Build my own CNN

Practice – CNN

- Run “6.2. MyCNN.ipynb"

Build my own CNN model

The width and height of the feature maps are calculated based on input image size = 64 x 64x 3

```python
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
```

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

```python
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)
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_mo
    (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_mo
  )
  (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

```python
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
----------------------------------------------------------------
```

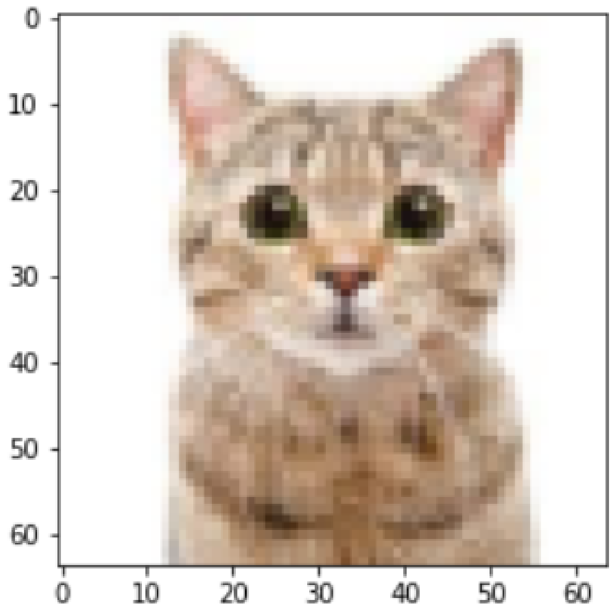
MLP in "4.2. Classification with CE loss"

```python
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

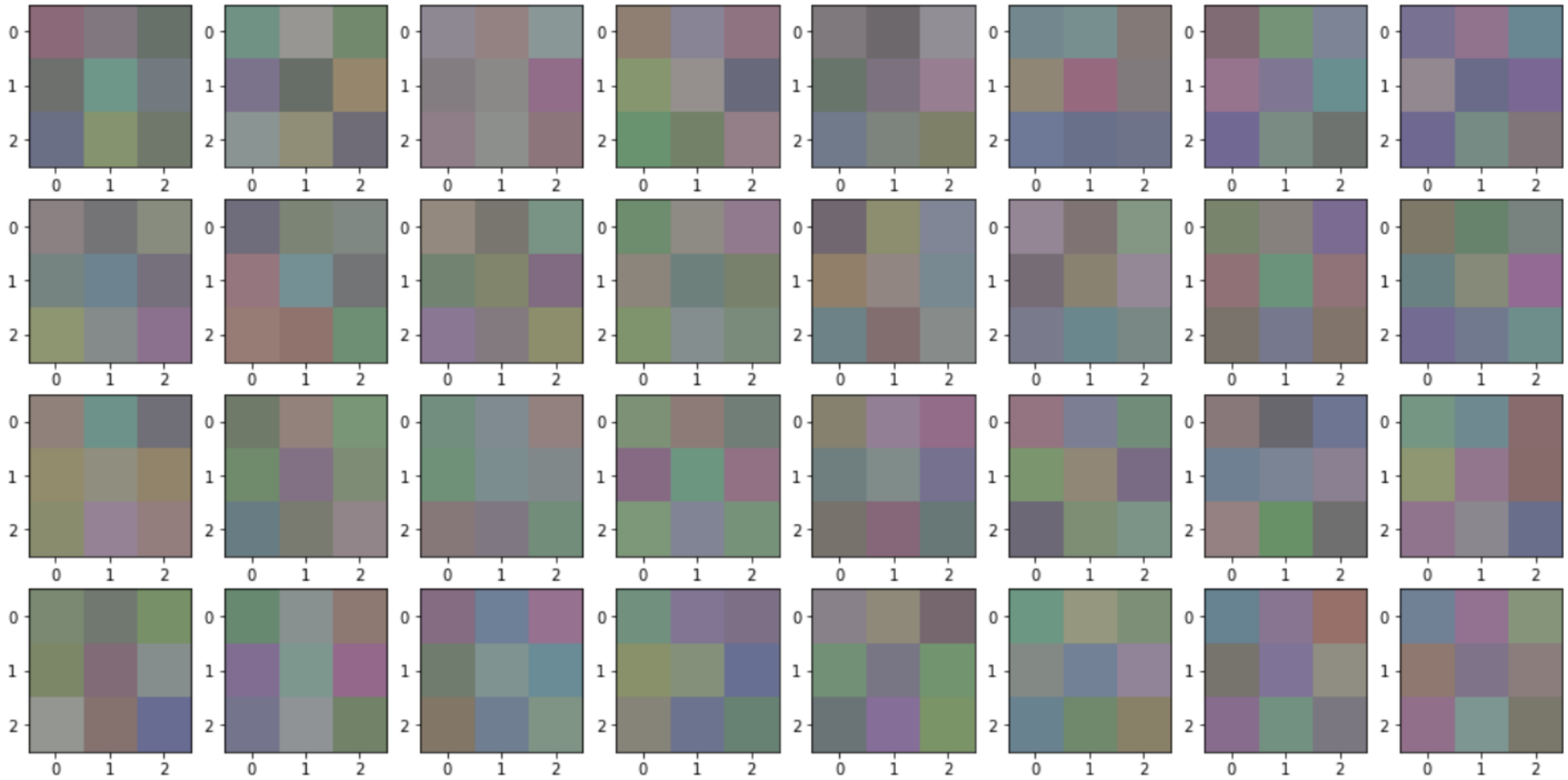
```
In [13]: #visualize the image after pre-processing
         # Tensor is channel first, to plot, we need to convert to channel last
         import numpy as np
         PILImgArray = np.zeros((PILImg.shape[1], PILImg.shape[2], 3))
         PILImgArray[:,:,0] = PILImg[0, :, :]
         PILImgArray[:,:,1] = 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

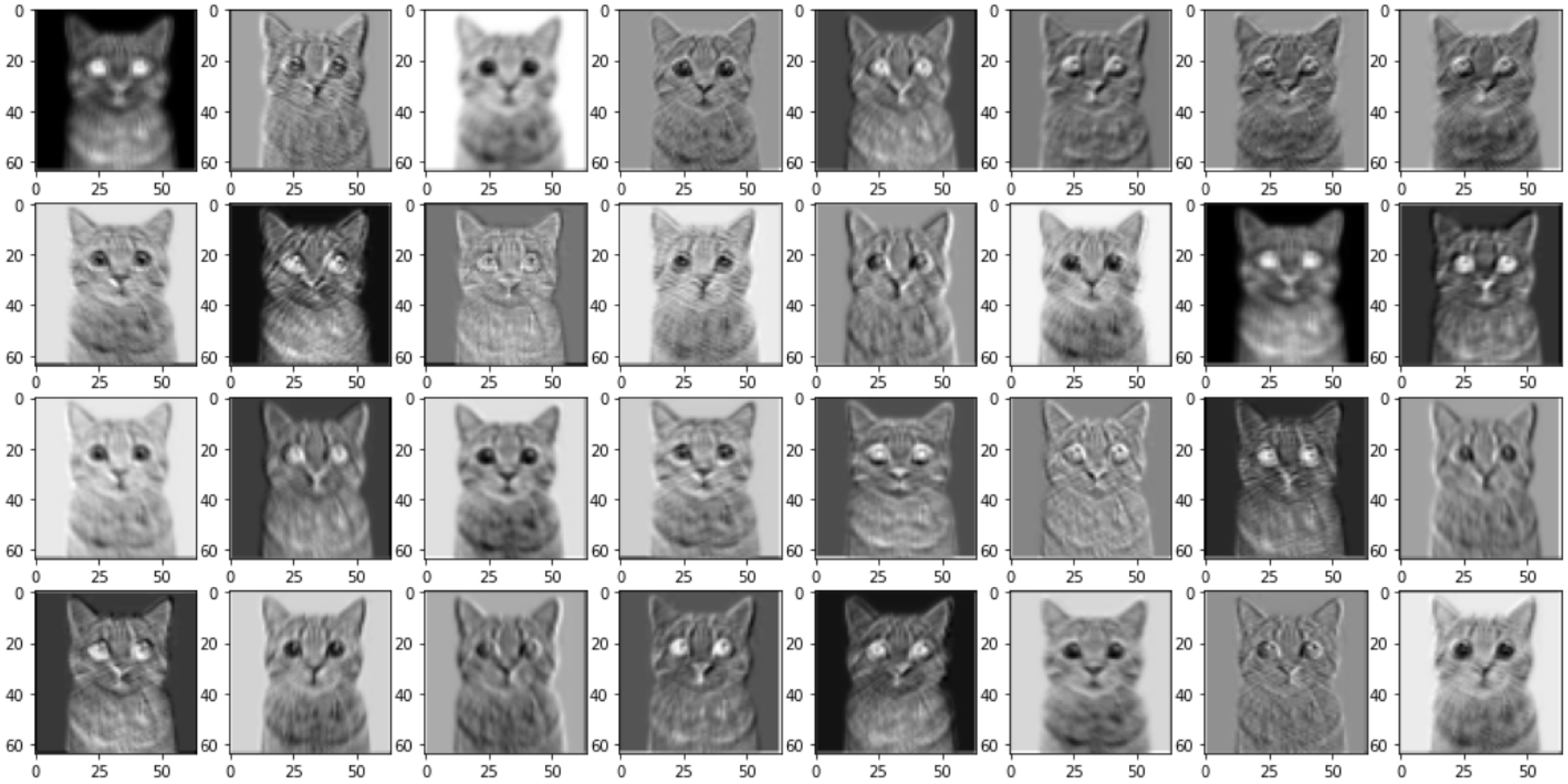
Initial filter weights

