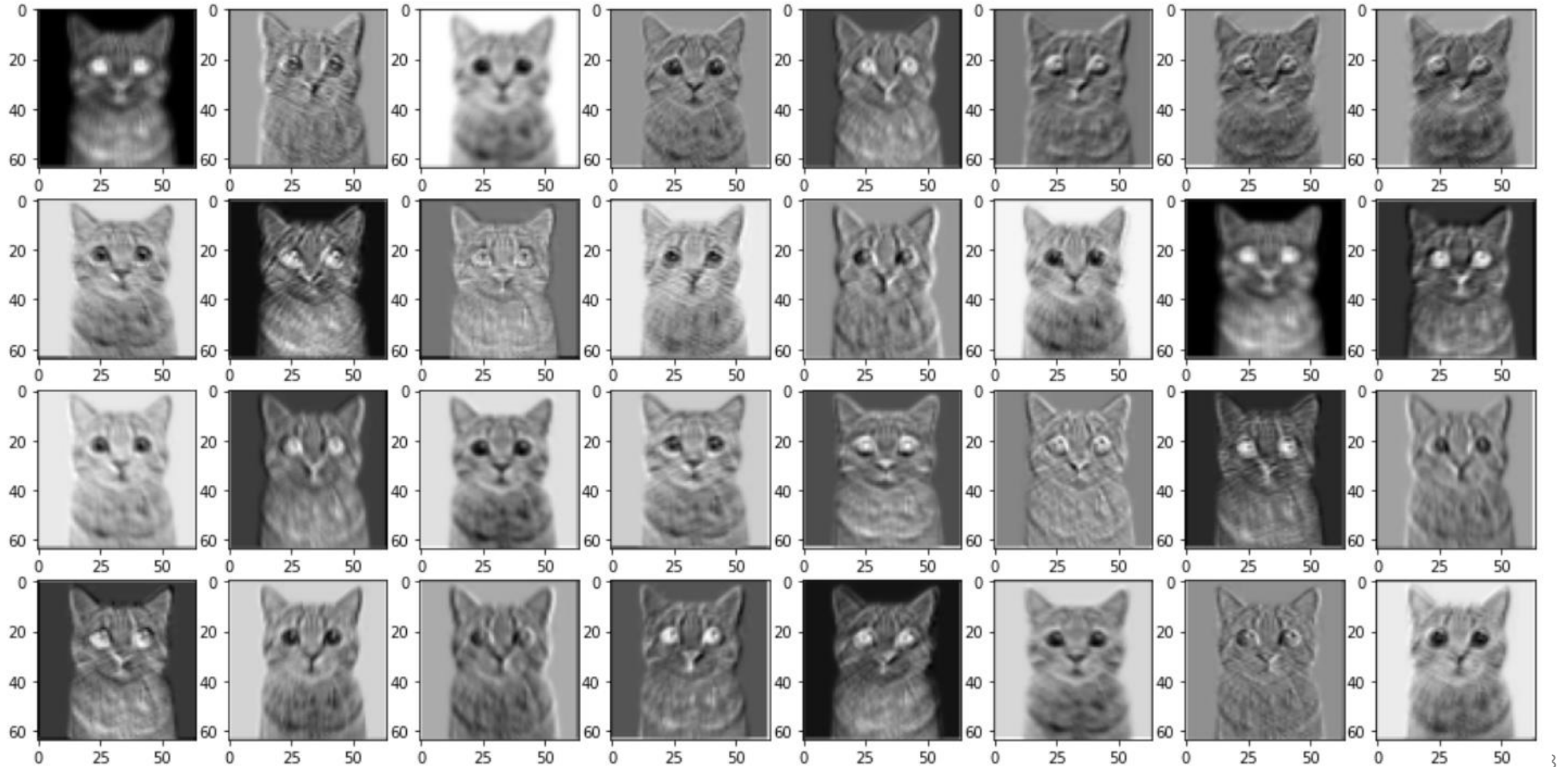
Input image size = 64 x 64x 3

Initial filter weights

```
MyCNN(  
  (features): Sequential(  
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding:  
    (1): ReLU(inplace=True)  
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1  
    (3): Conv2d(32, 8, kernel_size=(3, 3), stride=(1, 1), padding:  
    (4): ReLU(inplace=True)  
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1
```

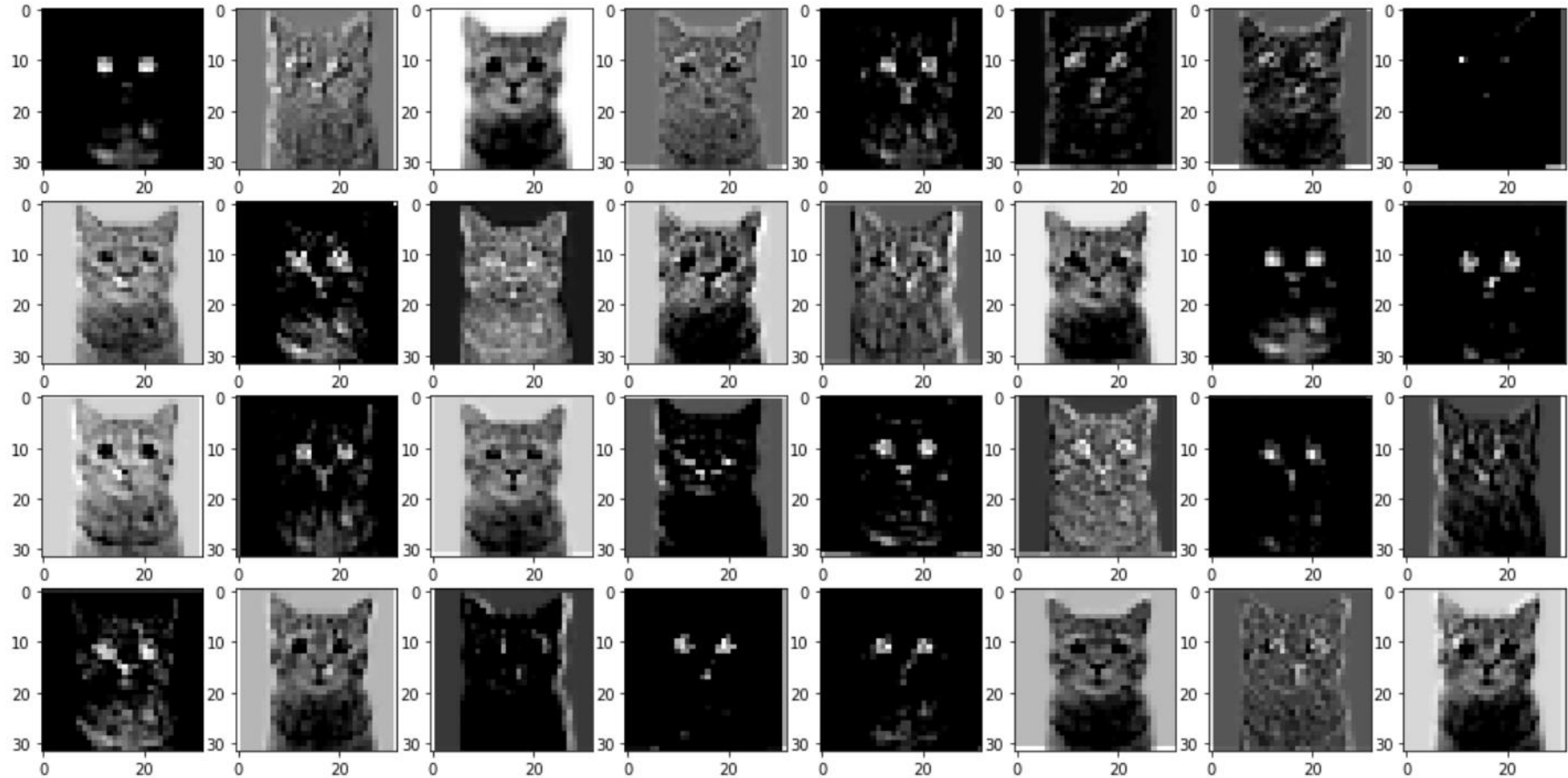


Output feature map, shape = 64x64x32



Feature map after max pooling, shape = 32x32x32

```
torch.Size([1, 32, 32, 32])
```



Flatten

```
class MyCNN(nn.Module):
    def __init__(self):
        super(MyCNN, self).__init__()
        self.features = nn.Sequential(
            #Assume input image H/W=64
            nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(64+2*1-3)/1+1 = 64
            nn.ReLU(inplace=True),
            nn.MaxPool2d(2, 2, 0), #H/W=(64+2*0-2)/2+1 = 32
            nn.Conv2d(32, 8, 3, 1, 1), #H/W=(32+2*1-3)/1+1 = 32
            nn.ReLU(inplace=True),
            nn.MaxPool2d(2, 2, 0), #H/W=(32+2*0-2)/2+1 = 16
        )
        self.classifier = nn.Sequential(
            nn.Dropout(),
            nn.Linear(8 * 16 * 16, 500),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(500, 100),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(100, 2),
        )

    def forward(self, x):
        x = self.features(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x
```

```
model = MyCNN().to(device)
print(model)
```

```
MyCNN(
  (features): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(32, 8, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=2048, out_features=500, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=500, out_features=100, bias=True)
    (5): ReLU(inplace=True)
    (6): Dropout(p=0.5, inplace=False)
    (7): Linear(in_features=100, out_features=2, bias=True)
  )
)
```

```
In [22]: WholeConvLayers = model.features
         out1 = WholeConvLayers(imageTensor.to(device))
         print(out1.shape)
```

```
torch.Size([1, 8, 16, 16])
```

```
In [23]: out2 = torch.flatten(out1, 1)
         print(out2.shape)
```

```
torch.Size([1, 2048])
```

```
In [24]: ClassifierMLP = model.classifier
         out = ClassifierMLP(out2)
```

HW5 (1)

- Let the input image size be 224x224x3. Modify your CNN.

