# National Tsing Hua University

# Fall 2023 11210IPT 553000

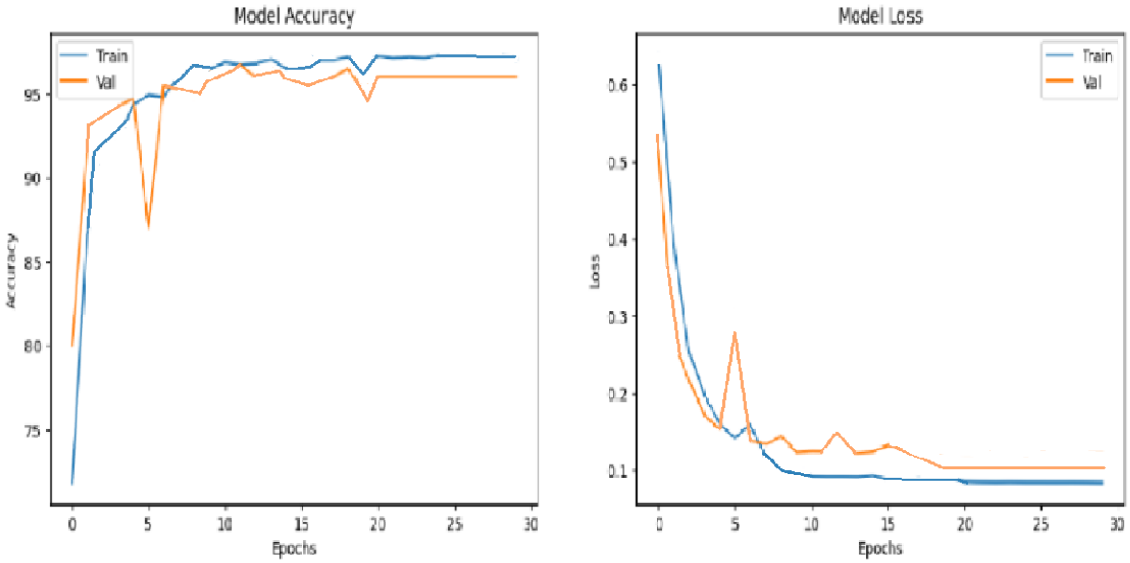
# Deep Learning in Biomedical Optical Imaging

# Homework 3

110066540 陳哲瑋

## 1. Task A: Reduce Overfitting

從 Train Loss 以及 Val Loss 的增減幅度來看就知道訓練模型會是怎樣的狀態，當 Train Loss 下降但 Val Loss 上升或不動，就代表它已經 Overfitting 了，當 Overfitting 時有大概有三種方法可以改善他: Regularization、減少層數、減少 Node 數，我嘗試用這三種方法來改善 ConvModel，首先先將層數變成一層但是結果還是 Overfitting，所以我查找了網路加入了 BatchNormld 函數，結果雖然改善但是還是 Overfitting，最後嘗試將 Node 改為 16，發現竟然已經不會產生 Overfitting 了其結果如圖一所示:




圖一

以下是改的過程首先為加入 BatchNorm1d 函數:

```
BN=nn.BatchNorm1d(32)
x = F.relu(self.conv1(x))
x = self.pool1(x)
```

但改善的效果不佳，先將將 layer 改為一層，後來查了網路發現有可能 Overfitting 的其中一原因是結果過度的跟隨訓練集於是將 kernel_size 改為 5，這樣可以透過改變周圍運算與元素來減少元素的獨立性。如下圖所示:

```
self.conv1 = nn.Conv2d(1, 32, kernel_size=5, stride=1, padding='same')

self.pool1 = nn.MaxPool2d(kernel_size=6, stride=16) # 128*128
```

最後發現 Val Loss 已不再上升了也還沒有開始下降，所以我大膽的將輸出的矩陣改為 16，通過模擬發現將 MaxPool 的 kernel_size 改成 6，雖然這會導致不良的轉換，但從結果顯示他所呈現的效果是最好的，如下圖所示:

```
self.conv1 = nn.Conv2d(1, 32, kernel_size=6, stride=1, padding='same')

self.pool1 = nn.MaxPool2d(kernel_size=6, stride=16) # 128*128
```

如果用測試集去模擬此模型可以發現他 Test accuracy 為 79.18%，這數值與原本 CNN 模型的 78.25%高了快 1%左右。

```
        labels_float = labels.float().unsqueeze(1)  # Convert labels to float and match shape with outputs
        predicted = torch.sigmoid(outputs) > 0.5

        test_correct += (predicted.float() == labels_float).sum().item()
        test_total += labels.size(0)

print(f'Test accuracy is {100. * test_correct / test_total}%')
```

```
Test accuracy is 79.18%
```

