說明：請各位使用此 template 進行 Report 撰寫，如果想要用其他排版模式也請註明題號以及題目內容（請勿擅自更改題號），最後上傳至 github 前，請務必轉成 PDF 檔，並且命名為 report.pdf，否則將不予計分。

PS.這次作業的所有題目都需附上說明或觀察到的現象。

---------------------------------------閱讀完以上文字請刪除------------------------------------

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1. (1%) 請說明這次使用的 model 架構，包含各層維度及連接方式。

Sol:

要用當然用我查到最屌的-model:densenet201-改

(這裡 in/out 是指 function 吃進去的維度, 不代表 feature 總數量)

Image size = (3, 48, 48)

Initialization:

1. Convolution (out=(64, 24, 24), n=64, kernel=(7, 7), stride=(2, 2), padding=(3, 3))
2. BatchNorm (out=(64, 24, 24),)
3. ReLU (out=(64, 24, 24),)
4. Pooling(out=(64, 12, 12),, kernel =3, stride=2, padding=1)

Layer: (維度為其第一層的範例)

1.BatchNorm (out=(64, 12, 12))
2.ReLU (out=(64, 12, 12))
3.Convolution (out=(128, 12, 12), n=128, kernel =(1, 1), stride=(1, 1))
4.BatchNorm (out=(128, 12, 12))
5.ReLU (out=(128, 12, 12))
6.Convolution (out=(32, 12, 12), kernel =(3, 3), stride=(1, 1), padding=(1, 1))

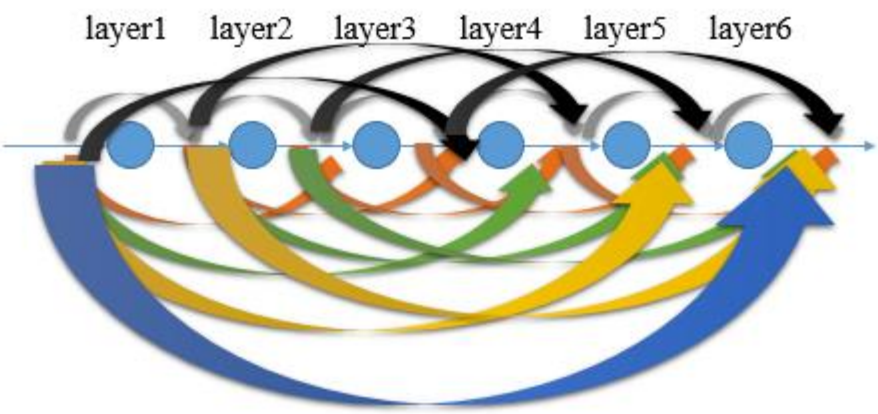
Transition: (維度為其第一次的範例)

1.BatchNorm (out=(256, 12, 12))
2.ReLU (out=(256, 12, 12))
3.Convolution(out=(128, 12, 12), n=128)
4. Pooling(out=(128, 12, 12))

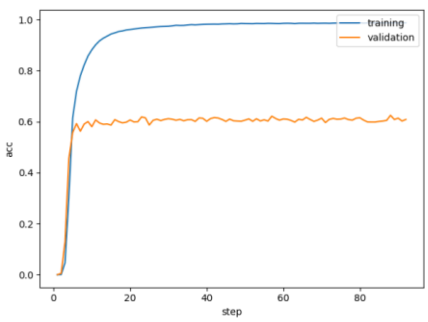
Initialization > block[6* Layer[> Transition > block[12* Layer] > Transition > block[48* Layer] > Transition > block[32* Layer] > BatchNorm (out=(1920, 1)) > linear (out=(1024, 1)) > ReLU > Dropout > linear (out=(512, 1)) > ReLU > Dropout > linear (out=(256, 1)) > ReLU > Dropout > linear (out=(7, 1))

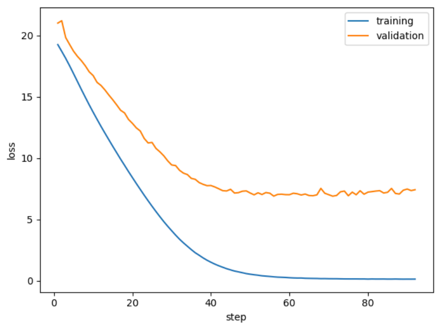
其中每一個 block 內的連接方式除了前後連接還增加了 dense connection.(除了第 1 層, 每層 layer 的 input 皆會受到前面多個層的 output 值)