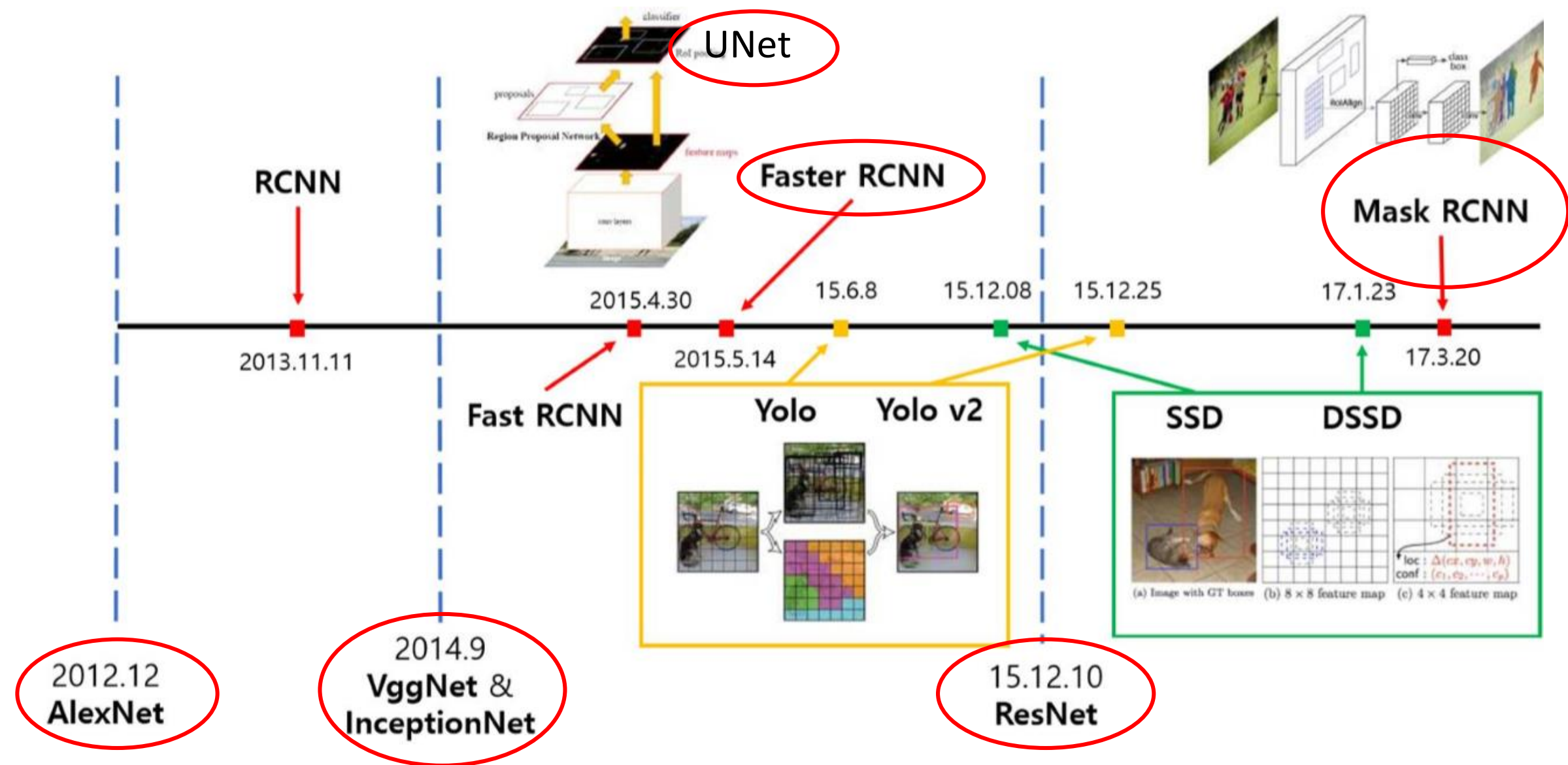
```
class MyCNN(nn.Module):
    def __init__(self):
        super(MyCNN, self).__init__()
        self.features = nn.Sequential(
            #Assume input image H/W=64
            nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(64+2*1-3)/1+1 = 64
            nn.ReLU(inplace=True),
            nn.MaxPool2d(2, 2, 0),      #H/W=(64+2*0-2)/2+1 = 32
            nn.Conv2d(32, 8, 3, 1, 1), #H/W=(32+2*1-3)/1+1 = 32
            nn.ReLU(inplace=True),
            nn.MaxPool2d(2, 2, 0),      #H/W=(32+2*0-2)/2+1 = 16
        )
        self.classifier = nn.Sequential(
            nn.Dropout(),
            nn.Linear(8 * 16 * 16, 500),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(500, 100),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(100, 2),
        )

    def forward(self, x):
        x = self.features(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x
```

```
[10]: from torchvision import transforms
transformer = transforms.Compose([
    transforms.Resize(64),
    transforms.CenterCrop(64),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5, 0.5
```


VGG16

CNN family



Practice – Load ImageNet pre-trained VGG

```
import torchvision  
model = torchvision.models.vgg16(pretrained=True)
```

Downloading: "<https://download.pytorch.org/models/vgg16-397923af.pth>"
100%  528M/528M [00:10<00:00, 54.9MB/s]

Practice: Draw the structure of VGG16

```
model.eval()  
model.to(device)
```

```
VGG(  
  (features): Sequential(  
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (1): ReLU(inplace=True)  
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (3): ReLU(inplace=True)  
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (6): ReLU(inplace=True)  
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (8): ReLU(inplace=True)  
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (11): ReLU(inplace=True)  
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (13): ReLU(inplace=True)  
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (15): ReLU(inplace=True)  
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (18): ReLU(inplace=True)  
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (20): ReLU(inplace=True)
```


Practice: Draw the structure of VGG16

```
(21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(22): ReLU(inplace=True)
(23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
(24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(25): ReLU(inplace=True)
(26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(27): ReLU(inplace=True)
(28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(29): ReLU(inplace=True)
(30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
(avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
(classifier): Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace=True)
  (2): Dropout(p=0.5, inplace=False)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace=True)
  (5): Dropout(p=0.5, inplace=False)
  (6): Linear(in_features=4096, out_features=1000, bias=True)
)
)
```


Transfer learning

Download images from Kaggle

The screenshot shows the Kaggle website interface. On the left, a sidebar contains navigation links: Home, Compete, Data (highlighted with a red circle), Code, Communities, Courses, and More. The main content area has a search bar at the top with the text 'Search'. Below it, the word 'Datasets' is displayed in large bold letters. A second search bar contains the text 'cartoon'. Below the search bar, a filter tag 'Computer Vision' is highlighted with a red circle. Underneath, a section titled '4 Datasets' lists two datasets. The first is 'Landscape Pictures' by Arnaud ROUGETET, updated a year ago, with a usability of 8.8, 4319 files, and 620 MB. The second is 'Tom & Jerry Detection' by Vijayakumar, also updated a year ago, with a usability of 7.5, 464 files, and 47 MB. This second dataset entry is circled in red.