```
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
```



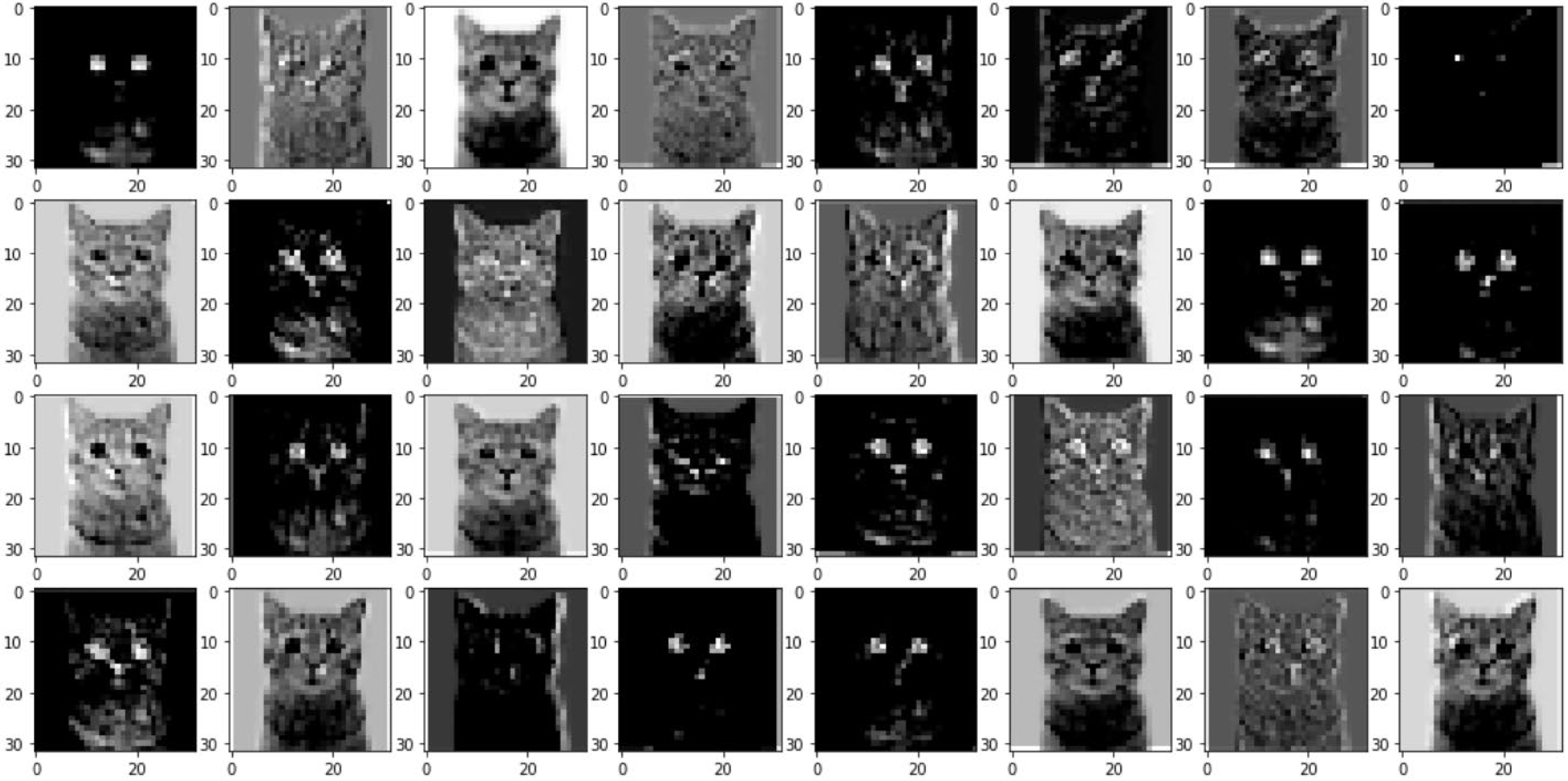
Output feature map, shape = 64x64x32

The width and height of the feature maps are calculated based on input image size = 64 x 64x 3



Feature map after max pooling, shape = 32x32x32

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



Flatten

```python
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
```

```python
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_mo
    (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_mo
  )
  (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]:
```python
WholeConvLayers = model.features
out1 = WholeConvLayers(imageTensor.to(device))
print(out1.shape)
```

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

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

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

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

Class practice

- 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
```

Class practice

Input size: 64 × 64 × 3

```
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
```

Input size: 224 × 224 × 3

```
class MyCNN(nn.Module):
  def __init__(self):
    super(MyCNN, self).__init__()
    self.features = nn.Sequential(    #Assume input image H/W=224
        nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(224+2*1-3)/1+1 = 224
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(224+2*0-2)/2+1 = 112
        nn.Conv2d(32, 8, 3, 1, 1), #H/W=(112+2*1-3)/1+1 = 112
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(112+2*0-2)/2+1 = 56
    )
    self.classifier = nn.Sequential(
        nn.Dropout(),
        nn.Linear(8 * 56 * 56, 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
```

Class practice

Input size: 224 × 224 × 3

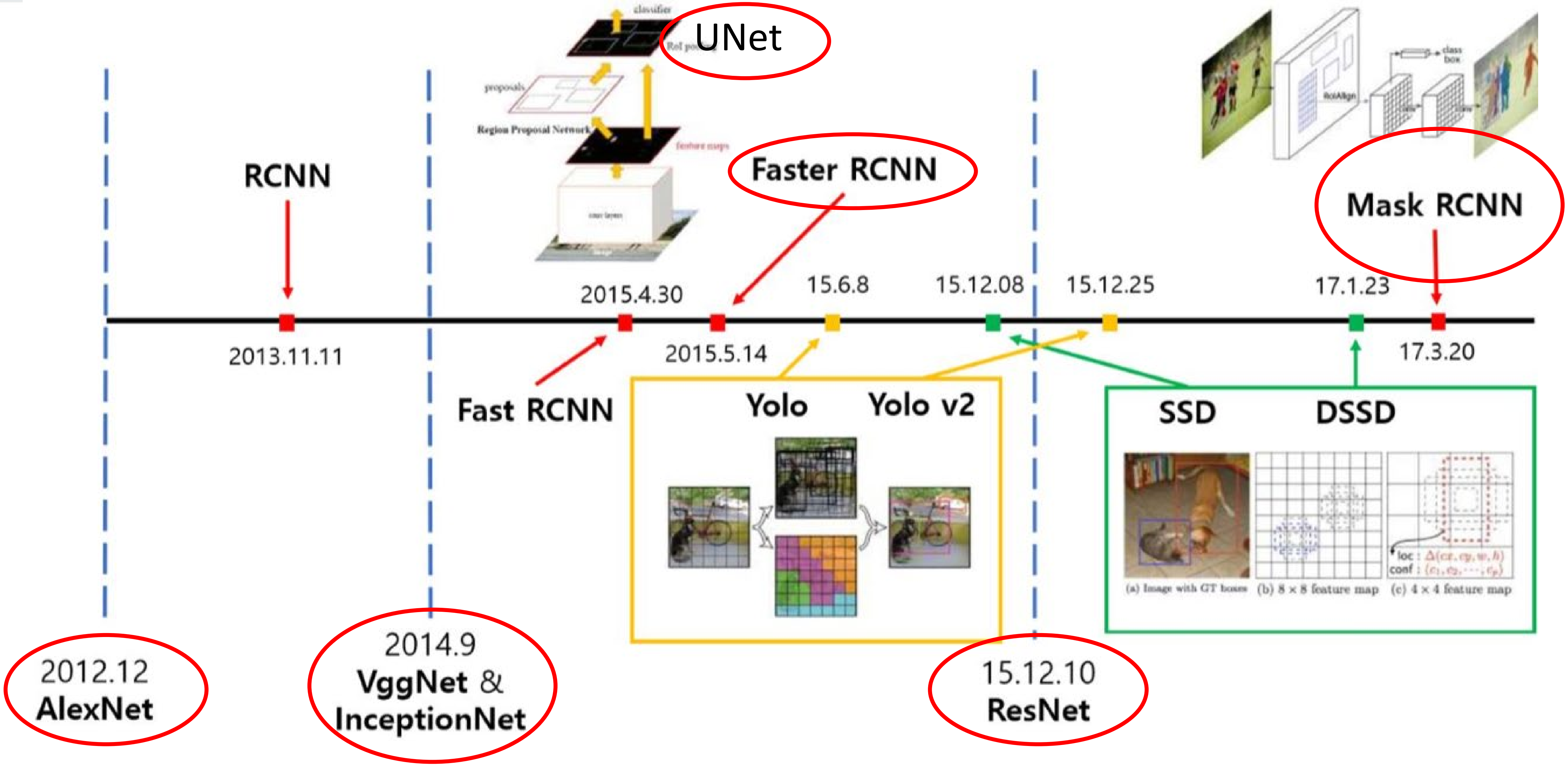
```
class MyCNN(nn.Module):
  def __init__(self):
    super(MyCNN, self).__init__()
    self.features = nn.Sequential(     #Assume input image H/W=224
        nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(224+2*1-3)/1+1 = 224
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(224+2*0-2)/2+1 = 112
        nn.Conv2d(32, 8, 3, 1, 1), #H/W=(112+2*1-3)/1+1 = 112
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(112+2*0-2)/2+1 = 56
    )
    self.classifier = nn.Sequential(
        nn.Dropout(),
        nn.Linear(8 * 56 * 56, 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
```

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

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1        [-1, 112, 224, 224]           3,136
              ReLU-2        [-1, 112, 224, 224]               0
         MaxPool2d-3        [-1, 112, 112, 112]               0
            Conv2d-4          [-1, 8, 112, 112]           8,072
              ReLU-5          [-1, 8, 112, 112]               0
         MaxPool2d-6            [-1, 8, 56, 56]               0
           Dropout-7                [-1, 25088]               0
            Linear-8                  [-1, 500]      12,544,500
              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: 12,606,010
Trainable params: 12,606,010
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 98.40
Params size (MB): 48.09
Estimated Total Size (MB): 147.06
----------------------------------------------------------------
```