以第一個 block 為例:



2. (1%) 請附上 model 的 training/validation history (loss and accuracy)





。

3. (1%) 畫出 confusion matrix 分析哪些類別的圖片容易使 model 搞混，並簡單說明。(ref: https://en.wikipedia.org/wiki/Confusion_matrix)

```
[[3783    4   69   43   81   11   50]
 [   8  421    7    3    6    1    1]
 [  63    2 3849   37   84   39   71]
 [  13    1   20 7169   24   22   35]
 [  68    4   63   40 4522    8  109]
 [  17    0   40   15    9 3070   21]
 [  40    0   37   63  101    9 4735]]
```

從 training+validation 整體的機率來看:

Class0 = 93.6%

Class1 = 94.1%

Class2 = 92.8%

Class3 = 98.4%

Class4 = 93.9%

Class5 = 96.7%

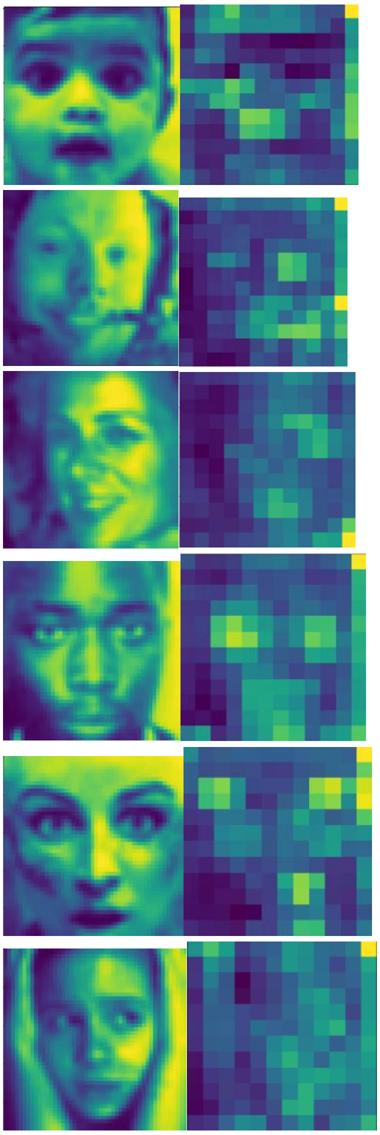
Class6 = 94.9%

以結果來看 Class0/ Class1/ Class2/ Class4/ Class6 均低於 95%, 容易出錯.

[關於第四及第五題]
可以使用簡單的 3-layer CNN model [64, 128, 512] 進行實作。

4. (1%) 畫出 CNN model 的 saliency map，並簡單討論其現象。
(ref: https://reurl.cc/Qpjg8b)

5. (1%) 畫出最後一層的 filters 最容易被哪些 feature activate。
(ref: https://reurl.cc/ZnrgYg)



6. (3%)Refer to math problem
https://hackmd.io/JIZ_0Q3dStSw0t0O0w6Ndw

P1

Q: (B, W, H, input_channels)

$\downarrow$ conv2D (input_channels, out_channels, k_1, k_2, s_1, s_2, p_1, p_2)

A: out (B, out_channels, $\frac{W+2p_1-(k_1-1)}{s_1}$, $\frac{H+2p_2-(k_2-1)}{s_2}$)

[illegible]

P2

$$\begin{cases} \mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i & — ① \\ \sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i-\mu_B)^2 & — ② \\ \hat{x}_i = \frac{x_i-\mu_B}{\sqrt{\sigma_B^2+\epsilon}} & — ③ \\ y_i = \gamma \cdot \hat{x}_i + \beta & — ④ \end{cases}$$

$$\frac{\partial l}{\partial \gamma} = \sum_{i=1}^{m}\frac{\partial l}{\partial y_i}\frac{\partial y_i}{\partial \gamma} \overset{④}{=} \sum_{i=1}^{m}\frac{\partial l}{\partial y_i}\hat{x}_i$$

$$\frac{\partial l}{\partial \beta} = \sum_{i=1}^{m}\frac{\partial l}{\partial y_i}\frac{\partial y_i}{\partial \beta} \overset{④}{=} \sum_{i=1}^{m}\frac{\partial l}{\partial y_i}$$