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Computer Vision X

4 Datasets

 **Landscape Pictures**
Arnaud ROUGETET · Updated a year ago
Usability 8.8 · 4319 Files (other) · 620 MB

 **Tom & Jerry Detection**
Vijayakumar · Updated a year ago
Usability 7.5 · 464 Files (other) · 47 MB

Tom & Jerry

Tom & Jerry Detection | Kaggle

kaggle.com/vijayjoyz/tom-jerry-detection

應用程式 Microsoft Azure N... 免費線上影片轉Gif... YouTube Google 學術搜尋 GitHub Colaboratory 李弘毅 ML 元智大學個人portal 其他書籤

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Dataset



Tom & Jerry Detection

Image Dataset For detecting tom & jerry

 Vijayakumar • updated a year ago (Version 1)

Data

Tasks

Code (2)

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Activity

Metadata

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New Notebook

Usability 7.5

License

Database: Open Database, Contents: Database Contents

Tags

arts and entertainment, computer science, classification, computer vision, comics and animation

Description

FaceDetection

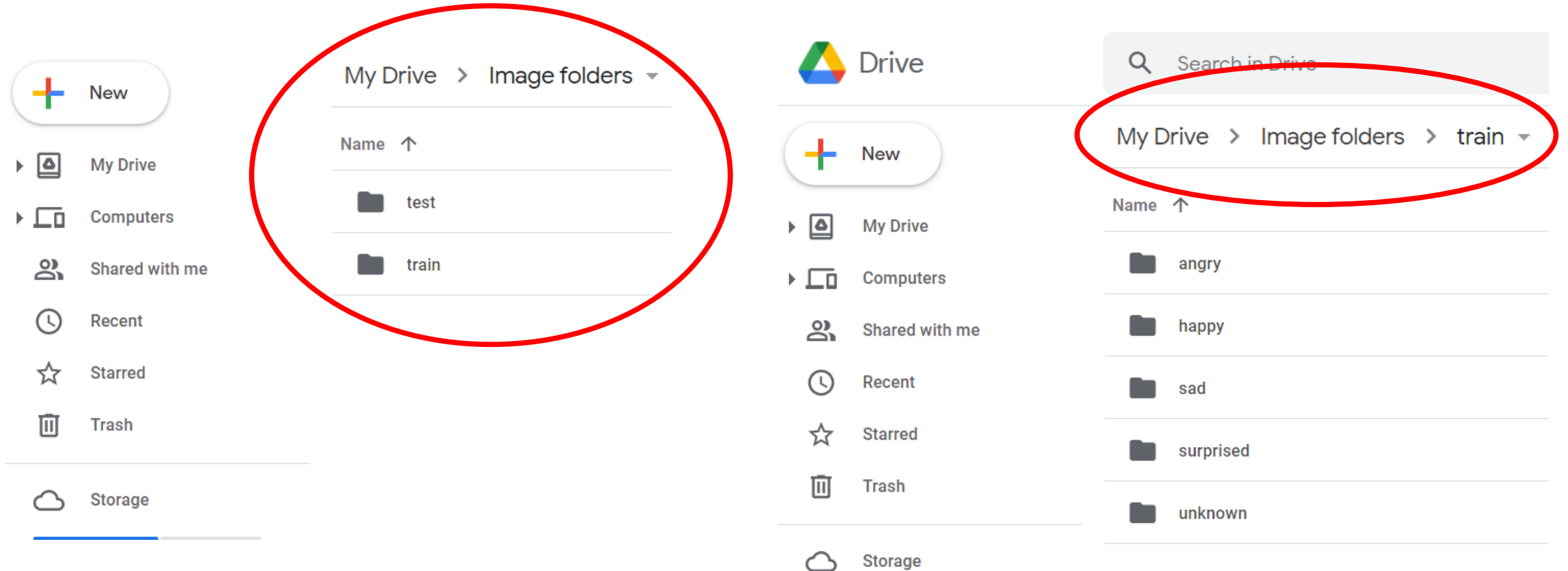
Face Recognition is a recognition technique used to detect the faces of individuals whose images saved in the data set. Despite the point that other methods of identification can be more accurate, face recognition has always remained a significant focus of research because of its non-meddling nature and because it is people's facile method of personal identification.

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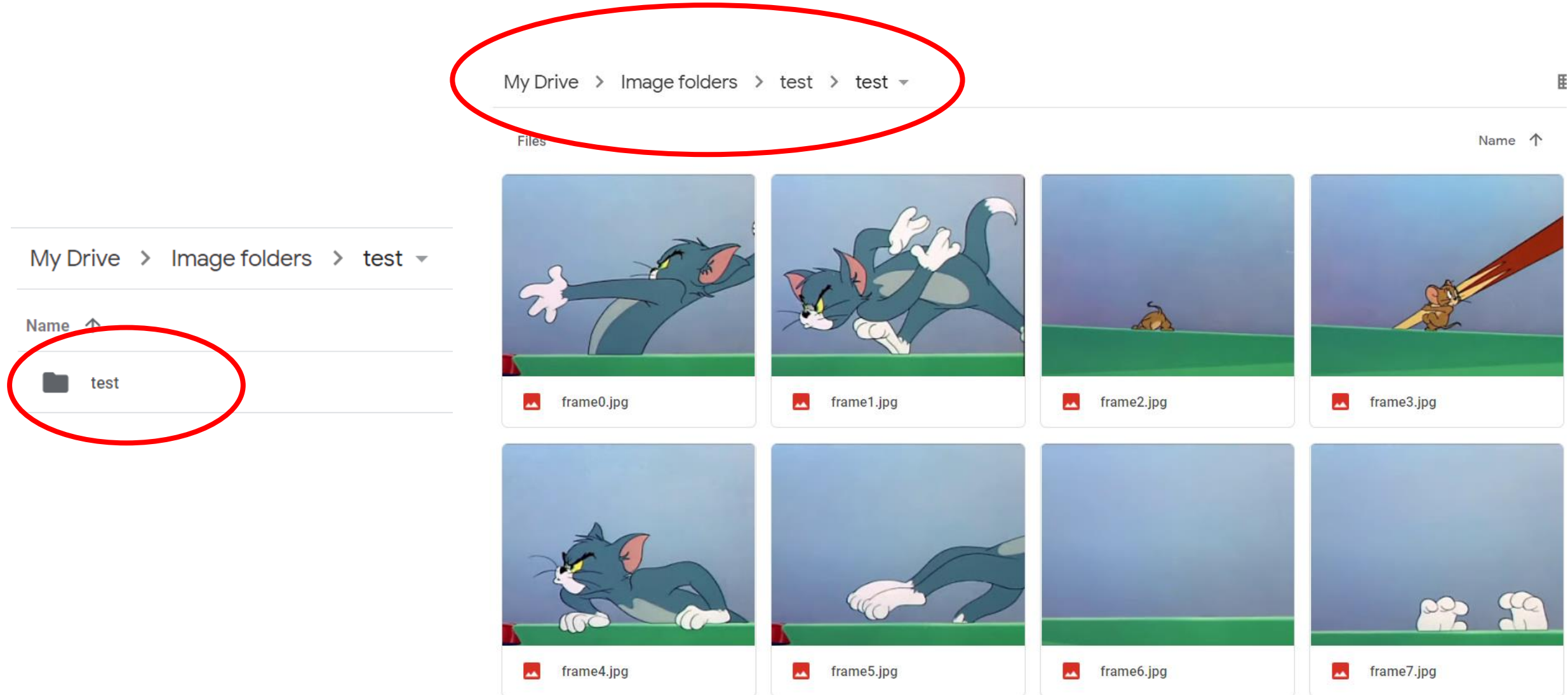
Got it

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Save images in your Google drive



Practice

- Run "7.3. Transfer learning.ipynb"



Build our own image classifier

- Suppose input image size = (224, 224, 3)
- Output has 5 classes: Angry, Happy, Sad, Surprised, Unknown

```
In [3]: import torch.nn as nn
        # fix the weight of convolution layers
        model.features.eval()

        # modify classifier
        model.classifier = torch.nn.Sequential(
            nn.Linear(25088, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(p=0.5, inplace=False),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(p=0.5, inplace=False),
            torch.nn.Linear(4096, 5))
```

Summary of parameters

Total params: 139,590,725
Trainable params: 139,590,725
Non-trainable params: 0

Input size (MB): 0.57
Forward/backward pass size (MB): 238.68
Params size (MB): 532.50
Estimated Total Size (MB): 771.75

MLP in "4.2. Classification with CE loss"

```
BATCH_SIZE = 30  
summary(MyNet, input_size=(BATCH_SIZE, 2))
```

Layer (type)	Output Shape	Param #
Linear-1	[-1, 30, 50]	150
ReLU-2	[-1, 30, 50]	0
Linear-3	[-1, 30, 100]	5,100
ReLU-4	[-1, 30, 100]	0
Linear-5	[-1, 30, 50]	5,050
ReLU-6	[-1, 30, 50]	0
Linear-7	[-1, 30, 2]	102

Total params: 10,402
Trainable params: 10,402
Non-trainable params: 0


Input size (MB): 0.00
Forward/backward pass size (MB): 0.09
Params size (MB): 0.04
Estimated Total Size (MB): 0.13


Connect to Google drive

```
from google.colab import drive  
drive.mount("/content/gdrive")
```

Go to this URL in a browser: <https://accounts.google.com/o/>



Enter your authorization code:


 使用 Google 帳戶登入



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以繼續使用「Google Drive for desktop」