VGG16

History of CNN families



圖來源: 李春煌 FasterRCNN講義 https://youtu.be/2i9CcmJp2yI

Practice – Load ImageNet pre-trained VGG

```python
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)
```

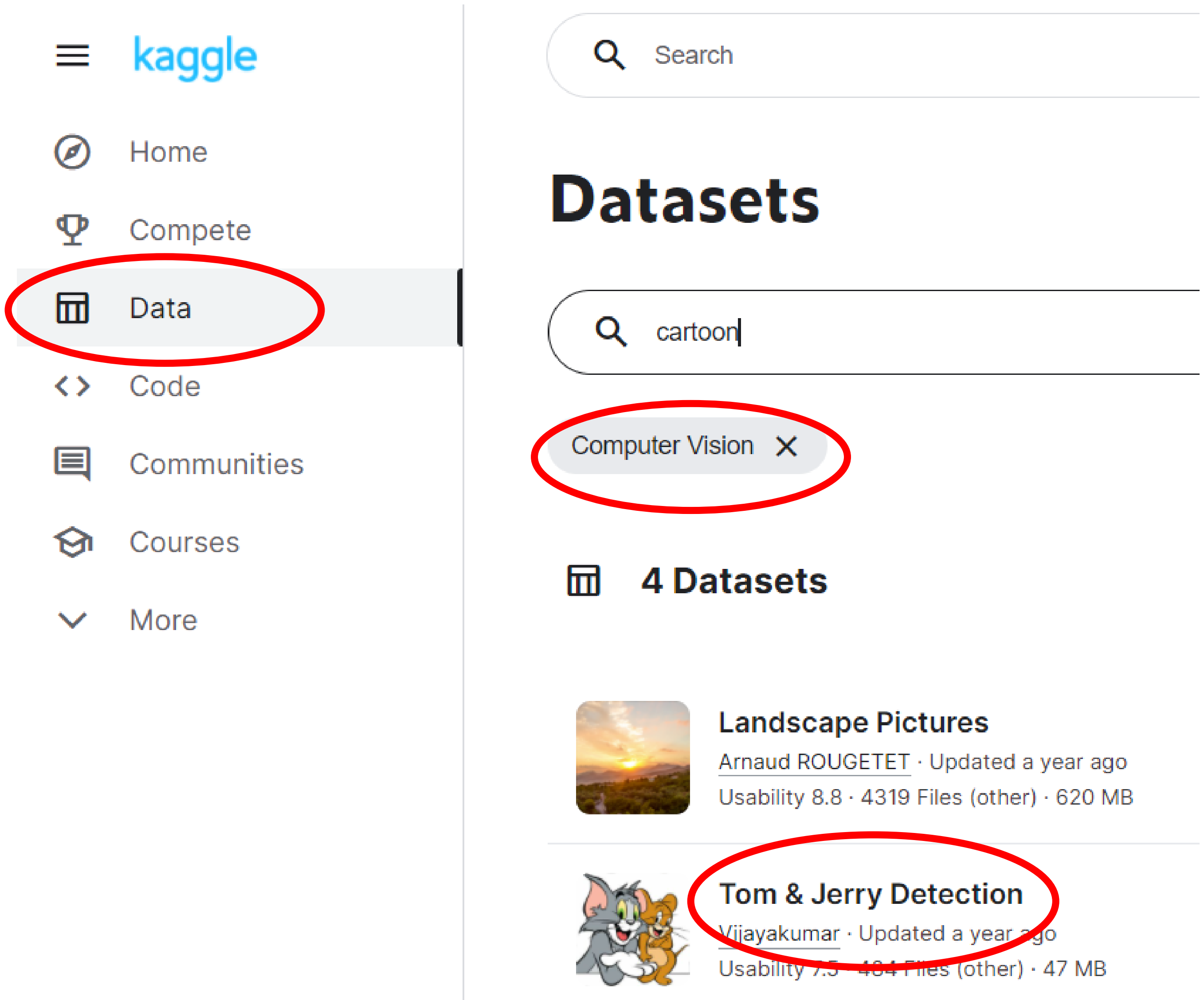
```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, 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

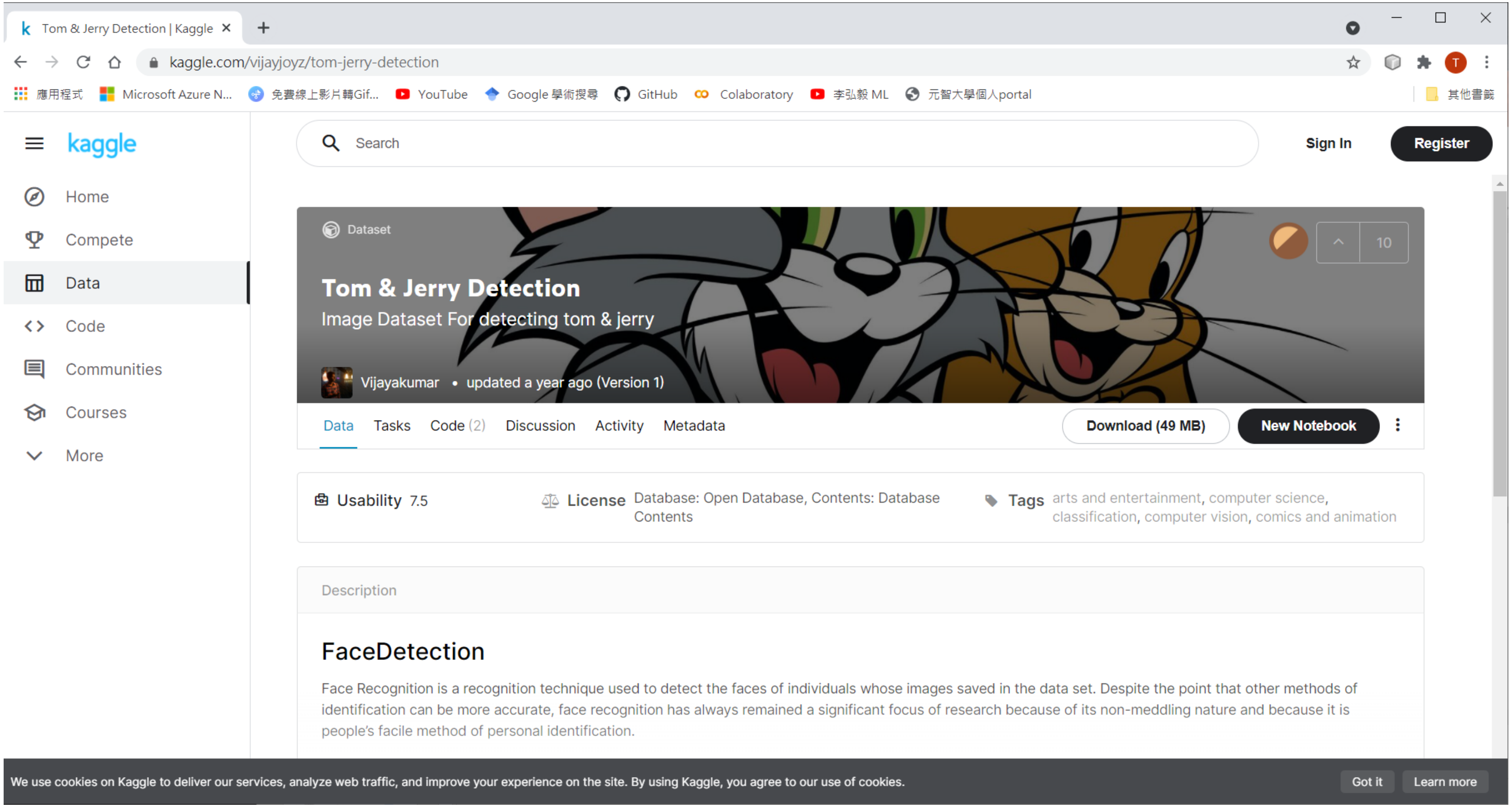
```
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (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