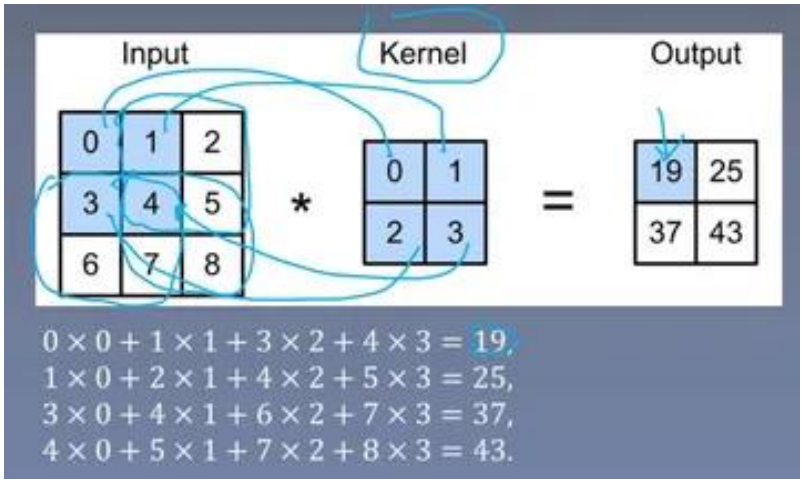
下表展示了修改參數前與修改參數後的差異:

| | 最後的 Train loss | 最後的 Train acc | 最後的 Val loss | 最後的 Val acc | 最佳 Val loss 的位置 | 最佳 Val loss 的數值 |
|---|---|---|---|---|---|---|
| 修改前 | 0.0093 | 99.16% | 0.0978 | 95.47% | Epoch21/30 | 0.961 |
| 修改後 | 0.0829 | 96.97% | 0.1315 | 95.81% | Epoch28/30 | 0.1304 |

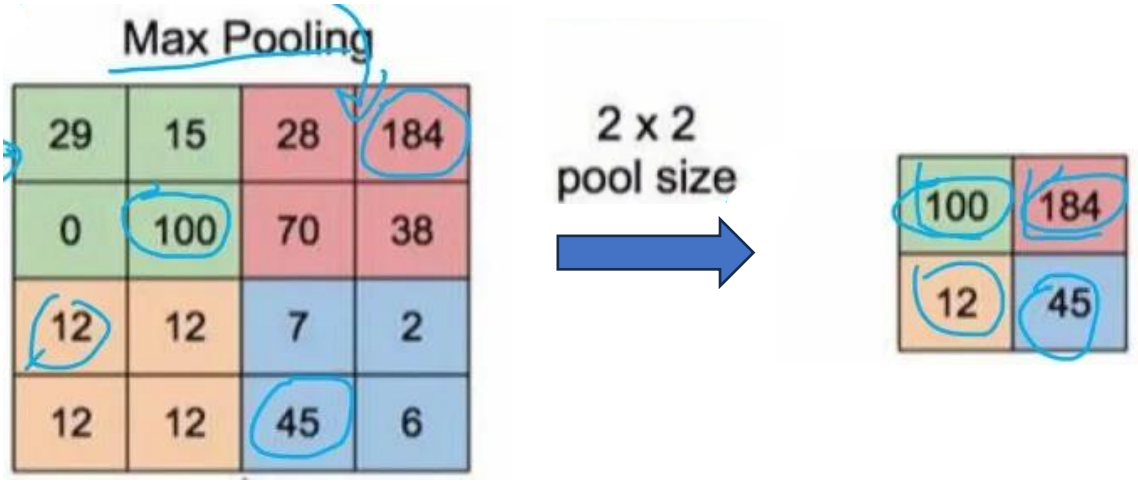
可以從發現到修改參數前之最後的 Train acc-最後的 Val acc=3.69%，且可看到 Val Loss 在 Epoch 21/30 後反而上升了，這顯示它 Overfitting 了。修改參數後之最後的 Train acc 減掉最後的 Val acc=1.16%，比改動前好了許多，且 Val Loss 的最佳值是在 Epoch 29/30 的地方，說明了此次改動對於整個機械學習是有相當好的提升。