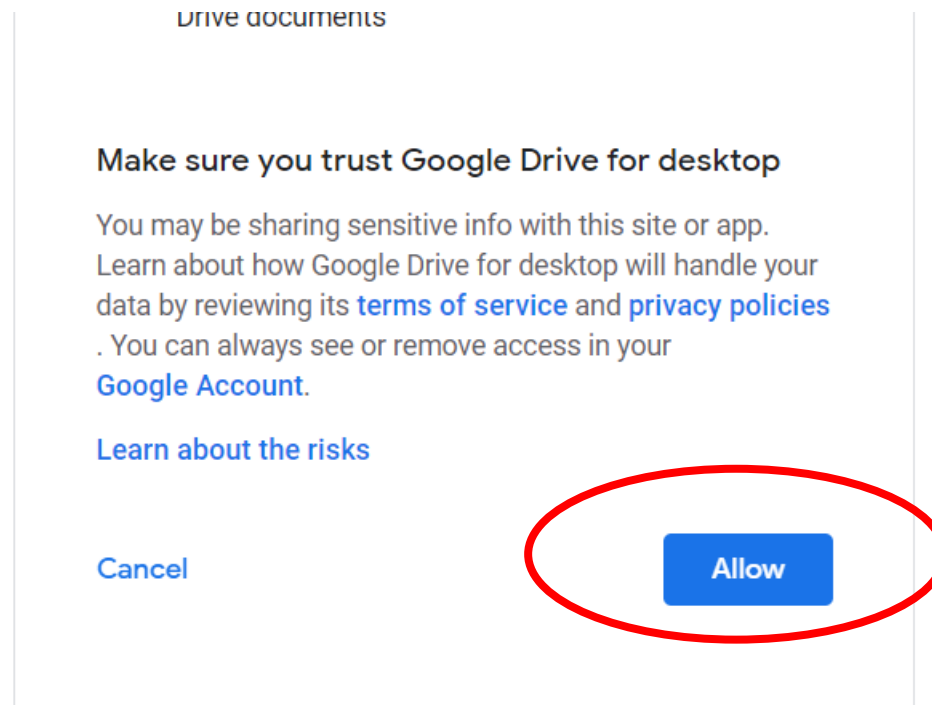
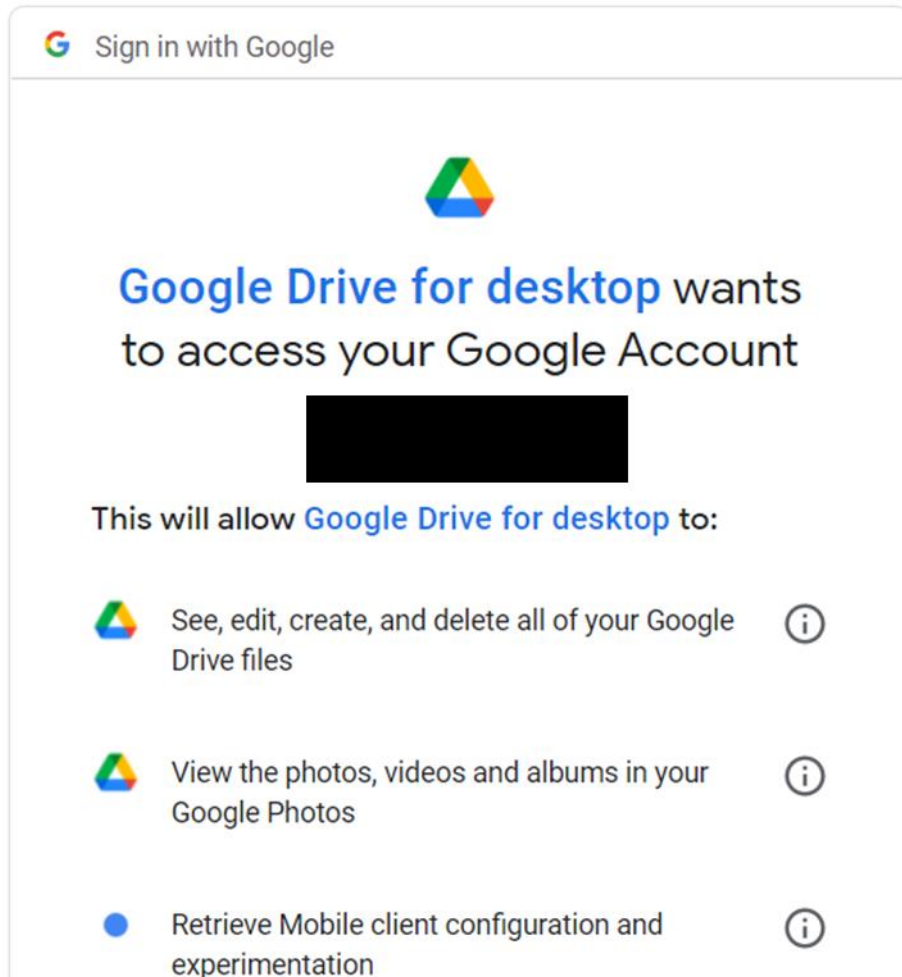
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Connect to Google drive



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Please copy this code, switch to your application and paste it there:

4/1AY0e-

g4roX6ceHqek0M4JnYfPrHwEJCdrz8DP6nsD5y1m7Uu7B



```
from google.colab import drive  
drive.mount("/content/gdrive")
```

Go to this URL in a browser: <https://accounts.google.com/o/oauth2>

Enter your authorization code:

4/1AY0e-g4roX6ceHqek0M

Past the link and
press Enter

```
[7] from google.colab import drive  
drive.mount("/content/gdrive")
```

Mounted at /content/gdrive

Batch training using Image Folder

```
In [8]: from torchvision import transforms
transformer = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5] )])
```

```
In [9]: from torchvision import datasets
train_dataset = datasets.ImageFolder(root = "/content/gdrive/MyDrive/Image folders/train", transform = transformer)
```

```
n [10]: classes = train_dataset.classes
classes_index = train_dataset.class_to_idx
print(classes)
print(classes_index)

['angry', 'happy', 'sad', 'surprised', 'unknown']
{'angry': 0, 'happy': 1, 'sad': 2, 'surprised': 3, 'unknown': 4}
```

```
n [11]: import torch.utils.data as Data
loader = Data.DataLoader(dataset=train_dataset, batch_size=4, shuffle=True)
```

Batch training using data in RAM

```
In [9]: tensorX = torch.FloatTensor(trainX).to(device)
        tensorY_hat = torch.LongTensor(trainY_hat).to(device)
        print(tensorX.shape, tensorY_hat.shape)

        torch.Size([128, 2]) torch.Size([128])
```

```
In [10]: torch_dataset = Data.TensorDataset(tensorX, tensorY_hat)
```

```
In [11]: loader = Data.DataLoader(
            dataset=torch_dataset,
            batch_size=5,
            shuffle=True,
            num_workers=0,      # subprocesses for loading data
        )
```

```
In [12]: for (batchX, batchY_hat) in loader:
            break
            print(batchX.shape, batchY_hat)

            torch.Size([5, 2]) tensor([0, 0, 0, 1, 1], device='cuda:0')
```

One batch has 4 images

```
[12]: for batchX, batchY_hat in loader:
        break;
        print(batchX.shape, batchY_hat.shape, batchY_hat)

torch.Size([4, 3, 224, 224]) torch.Size([4]) tensor([3, 2, 3, 2])
```

```
[13]: import numpy as np
        import matplotlib.pyplot as plt
        imgTensor = torchvision.utils.make_grid(batchX)
        imgArray = imgTensor.numpy()
        imgArray1 = np.zeros((imgArray.shape[1], imgArray.shape[2], 3))
        imgArray1[:, :, 0] = imgArray[0, :, :]
        imgArray1[:, :, 1] = imgArray[1, :, :]
        imgArray1[:, :, 2] = imgArray[2, :, :]
        imgArray1 = imgArray1*0.5+0.5
        plt.figure(figsize=(12, 6))
        plt.imshow(imgArray1)
        plt.show()
        print([classes[i] for i in batchY_hat])
```



```
['surprised', 'sad', 'surprised', 'sad']
```

Batch training loop

```
[16]: lossLst = []
accuracyLst = []
for epoch in range(1, 4):
    print("\nepoch = ", epoch, end = ", ")
    print("batch: ", end="")
    for step, (batch_x, batchY_hat) in enumerate(loader):
        if(step%5==0):
            print(step, end = ", ")
            tensorY = model(batch_x.to(device))
            loss = loss_func(tensorY, batchY_hat.to(device))
            lossLst.append(float(loss))
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            correct = 0
            tensorY = torch.softmax(tensorY, 1)
            MaxIdxOfEachRow = torch.max(tensorY, 1)[1]
            for i in range(batchY_hat.shape[0]):
                if (int(MaxIdxOfEachRow[i]) == int(batchY_hat[i])):
                    correct += 1
            accuracy = correct/batchY_hat.shape[0]
            accuracyLst.append(accuracy)
```