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
kaggle
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Data
Code
Communities
Courses
More
Dataset
10
Tom & Jerry Detection
Image Dataset For detecting tom & jerry
Vijayakumar • updated a year ago (Version 1)
Data
Tasks
Code (2)
Discussion
Activity
Metadata
Download (49 MB)
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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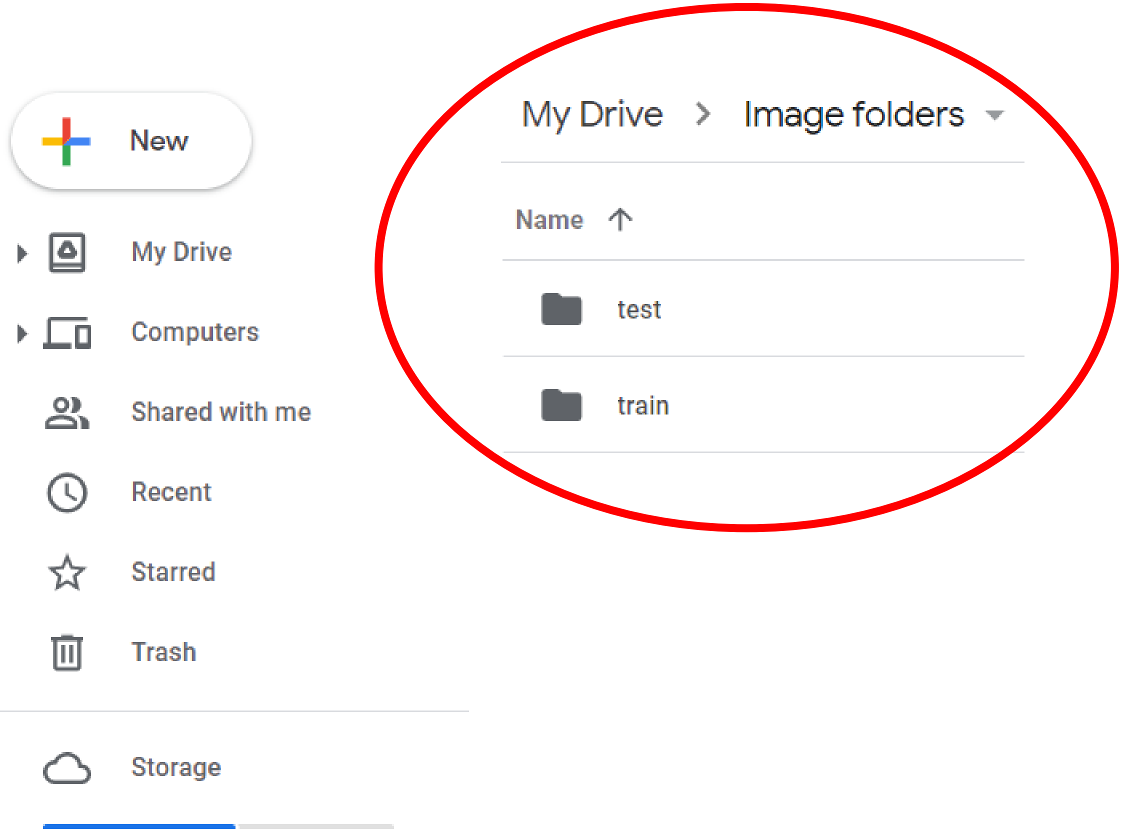
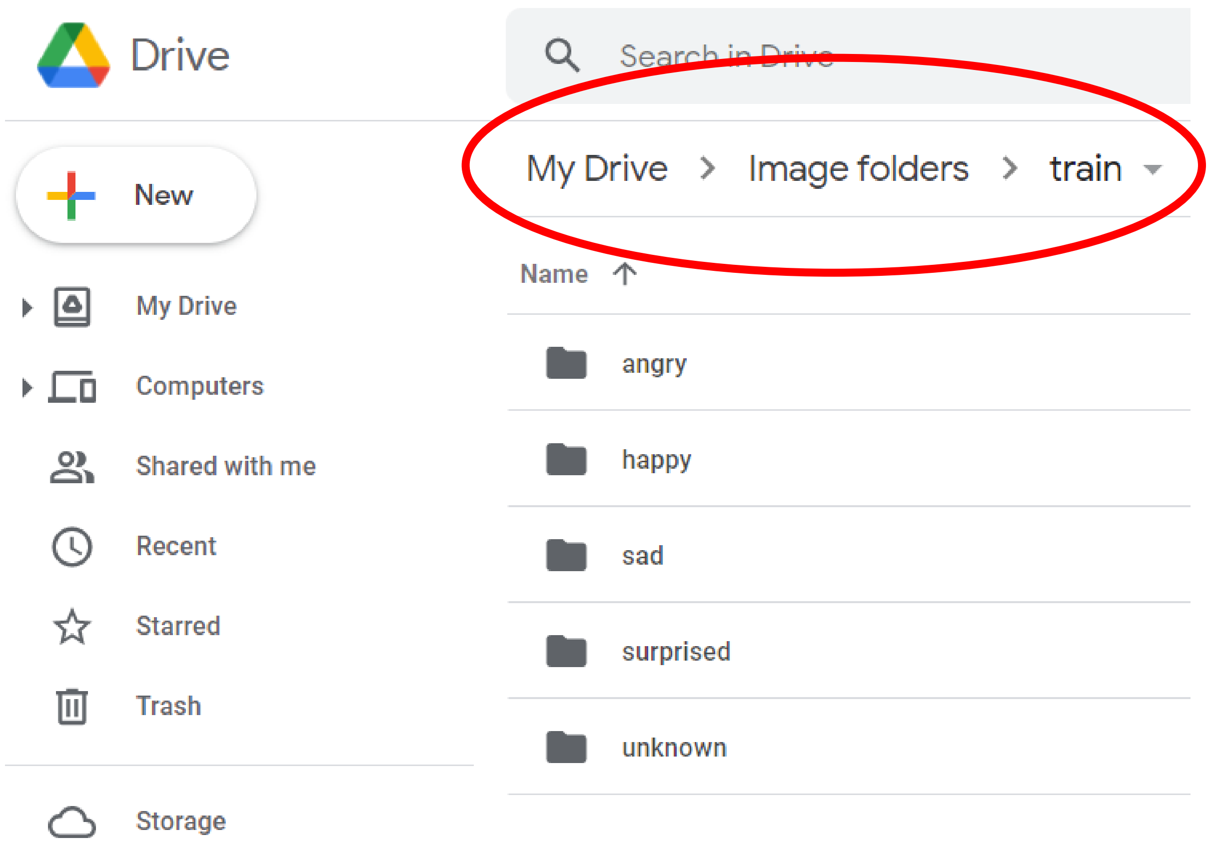
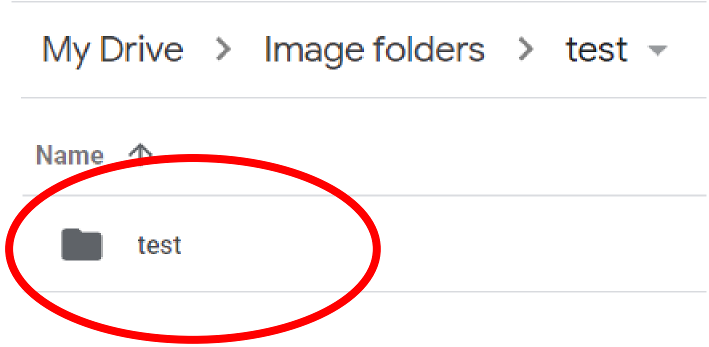
Got it
Learn more