## 2. Task B: Performance Comparison between CNN and ANN

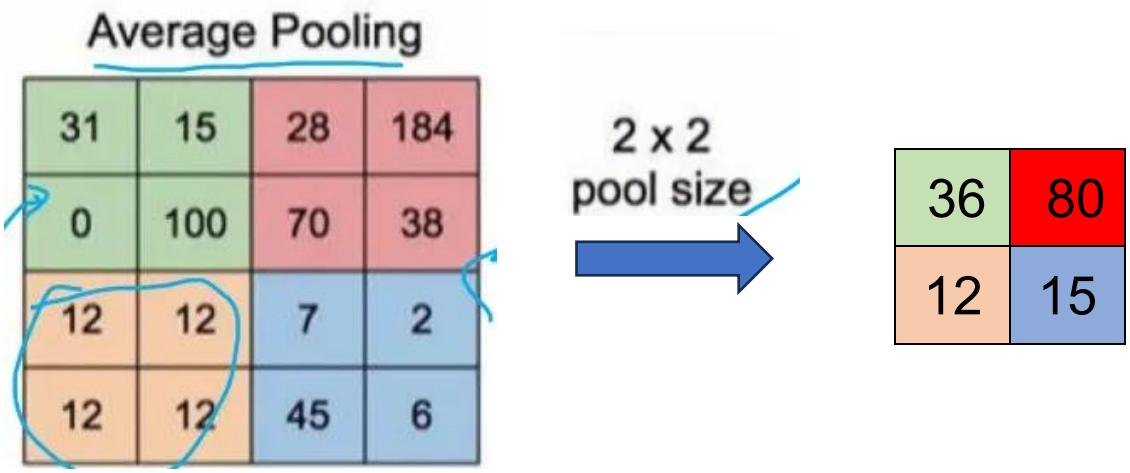
ANN 與 CNN 結構的差異:
CNN 一般會分為 Convolution、Pooling、Input、Output 四個 Layer
Convolution Layer 作用為將 Input Layer 傳進來的矩陣分成不同區塊進行處裡，如下圖所示:




而 Pooling Layer 的功用是將 Convolution Layer 輸出矩陣的維度縮小，主要有兩種方法來縮小矩陣
一種是 Max Pooling:




另一種為 Average Pooling:



ANN 一般則會分為 Input、Hidden、Output 三個 Layer，資料從 Input Layer 傳至 Hidden Layer 後會被分類並處理，如果 y 為 input、Activation function:σ、weights:w、training label:x、bias:b、，單 Node 的輸入與輸出的關係可寫為 x=σ(wy+b)，如果只有單 Layer 那這個值會直接被傳到 Output Layer，但如果為複數層那將會重複上述之動作 x2=σ(wx1+b)。當數值被傳到 Output Layer 後會將此資料分類，來分他為單一 Node 又或為數個 Node。

下表格為 CNN 以及 ANN 的比較表，其中較重要的參數為 Final Train acc、Final Val acc、Final Val Loss、最佳 Val Loss 的位置、最佳 Val loss 的數值及 Test accuracy:

| | Final Train acc | Final Val acc | Final Val Loss | 最佳 Val Loss 的位置 | 最佳 Val loss 的數值 | Test accuracy | Time |
|---|---|---|---|---|---|---|---|
| CNN | 100% | 96.89% | 0.1297 | 12/30 | 0.1091 | 77.86% | 75s |
| ANN | 98.1% | 95.16% | 0.1859 | 22/30 | 0.1812 | 72.56% | 18s |