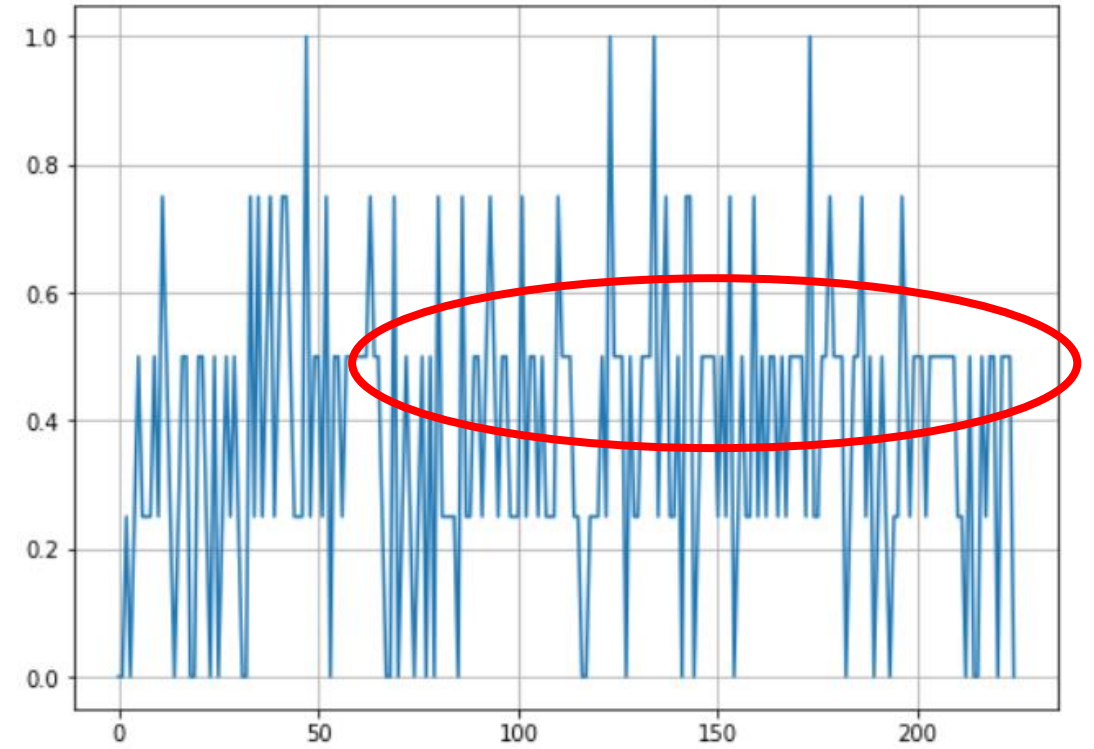
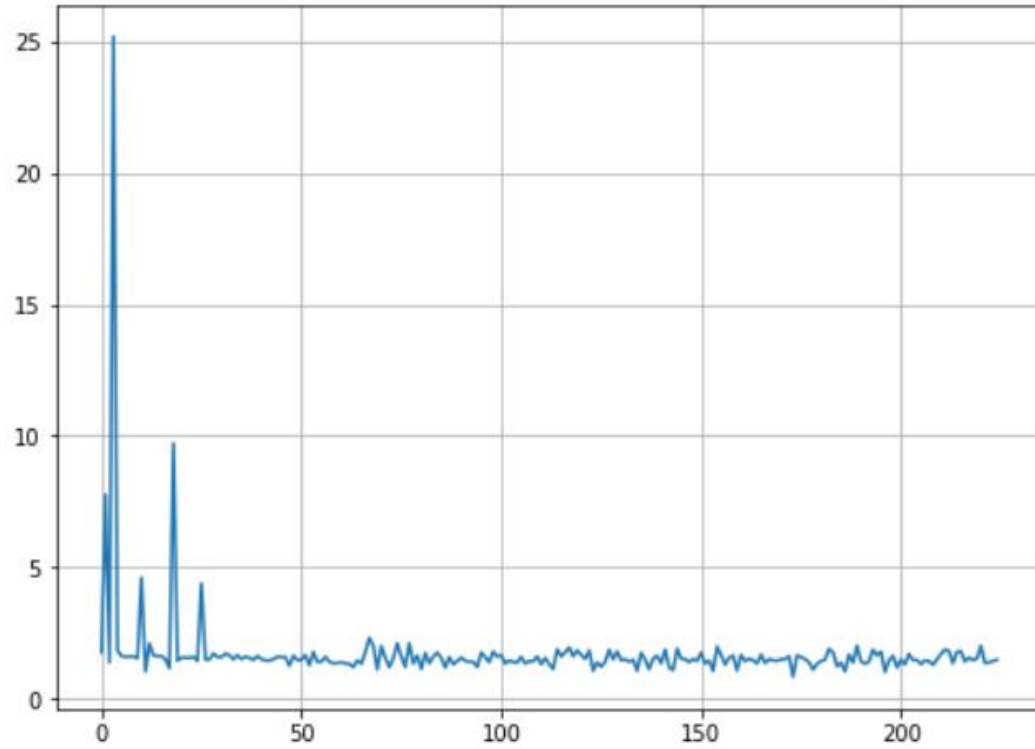
```
epoch = 1, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
epoch = 2, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
epoch = 3, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
```

MLP in "4.2. Classification with CE loss"

```
lossLst = []
accuracyLst = []
for epoch in range(1, 500):
    for (batchX, batchY_hat) in loader:
        tensorY = MyNet(batchX)
        loss = loss_func(tensorY, batchY_hat)
        lossLst.append(float(loss))
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        correct = 0
        tensorY = torch.softmax(tensorY, 1)
        MaxIdxOfEachRow = torch.max(tensorY, 1)[1]
        for i in range(batchY_hat.shape[0]):
            if (int(MaxIdxOfEachRow[i]) == int(batchY_hat[i])):
                correct += 1
        accuracy = correct/batchY_hat.shape[0]
        accuracyLst.append(accuracy)
```


Why training is not good?



Biased prediction, why?

```
In [24]: tensorY = torch.softmax(tensorY, 1)  
print(tensorY)
```

```
tensor([[0.1225, 0.1490, 0.1598, 0.2189, 0.3498]], device='cuda:0',  
        grad_fn=<SoftmaxBackward>)
```

```
In [25]: print(classes)
```

```
['angry', 'happy', 'sad', 'surprised', 'unknown']
```

Transfer learning design 2

Use first 10 layers in convolution section

Let input image size = (224, 224, 3), Output has 5 classes: Angry, Happy, Sad, Surprised, Unknown

```
[3] import torch.nn as nn
class MyCNN(nn.Module):
    def __init__(self):
        super(MyCNN, self).__init__()
        self.features = vgg19.features[0:10] #layer 0-9
        self.classifier = nn.Sequential(
            nn.Dropout(),
            nn.Linear(56*56*128, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(p=0.5, inplace=False),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(p=0.5, inplace=False),
            nn.Linear(4096, 5),
        )
    def forward(self, x):
        x = self.features(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x
```

1,661M parameters !

```
[5] from torchsummary import summary  
summary(model, input_size=(3, 224, 224))
```

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 64, 224, 224]	1,792
ReLU-2	[-1, 64, 224, 224]	0
Conv2d-3	[-1, 64, 224, 224]	36,928
ReLU-4	[-1, 64, 224, 224]	0
MaxPool2d-5	[-1, 64, 112, 112]	0
Conv2d-6	[-1, 128, 112, 112]	73,856
ReLU-7	[-1, 128, 112, 112]	0
Conv2d-8	[-1, 128, 112, 112]	147,584
ReLU-9	[-1, 128, 112, 112]	0
MaxPool2d-10	[-1, 128, 56, 56]	0
Dropout-11	[-1, 401408]	0
Linear-12	[-1, 4096]	1,644,171,264
ReLU-13	[-1, 4096]	0
Dropout-14	[-1, 4096]	0
Linear-15	[-1, 4096]	16,781,312
ReLU-16	[-1, 4096]	0
Dropout-17	[-1, 4096]	0
Linear-18	[-1, 5]	20,485

```
Total params: 1,661,233,221  
Trainable params: 1,661,233,221  
Non-trainable params: 0
```

Total params: 139,590,725
Trainable params: 139,590,725
Non-trainable params: 0

Input size (MB): 0.57
Forward/backward pass size (MB): 238.68
Params size (MB): 532.50
Estimated Total Size (MB): 771.75

CUDA out of memory!

```
epoch = 1, batch: 0,
```

```
-----  
RuntimeError                                Traceback (most recent call last)
```

```
<ipython-input-17-94eca5998520> in <module>()
```

```
    11     lossLst.append(float(loss))  
    12     optimizer.zero_grad()  
--> 13     loss.backward()  
    14     optimizer.step()  
    15
```

1 frames

```
/usr/local/lib/python3.7/dist-packages/torch/autograd/_init_.py in backward(tensors,  
grad_tensors, retain_graph, create_graph, grad_variables, inputs)
```

```
    145     Variable._execution_engine.run_backward(  
    146         tensors, grad_tensors_, retain_graph, create_graph, inputs,  
--> 147         allow_unreachable=True, accumulate_grad=True) # allow_unreachable flag  
    148  
    149
```

```
RuntimeError: CUDA out of memory. Tried to allocate 6.12 GiB (GPU 0; 11.17 GiB total  
capacity; 6.46 GiB already allocated; 4.27 GiB free; 6.47 GiB reserved in total by PyTorch)
```

HW5 (2) – Can CNN recognize your facial expression?