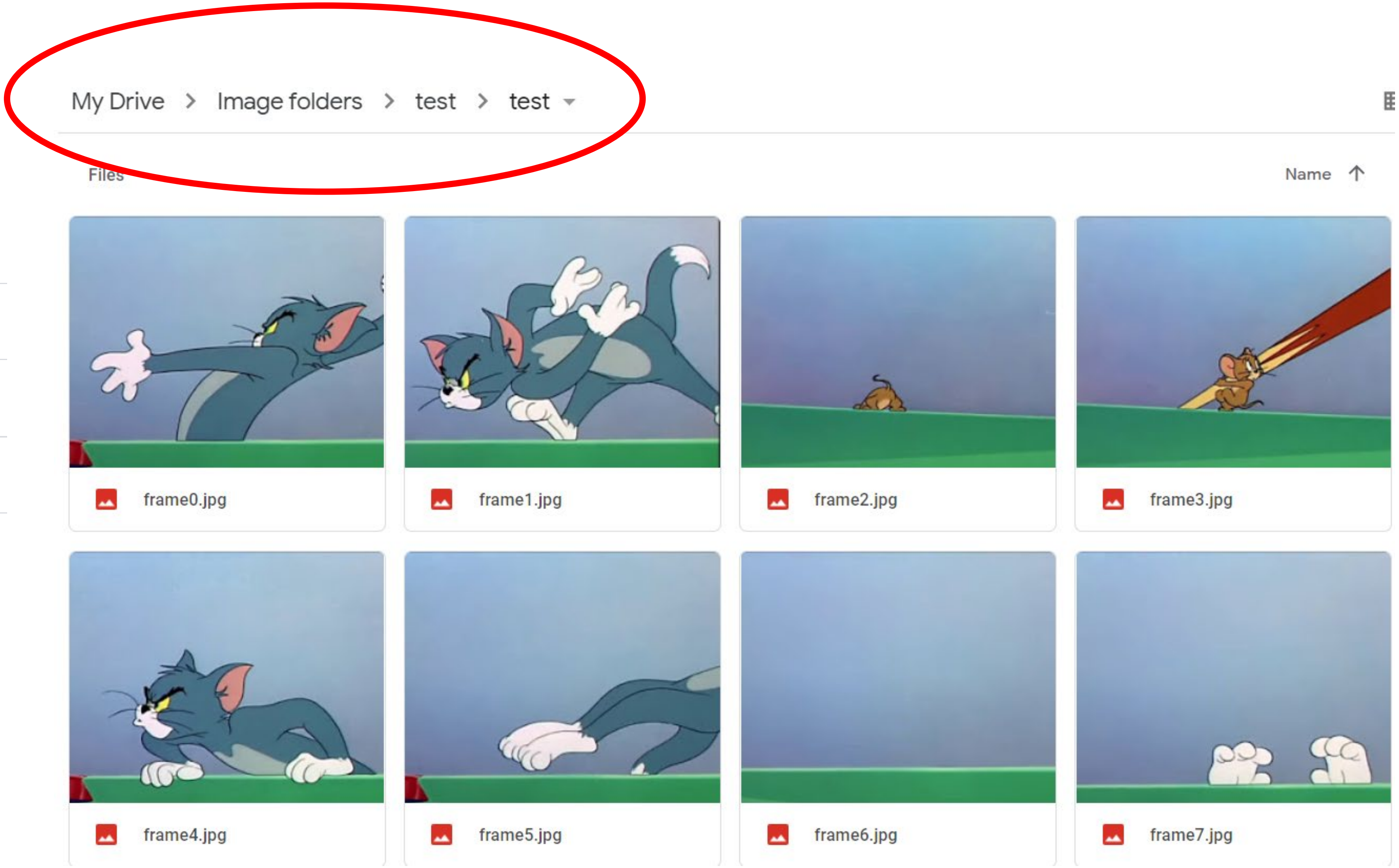
Save images in your Google drive





Save images in your Google drive





Practice

- Run “6.3. 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]:
```python
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

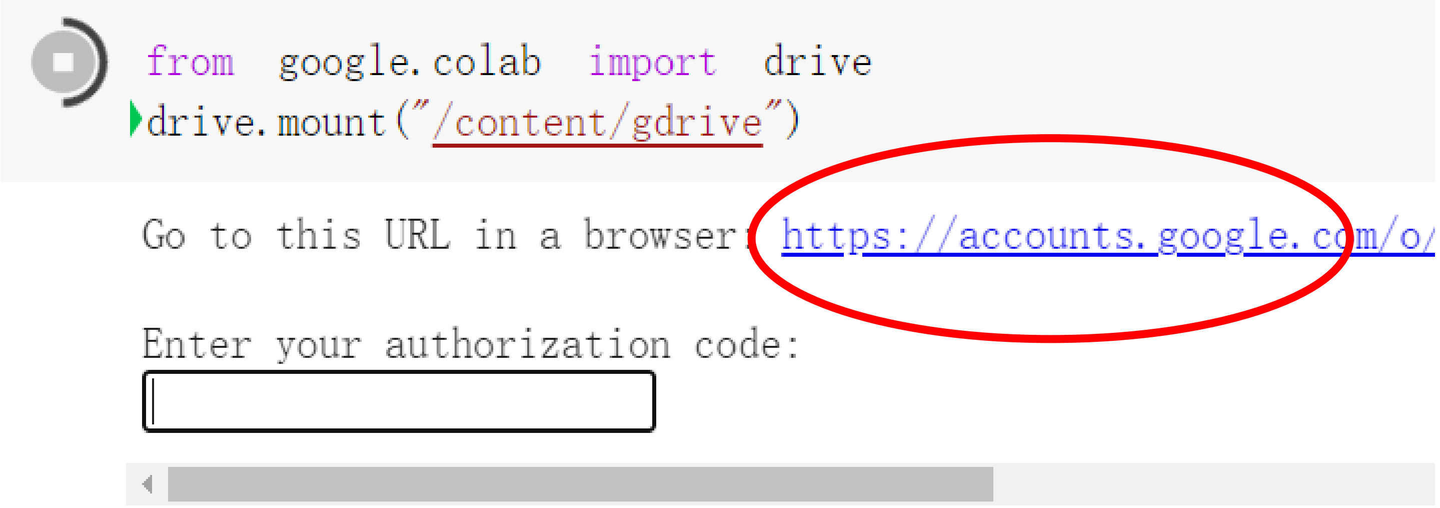
```
Total params: 139,590,725
Trainable params: 139,590,725
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 238.68
Params size (MB): 532.50
Estimated Total Size (MB): 771.75
----------------------------------------------------------------
```

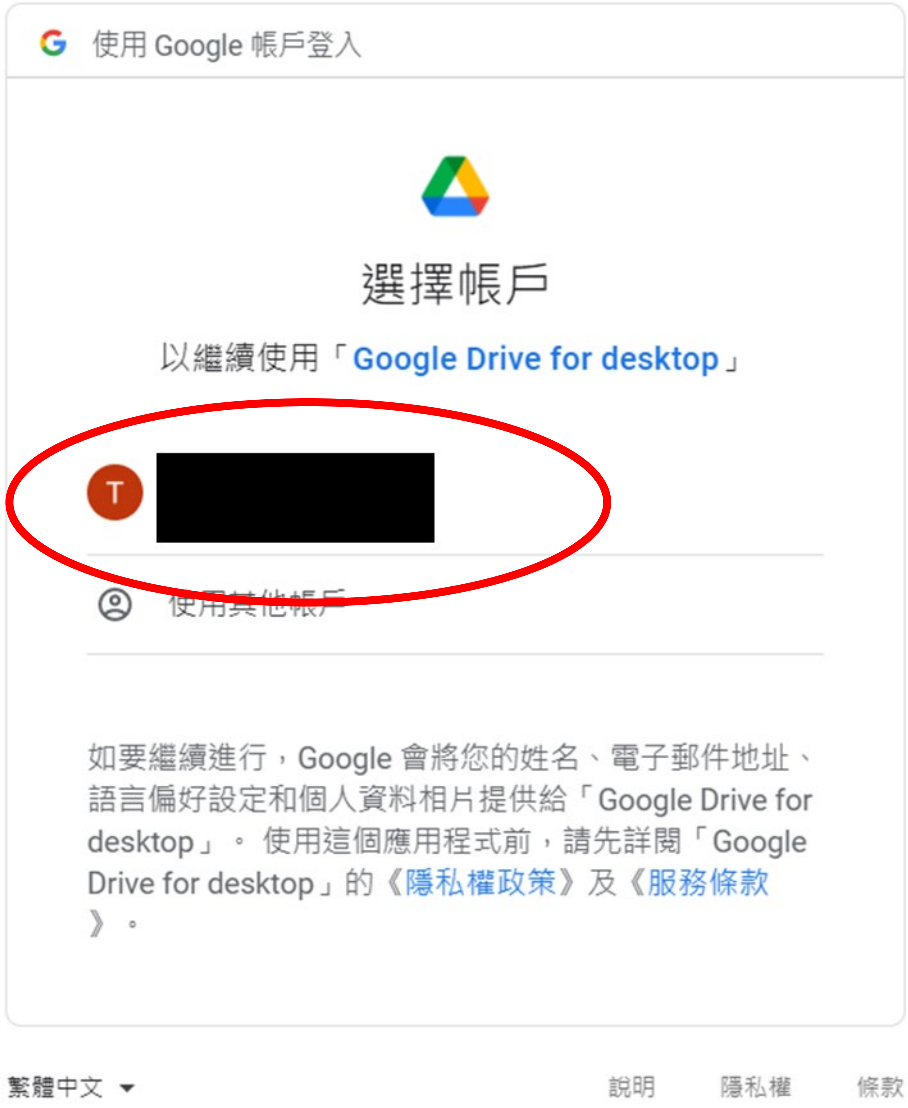
MLP in "4.2. Classification with CE loss"

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

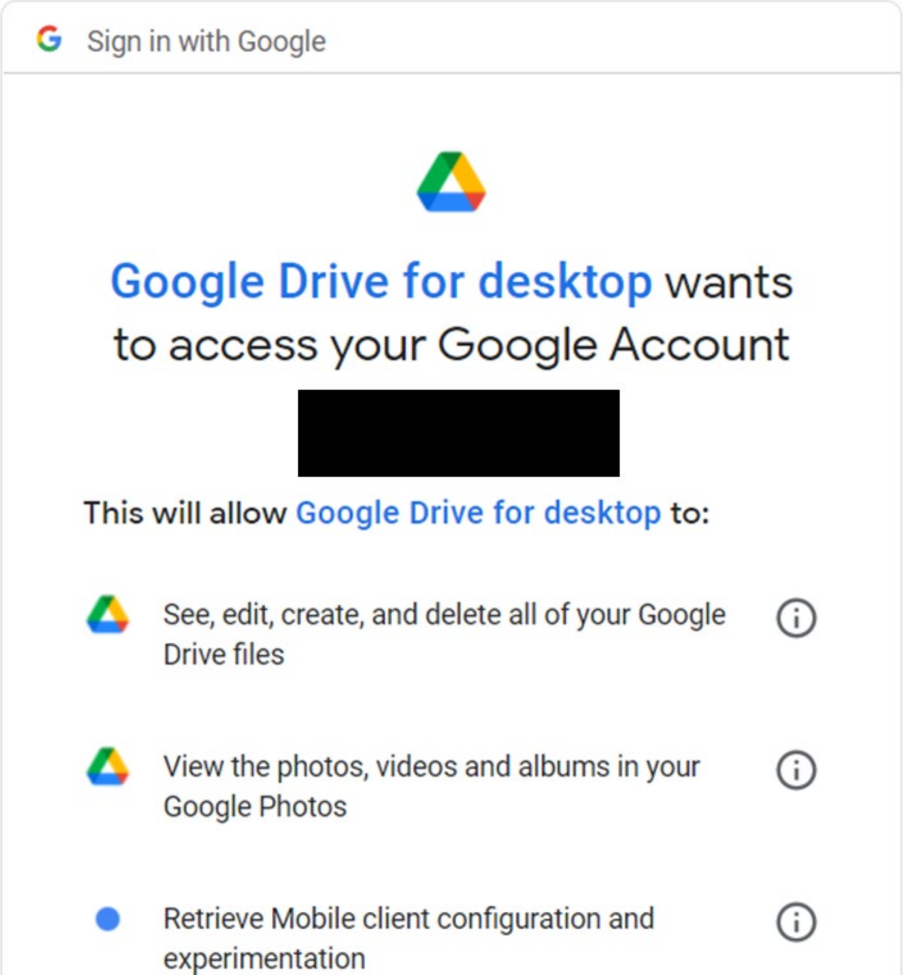
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1               [-1, 30, 50]             150
              ReLU-2               [-1, 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
----------------------------------------------------------------
```