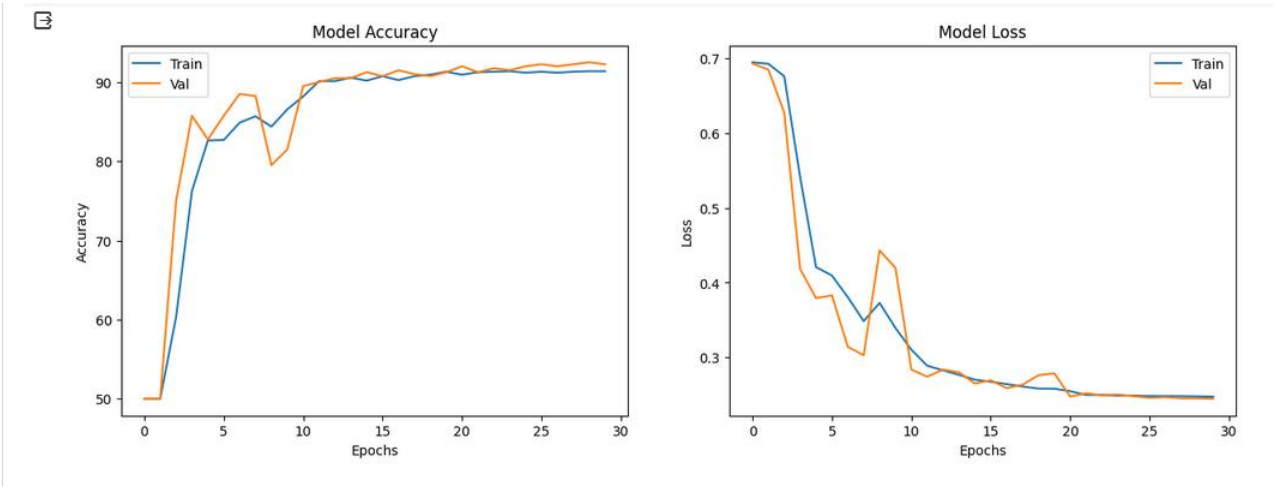
從結果可以明顯看到 CNN 的有相當明顯的優點，CNN 的 Train acc 及 Val acc 都比 ANN 高，CNN 的 Test accuracy 也比 ANN 高了 5.3%。而 ANN 的優點就是其運行時間為 18 秒，比 CNN 的 75 秒短了相當多，兩者都會有 Overfitting 情況產生，要改善 ANN 的 Overfitting 情況也比 CNN 更簡單因為其最佳 Val Loss 位置在 22 比 CNN 的 12 還要後面也是其少數的優點。

**3. Task C: Global Average Pooling in CNNs**

GAP 是將最後的 Pooling 層分層後輸出，發現原本的模型會產生 Underfitting 的情形，要改善這問題的方法就是將模型的複雜度提升，故將原本三層的 Hidden Layer 改為四層，以下為表格來做比對:

| | Final Train acc | Final Val acc | Final Val Loss | 最佳 Val Loss 的位置 | 最佳 Val loss 的數值 | Test accuracy |
|---|---|---|---|---|---|---|
| 三層的 Hidden Layer | 88.18% | 88.96% | 0.2924 | 27/30 | 0.3198 | 78.46% |
| 四層的 Hidden Layer | 91.38% | 92.25% | 0.2449 | 30/30 | 0.2449 | 80.75% |

訓練結果:




從表格可很明顯看到多加一層後整體的效能就有改變了，基本上每個數值都有明顯的上升，所以證明此方法是可行的。

## Load Trained Model and Evaluate

```
# Load the trained weights
model.load_state_dict(torch.load('model_classification.pth'))

# Set the model to evaluation mode
model.eval()

test_correct = 0
test_total = 0

with torch.no_grad():
    for images, labels in test_loader:

        images = images.cuda()
        images = images / 255.

        labels = labels.cuda()

        outputs = model(images)

        labels_float = labels.float().unsqueeze(1)  # Convert labels to float and match shape with outputs
        predicted = torch.sigmoid(outputs) > 0.5

        test_correct += (predicted.float() == labels_float).sum().item()
        test_total += labels.size(0)

print(f'Test accuracy is {100. * test_correct / test_total}%')
```

```
Test accuracy is 80.75%
```

```
)
100% 30/30 [01:12<00:00, 2.44s/it]
Epoch 1/30, Train loss: 0.6942, Train acc: 50.00%, Val loss: 0.6925, Val acc: 50.00%, Best Val loss: 0.6925 Best Val acc: 50.00%
Epoch 2/30, Train loss: 0.6922, Train acc: 50.00%, Val loss: 0.6844, Val acc: 50.00%, Best Val loss: 0.6844 Best Val acc: 50.00%
Epoch 3/30, Train loss: 0.6755, Train acc: 60.31%, Val loss: 0.6269, Val acc: 75.00%, Best Val loss: 0.6269 Best Val acc: 75.00%
Epoch 4/30, Train loss: 0.5410, Train acc: 76.25%, Val loss: 0.4181, Val acc: 85.75%, Best Val loss: 0.4181 Best Val acc: 85.75%
Epoch 5/30, Train loss: 0.4207, Train acc: 82.62%, Val loss: 0.3793, Val acc: 82.75%, Best Val loss: 0.3793 Best Val acc: 85.75%
Epoch 6/30, Train loss: 0.4095, Train acc: 82.69%, Val loss: 0.3830, Val acc: 85.75%, Best Val loss: 0.3793 Best Val acc: 85.75%
Epoch 7/30, Train loss: 0.3806, Train acc: 84.88%, Val loss: 0.3142, Val acc: 88.50%, Best Val loss: 0.3142 Best Val acc: 88.50%
Epoch 8/30, Train loss: 0.3486, Train acc: 85.69%, Val loss: 0.3031, Val acc: 88.25%, Best Val loss: 0.3031 Best Val acc: 88.50%
Epoch 9/30, Train loss: 0.3730, Train acc: 84.38%, Val loss: 0.4429, Val acc: 79.50%, Best Val loss: 0.3031 Best Val acc: 88.50%
Epoch 10/30, Train loss: 0.3394, Train acc: 86.56%, Val loss: 0.4196, Val acc: 81.50%, Best Val loss: 0.3031 Best Val acc: 88.50%
Epoch 11/30, Train loss: 0.3105, Train acc: 88.19%, Val loss: 0.2839, Val acc: 89.50%, Best Val loss: 0.2839 Best Val acc: 89.50%
Epoch 12/30, Train loss: 0.2890, Train acc: 90.12%, Val loss: 0.2744, Val acc: 90.00%, Best Val loss: 0.2744 Best Val acc: 90.00%
Epoch 13/30, Train loss: 0.2828, Train acc: 90.12%, Val loss: 0.2838, Val acc: 90.50%, Best Val loss: 0.2744 Best Val acc: 90.50%
Epoch 14/30, Train loss: 0.2768, Train acc: 90.56%, Val loss: 0.2803, Val acc: 90.50%, Best Val loss: 0.2744 Best Val acc: 90.50%
Epoch 15/30, Train loss: 0.2703, Train acc: 90.19%, Val loss: 0.2653, Val acc: 91.25%, Best Val loss: 0.2653 Best Val acc: 91.25%
Epoch 16/30, Train loss: 0.2676, Train acc: 90.75%, Val loss: 0.2695, Val acc: 90.75%, Best Val loss: 0.2653 Best Val acc: 91.25%
Epoch 17/30, Train loss: 0.2645, Train acc: 90.25%, Val loss: 0.2591, Val acc: 91.50%, Best Val loss: 0.2591 Best Val acc: 91.50%
Epoch 18/30, Train loss: 0.2613, Train acc: 90.75%, Val loss: 0.2637, Val acc: 91.00%, Best Val loss: 0.2591 Best Val acc: 91.50%
Epoch 19/30, Train loss: 0.2585, Train acc: 90.94%, Val loss: 0.2763, Val acc: 90.75%, Best Val loss: 0.2591 Best Val acc: 91.50%
Epoch 20/30, Train loss: 0.2583, Train acc: 91.31%, Val loss: 0.2788, Val acc: 91.25%, Best Val loss: 0.2591 Best Val acc: 91.50%
Epoch 21/30, Train loss: 0.2550, Train acc: 90.94%, Val loss: 0.2478, Val acc: 92.00%, Best Val loss: 0.2478 Best Val acc: 92.00%
Epoch 22/30, Train loss: 0.2500, Train acc: 91.25%, Val loss: 0.2522, Val acc: 91.25%, Best Val loss: 0.2478 Best Val acc: 92.00%
Epoch 23/30, Train loss: 0.2500, Train acc: 91.31%, Val loss: 0.2494, Val acc: 91.75%, Best Val loss: 0.2478 Best Val acc: 92.00%
Epoch 24/30, Train loss: 0.2492, Train acc: 91.38%, Val loss: 0.2505, Val acc: 91.50%, Best Val loss: 0.2478 Best Val acc: 92.00%
Epoch 25/30, Train loss: 0.2491, Train acc: 91.19%, Val loss: 0.2481, Val acc: 92.00%, Best Val loss: 0.2478 Best Val acc: 92.00%
Epoch 26/30, Train loss: 0.2486, Train acc: 91.31%, Val loss: 0.2463, Val acc: 92.25%, Best Val loss: 0.2463 Best Val acc: 92.25%
Epoch 27/30, Train loss: 0.2486, Train acc: 91.19%, Val loss: 0.2472, Val acc: 92.00%, Best Val loss: 0.2463 Best Val acc: 92.25%
Epoch 28/30, Train loss: 0.2484, Train acc: 91.31%, Val loss: 0.2455, Val acc: 92.25%, Best Val loss: 0.2455 Best Val acc: 92.25%
Epoch 29/30, Train loss: 0.2481, Train acc: 91.38%, Val loss: 0.2455, Val acc: 92.50%, Best Val loss: 0.2455 Best Val acc: 92.50%
Epoch 30/30, Train loss: 0.2477, Train acc: 91.38%, Val loss: 0.2449, Val acc: 92.25%, Best Val loss: 0.2449 Best Val acc: 92.50%
```