- Use transfer learning to train an image classifier to recognize happy and angry faces.



HW5 (2) – Recognize Alzheimer disease from MRI

Results by searching "dementia" in Kaggle

3 Results

Sort by: Relevancy



Dataset

Dataset_Alzheimer

by Yasir Hussein Shakir

3 months ago • 34 MB • 7

Alzheimer's treatments cannot stop Alzheimer's from progressing, they

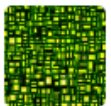


Dataset

Alzheimer_binaryclassification

by Smiti14

2 months ago • 33 MB • 0



Dataset

combo01

by SHIYONA DASH

2 months ago • 94 MB • 0

Alzheimer_s Dataset

名稱

test

train

Alzheimer_s Dataset > train

名稱

MildDemented

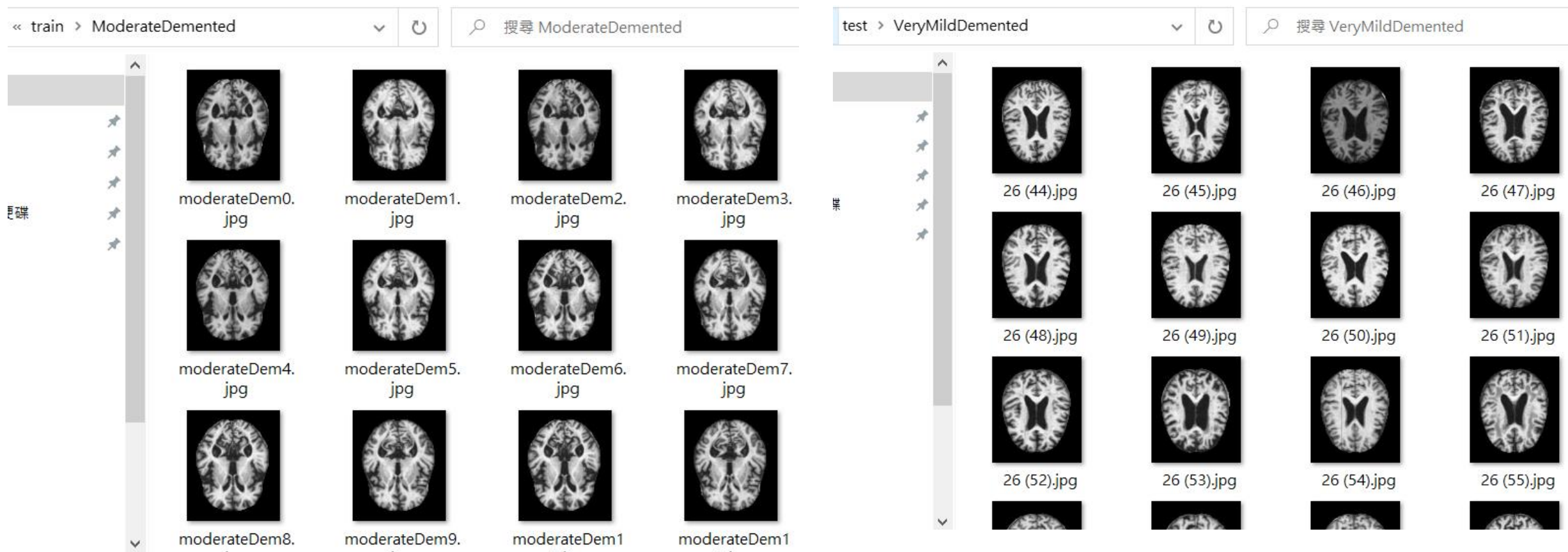
ModerateDemented

NonDemented

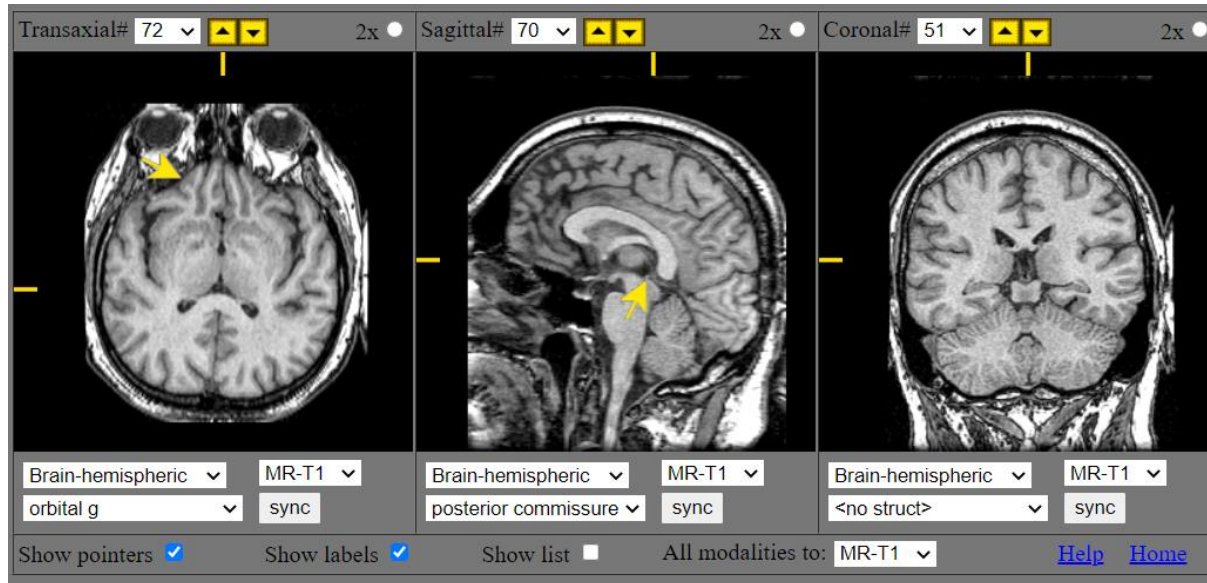
VeryMildDemented

端硬碟

HW5 (2) – Recognize Alzheimer disease from MRI



If you want to understand more about MRI brain scan images



<https://www.med.harvard.edu/aANliB/cases/caseNA/pb9.htm>

• Normal Brain:

- [Normal Anatomy in 3-D with MRI/PET \(Javascript\)](#)
- [Atlas of normal structure and blood flow](#)
 - [Top 100 Brain Structures](#)
 - [Can you name these brain structures?](#)
- [Normal aging: structure and function](#)
- [Normal aging: structure and function](#)
- [Normal aging: coronal plane](#)
- [Vascular anatomy](#)

• Cerebrovascular Disease (stroke or "brain attack"):

- [NEW: Multiple embolic infarction, diffusion and FLAIR imaging](#)
- [Acute stroke: speech arrest](#)
- [Acute stroke: speaks nonsense words, "fluent aphasia" \(time-lapse movies\)](#)
- [Acute stroke: writes, but can't read, "alexia without agraphia"](#)
- [Subacute stroke: hesitating speech, "transcortical aphasia"](#)
- [Subacute stroke: loss of sensation](#)
- [Chronic subdural hematoma](#)
- [Cavernous angioma](#)
- [Arteriovenous malformation, with MRA](#)
- [Vascular dementia](#)
- [Acute stroke \(MR diffusion imaging\) with MRA: Carotid or Circle of Willis](#)
- [Hypertensive encephalopathy](#)
- [Multiple embolic infarctions](#)
- [Hypertensive encephalopathy](#)
- [Fatal stroke](#)

<https://www.med.harvard.edu/aANliB/home.html>

HW5 (2) – Can we recognize dementia disease from facial expression ?

Facial expressions can detect Parkinson's disease: preliminary evidence from videos collected online

Mohammad Rafayet Ali, Taylor Myers, Ellen Wagner, Harshil Ratnu, E. Ray Dorsey, Ehsan Hoque



<https://arxiv.org/abs/2012.05373>

中文解讀: https://ai-scholar.tech/zh/articles/image-recognition/facial_expressions_perkinson

HW5 (2) – Can CNN detect Autism from a facial image?