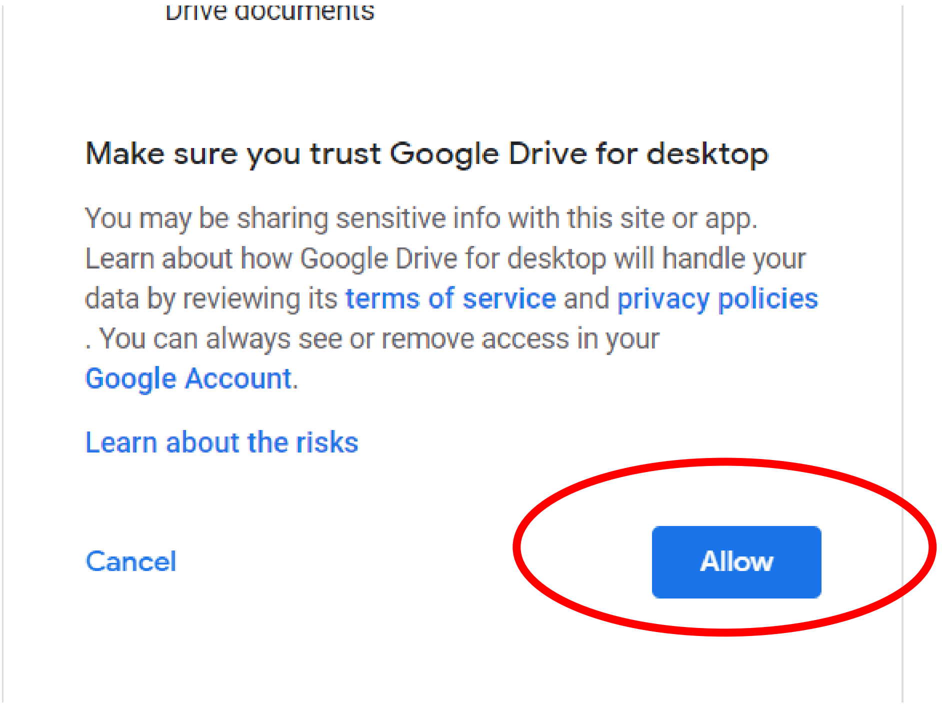
Connect to Google drive





Connect to Google drive





Connect to Google drive

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}
```

If you use Anaconda, directly set ImageFolder path.

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

Review: MLP

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)
```

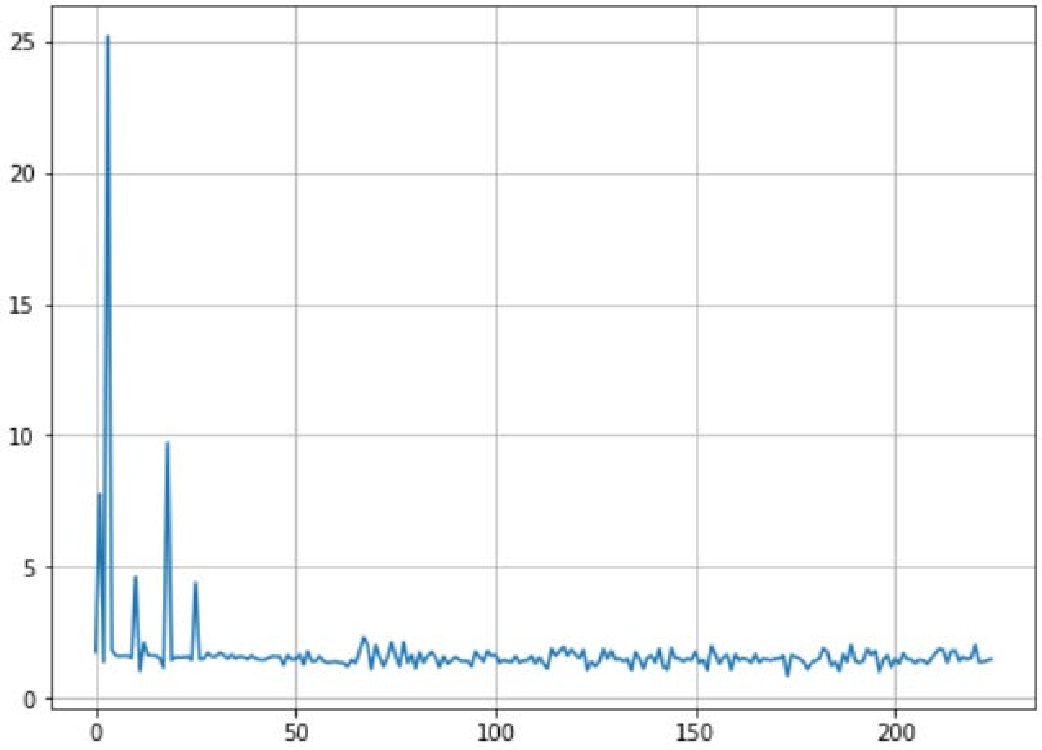
```
epoch =  1, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 
epoch =  2, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 
epoch =  3, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 
```