$$\frac{\partial l}{\partial \hat{x}_i} = \frac{\partial l}{\partial y_i}\frac{\partial y_i}{\partial \hat{x}_i} \overset{④}{=} \frac{\partial l}{\partial y_i}\gamma$$

$$\frac{\partial l}{\partial x_i} = \frac{\partial l}{\partial \hat{x}_i}\frac{\partial \hat{x}_i}{\partial x_i} + \frac{\partial l}{\partial \mu_B}\frac{\partial \mu_B}{\partial x_i} + \frac{\partial l}{\partial \sigma_B^2}\frac{\partial \sigma_B^2}{\partial x_i} \xrightarrow{①②③} \frac{\partial l}{\partial \hat{x}_i}\frac{1}{\sqrt{\sigma_B^2+\epsilon}} + \frac{\partial l}{\partial \mu_B}\frac{1}{m} + \frac{\partial l}{\partial \sigma_B^2}\frac{2}{m}(x_i-\mu_B)$$

$$\frac{\partial l}{\partial \sigma_B^2} = \frac{\partial l}{\partial \hat{x}_i}\frac{\partial \hat{x}_i}{\partial \sigma_B^2} \overset{③}{=} \sum_{i=1}^{m}\frac{\partial l}{\partial \hat{x}_i}\cdot -\frac{1}{2}(x_i-\mu_B)(\sigma_B^2+\epsilon)^{-\frac{3}{2}}$$

$$\frac{\partial l}{\partial \mu_B} = \frac{\partial l}{\partial \sigma_B^2}\frac{\partial \sigma_B^2}{\partial \mu_B} + \frac{\partial l}{\partial \hat{x}_i}\frac{\partial \hat{x}_i}{\partial \mu_B} \xrightarrow{②③} \sum_{i=1}^{m}\frac{\partial l}{\partial \sigma_B^2}\frac{-2}{m}(x_i-\mu_B) + \sum_{i=1}^{m}\frac{\partial l}{\partial \hat{x}_i}\frac{-1}{\sqrt{\sigma_B^2+\epsilon}}$$

(P3) $\hat{y_t} = \dfrac{e^{z_t}}{\sum e^{z_i}}$. $L_t(y_t, \hat{y_t}) = -y_t \log \hat{y_t}$. $L(y, \hat{y}) = -\sum_i y_i \log \hat{y_i}$

$$\frac{\partial L_t}{\partial z_t} = \begin{cases} \left(\sum_{i \neq t} \frac{\partial L_i}{\partial \hat{y_i}} \frac{\partial \hat{y_i}}{\partial z_i}\right) \\ + \frac{\partial L_t}{\partial \hat{y_t}} \frac{\partial \hat{y_t}}{\partial z_t} \end{cases} \quad . \quad \frac{\partial \hat{y_t}}{\partial z_t} = \frac{\partial}{\partial z_t}\left(\frac{e^{z_t}}{e^{z_t}+c}\right) = e^{z_t}(e^{z_t}+c)^{-1} - (e^{z_t}+c)^{-2} e^{z_t} e^{z_t}$$

$$= \hat{y_t} - \hat{y_t}^2$$

$$= \begin{cases} \frac{\partial L_t}{\partial \hat{y_t}}(\hat{y_t} - \hat{y_t}^2) \\ + \sum_{i \neq t} \frac{\partial L_i}{\partial \hat{y_i}} \frac{\partial \hat{y_i}}{\partial z_i} \end{cases} \quad , \quad \frac{\partial L_t}{\partial \hat{y_t}} = \frac{\partial}{\partial \hat{y_t}}(-y_t \log \hat{y_t})$$

$$= \left[y_t - y_t \hat{y_t} - \sum_{i \neq t} y_i \hat{y_t} \right]$$

$$= -\left[y_t(1 - \hat{y_t}) - \sum_{i \neq t} y_i \hat{y_t} \right]$$

$$= -\left[y_t - \hat{y_t} y_t - \hat{y_t} \sum_{i \neq k} y_i \right]$$

$$= -\left[y_t - \hat{y_t} \left(\sum_i y_i\right) \right]$$

$$= \hat{y_t} - y_t$$