Datasets

Q facial image

Datasets Tasks Computer Science Education Cla

1 Tasks

Detect Autism with 98% accuracy
Gerry · 0 Submissions

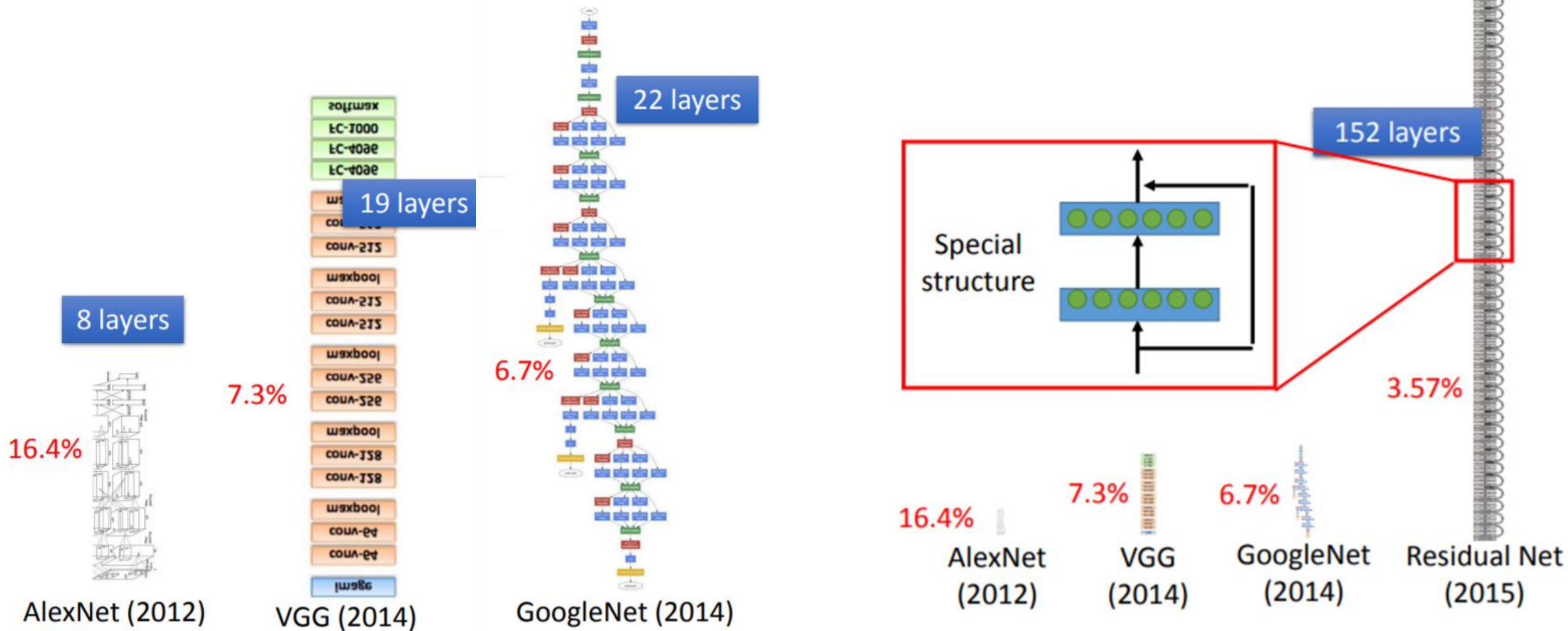
 Detect Autism from a facial image
Gerry · Usability 7.5

- consolidated
- test
- train
- valid
- autism-2
- autism-S-224-89.33.h5

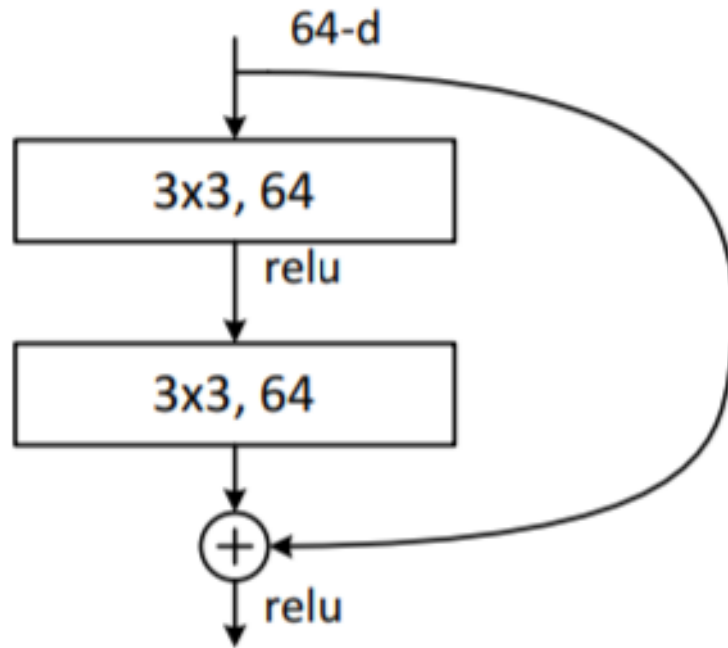


ResNet

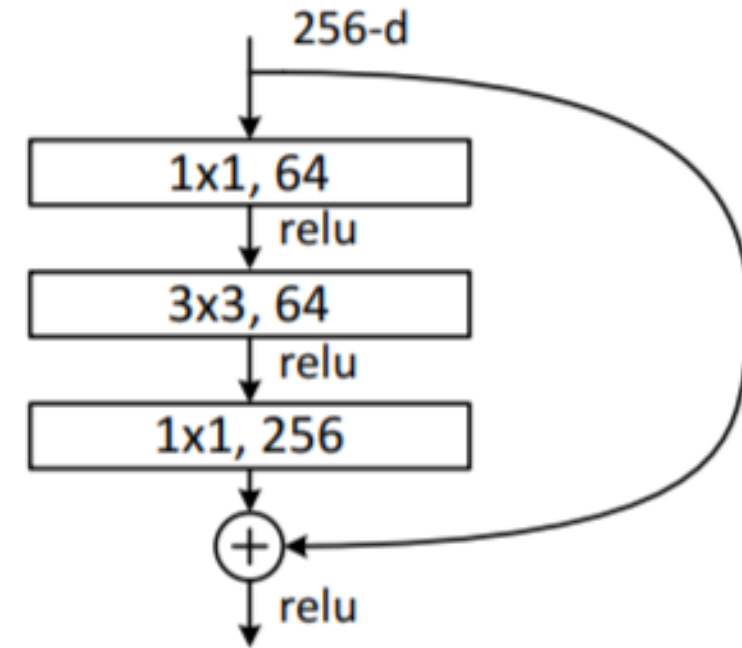
Going deeper and deeper...



ResNet



Basic block



Bottleneck block

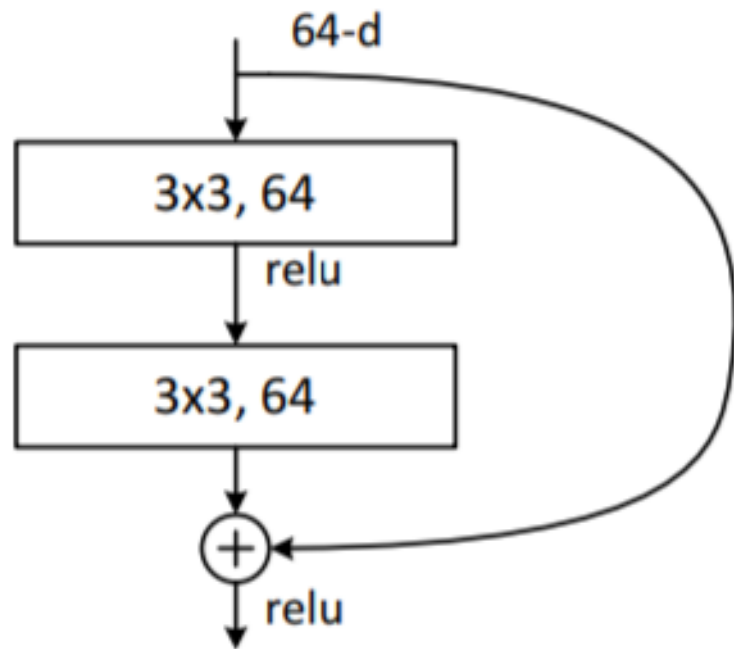
He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

Practice

- Run "7.4. Build ResNet from scratch.ipynb"