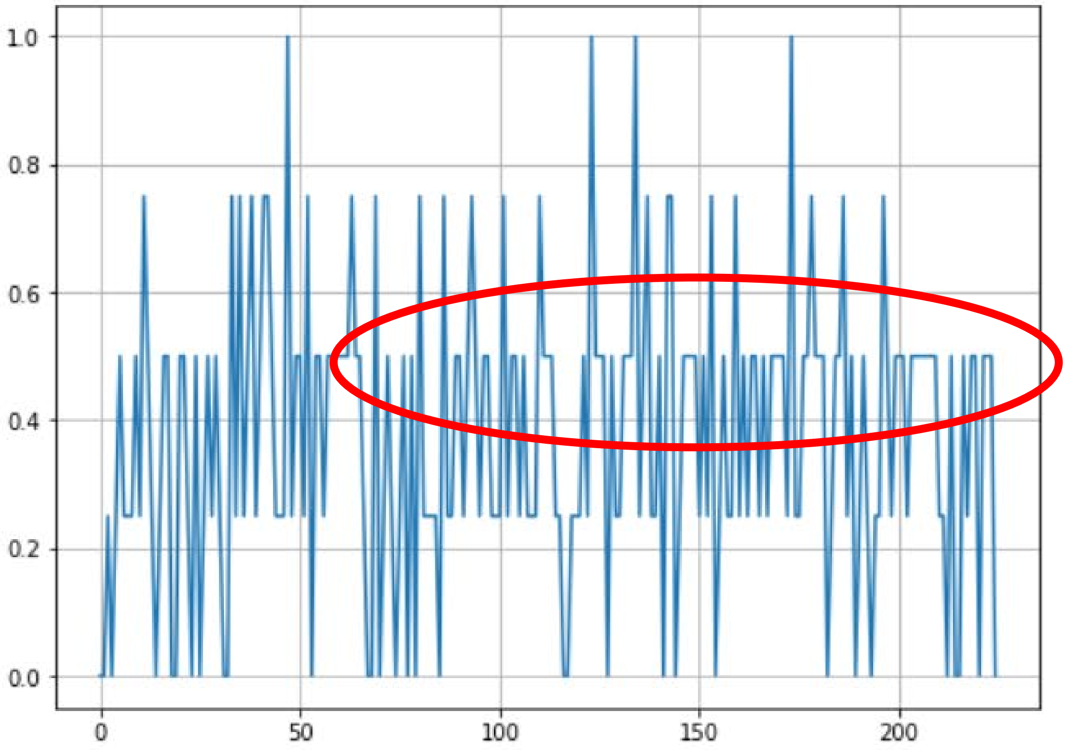
MLP in "4.2. Classification with CE loss"

```
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)
```

HW3 – Image classifier

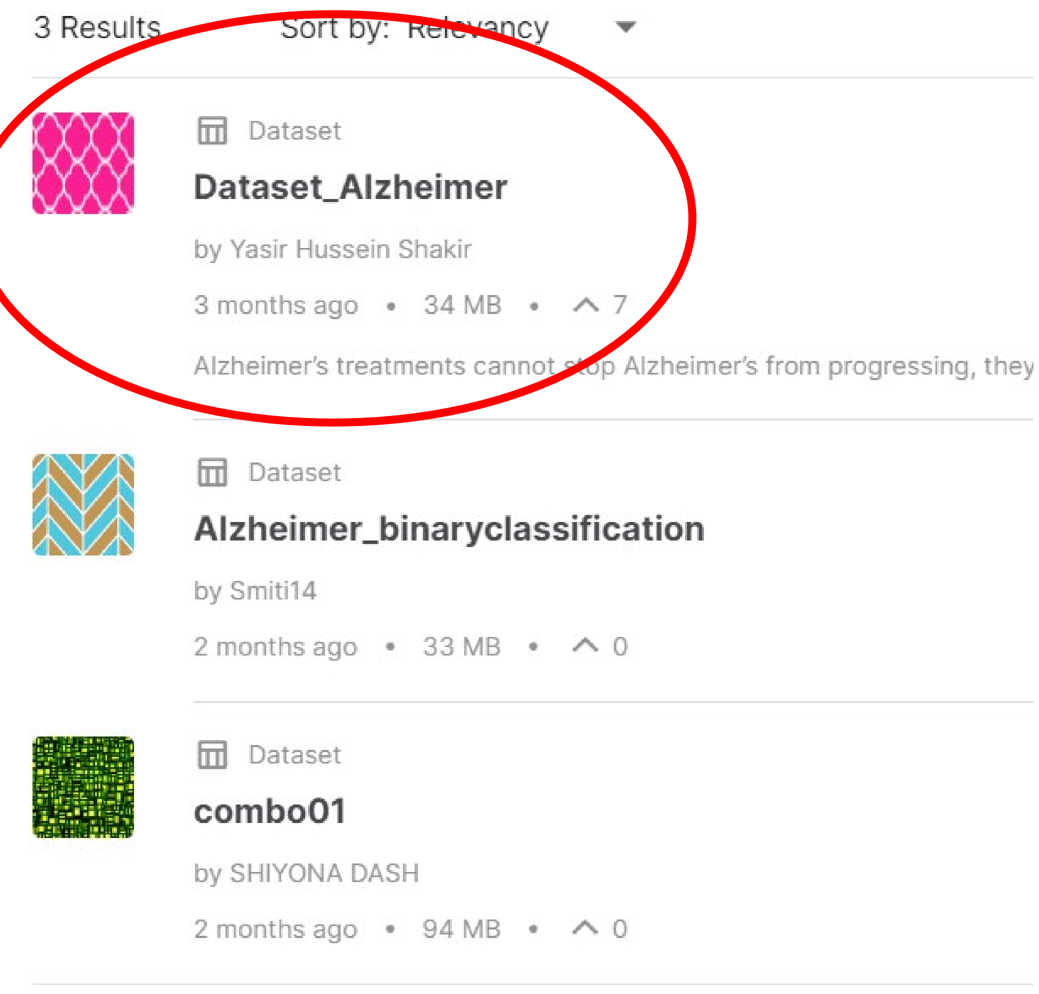
1. Build your own CNN and train from scratch.
2. Fine-tune a pre-trained VGG16 by modifying its MLP classifier (Transfer learning).
3. Compare the performance of 1 and 2 and discuss.

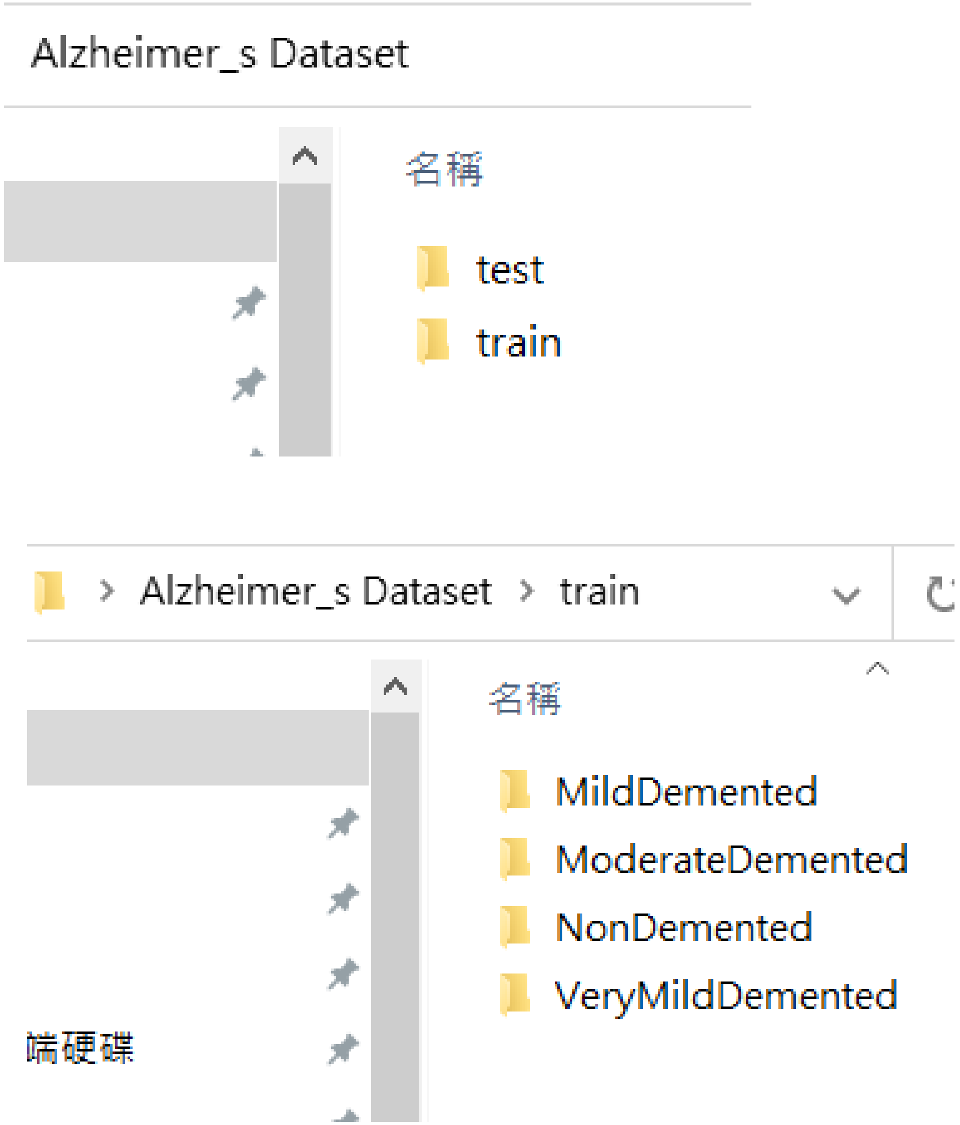
Experiences we learned from Tom & Jerry example:

- If your GPU RAM is not large and you want training batch size to be larger, try to reduce your input image to a smaller size, e.g., 64x64x3.
- Avoid confused images within group, similar images between groups, and un-balanced data. (Smaller differences within group, larger differences between groups. 組內差異小，組間差異大)