Basic loop



```
class BasicBlock(nn.Module):
    expansion = 1
    def __init__(self, inplanes, planes, stride=1, downsample=None):
        super(BasicBlock, self).__init__()
        self.conv1=conv3x3(inplanes,planes,stride)
        self.bn1=nn.BatchNorm2d(planes)
        self.relu=nn.ReLU(inplace=True)
        self.conv2=conv3x3(planes,planes)
        self.bn2=nn.BatchNorm2d(planes)
        self.downsample=downsample
        self.stride=stride

        if(stride!=1 or inplanes!=planes*self.expansion):
            self.downsample=nn.Sequential(
                nn.Conv2d(inplanes,planes*self.expansion,kernel_size=1,stride
                nn.BatchNorm2d(planes*self.expansion),
            )

    def forward(self, x):
        residual = x
        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu(out)
        out = self.conv2(out)
        out = self.bn2(out)

        # Downsample:feature Map size/2 || Channel increase
        if (self.downsample is not None):
            residual = self.downsample(x)
        print("out= ", out.shape, "residual= ", residual.shape)
        out+=residual
        out=self.relu(out)
        return out
```


Batch Normalization

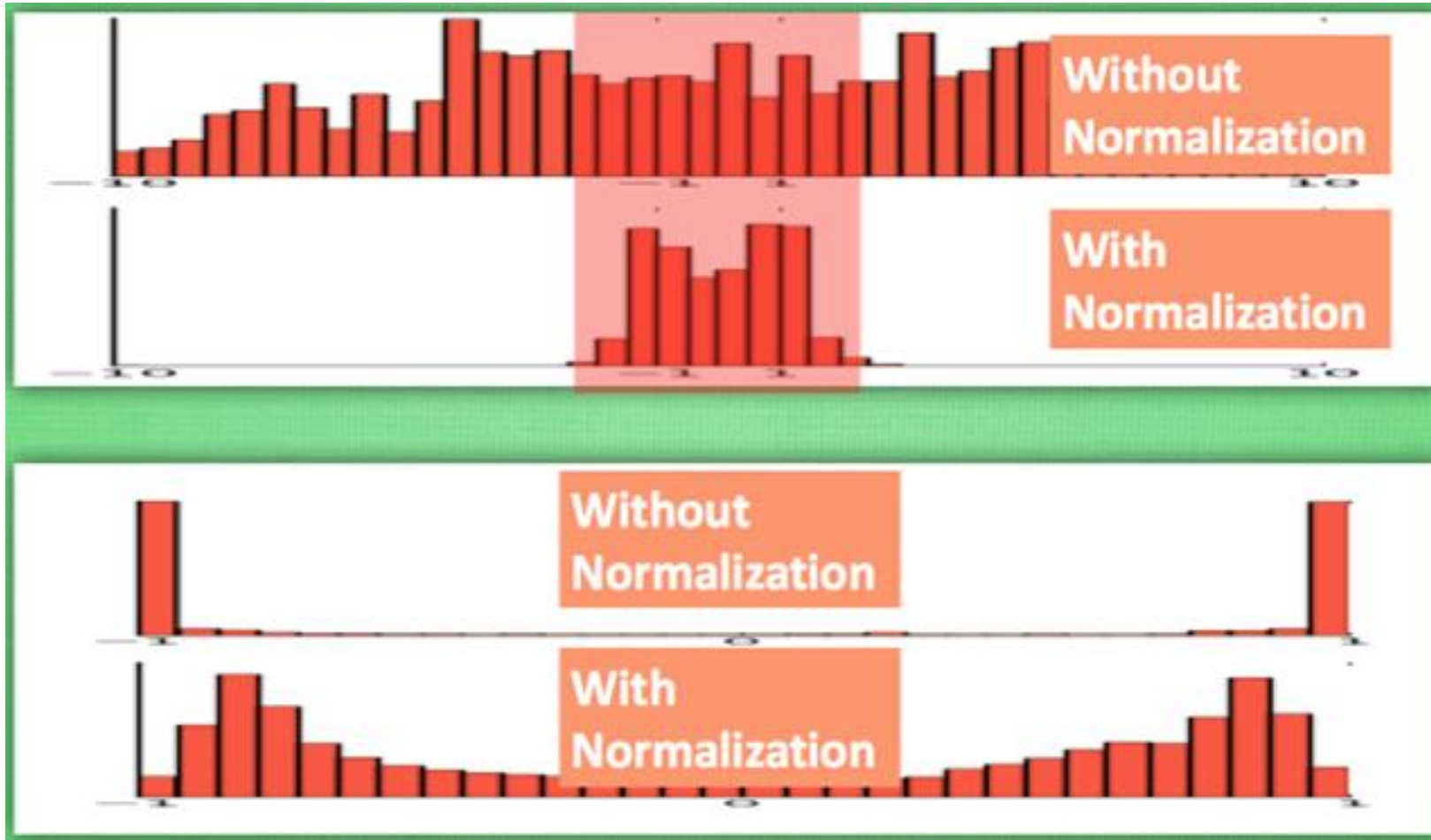
Applies Batch Normalization over a 4D input (a mini-batch of 2D inputs with additional channel dimension) as described in the paper [Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift](#).

$$y = \frac{x - \mathbb{E}[x]}{\sqrt{\text{Var}[x] + \epsilon}} * \gamma + \beta$$

- The mean and standard-deviation are calculated per-dimension over the mini-batches.
- By default, the elements of γ are set to 1 and the elements of β are set to 0.

<https://pytorch.org/docs/stable/generated/torch.nn.BatchNorm2d.html>

Batch Normalization



<https://medium.com/ching-i/batch-normalization-%E4%BB%8B%E7%B4%B9-135a24928f12>

```

class MyResNet(nn.Module):
    def __init__(self, block, layers, num_classes=2):
        super(MyResNet, self).__init__()
        self.inplanes = 64
        self.dilation = 1
        self.conv1=nn.Conv2d(3,self.inplanes,kernel_size=7,stride=2,
        self.maxpool=nn.MaxPool2d(kernel_size=3,stride=2, padding=1)
        self.layer1=self._make_layer(block,64,layers[0])
        self.layer2=self._make_layer(block,128,layers[1],stride=2)
        self.avgpool=nn.AdaptiveAvgPool2d((1,1))
        self.fc=nn.Linear(128*block.expansion,num_classes)
        self.linear=nn.Linear(128*block.expansion,num_classes)

    def _make_layer(self, block, planes, blocks, stride=1):
        layers=[]
        layers.append(block(self.inplanes,planes,stride))
        self.inplanes=planes*block.expansion

        for i in range(1,blocks):
            layers.append(block(self.inplanes,planes))
        return nn.Sequential(*layers)

    def forward(self, x):
        x=self.conv1(x)
        x=self.maxpool(x)
        x=self.layer1(x)
        x=self.layer2(x)
        x=self.avgpool(x)
        x=torch.flatten(x, 1)
        x=self.fc(x)
        return x

```

```

model=MyResNet(BasicBlock,[1,1]).to(device)
print(model)

```

```

MyResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=128, out_features=2, bias=True)
  (linear): Linear(in_features=128, out_features=2, bias=True)
)

```

Practice – Draw the structure of MyResNet

```
MyResNet(  
    (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)  
    (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
```

```
[14]: out1=model.conv1(imageTensor.to(device))  
      print(out1.shape)
```

```
torch.Size([1, 64, 112, 112])
```

```
[15]: out2=model.maxpool(out1)  
      print(out2.shape)
```

```
torch.Size([1, 64, 56, 56])
```

Practice – Draw the structure of MyResNet

```
(layer1): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
```

```
[16]: out3=model.layer1(out2)

out= torch.Size([1, 64, 56, 56]) residual= torch.Size([1, 64, 56, 56])
```

Practice – Draw the structure of MyResNet

```
(layer2): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
)
```

```
[17]: out4 = model.layer2(out3)

      out= torch.Size([1, 128, 28, 28]) residual= torch.Size([1, 128, 28, 28])
```

Practice – Draw the structure of MyResNet

```
(avgpool): AdaptiveAvgPool2d(output_size=(1, 1))  
(fc): Linear(in_features=128, out_features=2, bias=True)  
(linear): Linear(in_features=128, out_features=2, bias=True)
```

```
[18]: out5= model.avgpool(out4)  
      print(out5.shape)  
  
      torch.Size([1, 128, 1, 1])
```

```
[19]: out6=torch.flatten(out5,1)  
      print(out6.shape)  
  
      torch.Size([1, 128])
```

```
[20]: out7 = model.fc(out6)  
      print(out7)  
  
      tensor([[ -0.0661, -0.1440]], device=
```

Practice – Load pre-trained ResNet

In [2]: `import torchvision`

`model = torchvision.models.resnet18(pretrained=True)`

Downloading: "<https://download.pytorch.org/models/resnet18-5c106cde.pth>" to

HBox(children=(FloatProgress(value=0.0, max=46827520.0), HTML(value='')))

ResNet

```
ResNet(  
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)  
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
  (relu): ReLU(inplace=True)  
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)  
  (layer1): Sequential(  
    (0): BasicBlock(  
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
      (relu): ReLU(inplace=True)  
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
    )  
    (1): BasicBlock(  
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
      (relu): ReLU(inplace=True)  
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
    )  
  )  
)
```

ResNet

```
(layer2): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): BasicBlock(
    (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
```