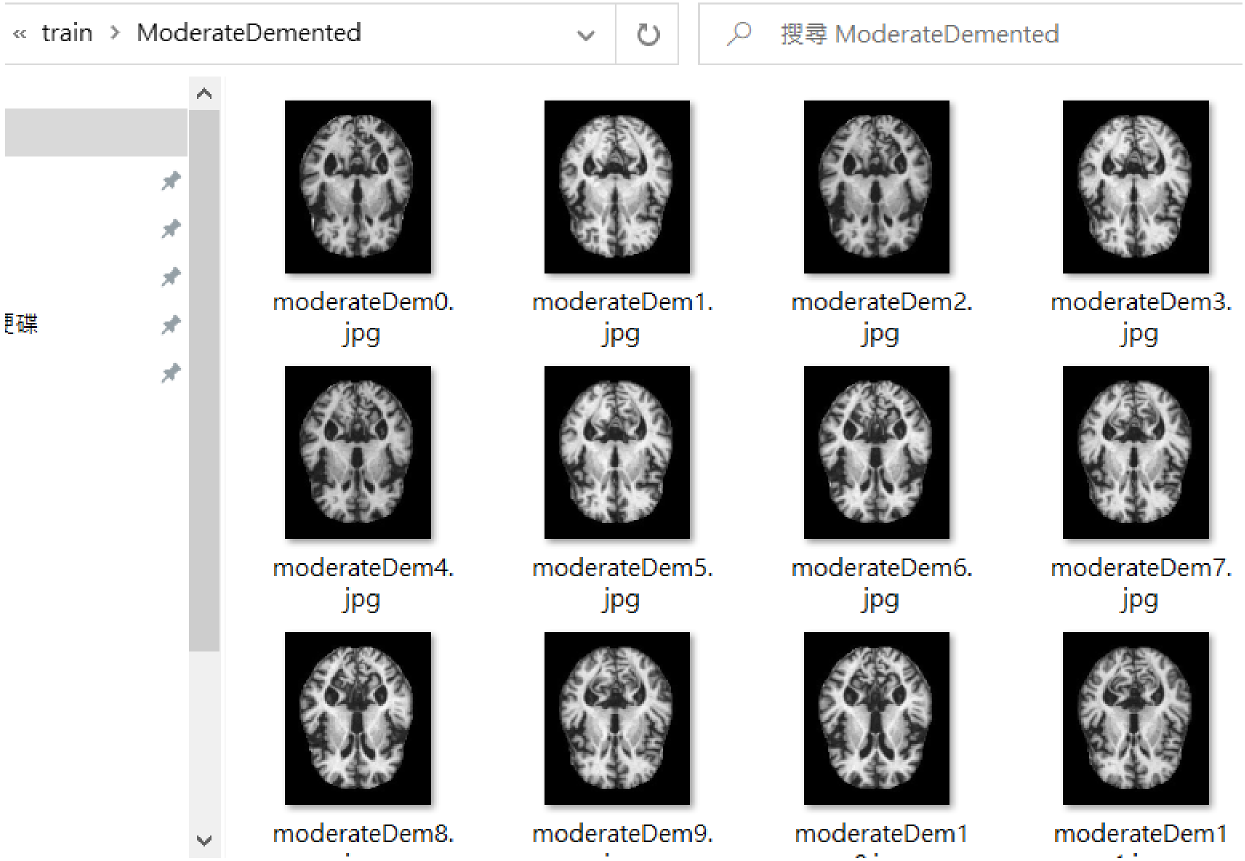
HW idea – Recognize Alzheimer disease from MRI

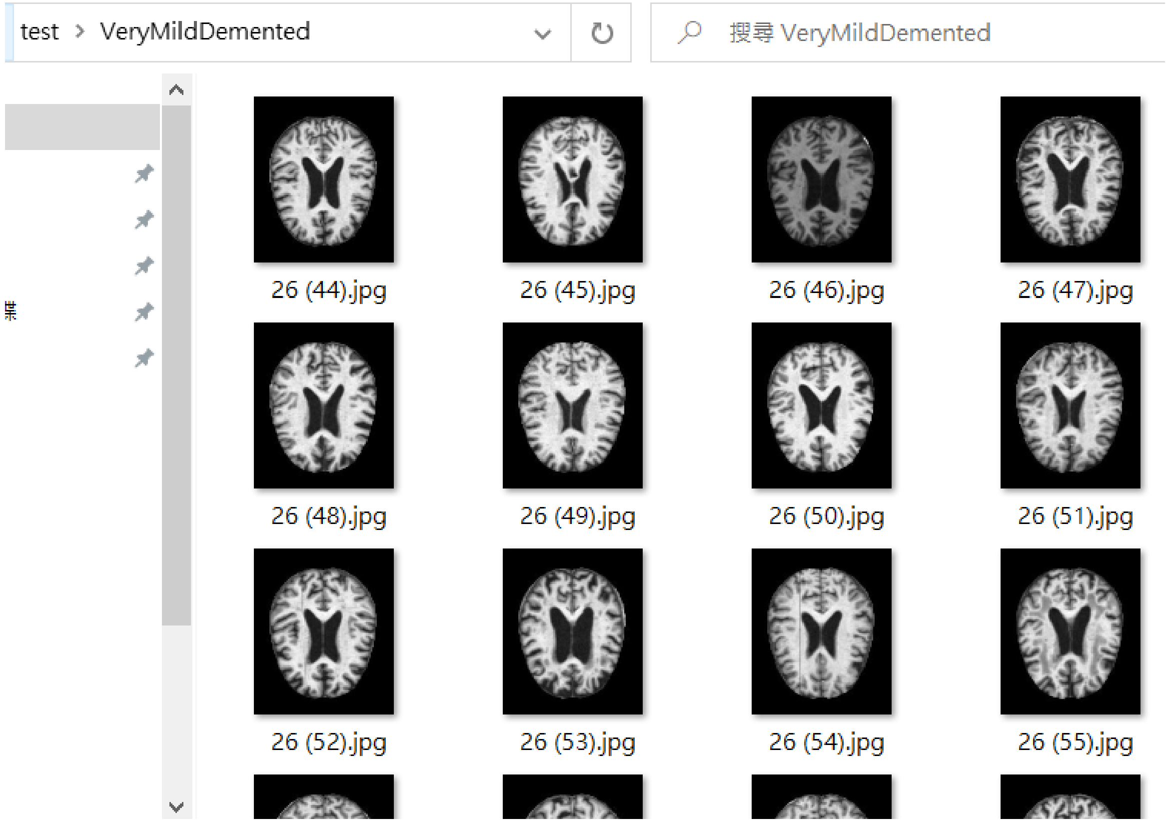
Results by searching "dementia" in Kaggle



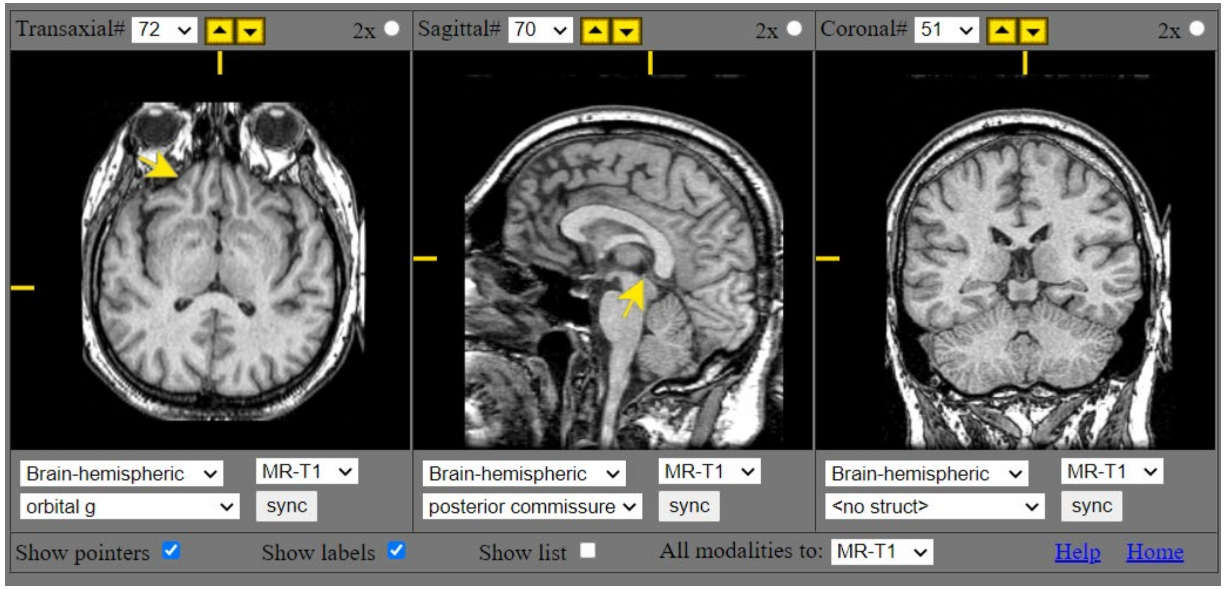


Recognize Alzheimer disease from MRI





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

HW idea – 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

Can CNN detect Autism from a facial image?

Datasets

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