

ML hw3 report

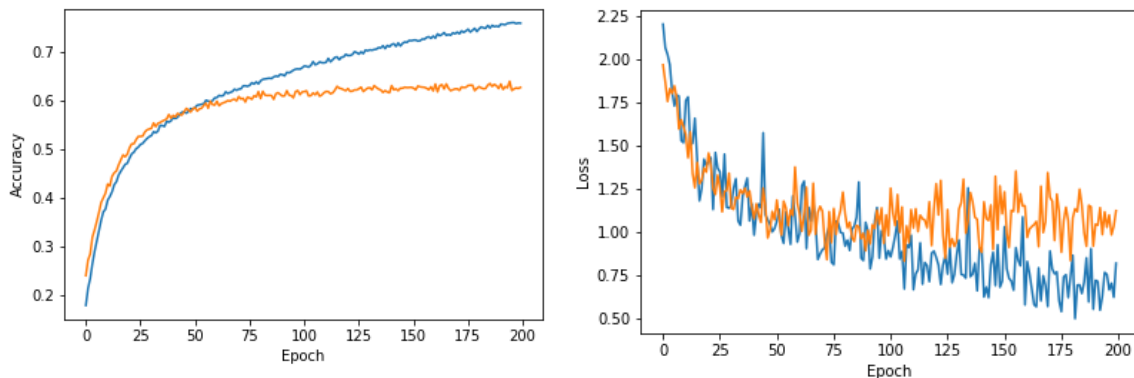
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(1%) 請說明這次使用的model架構，包含各層維度及連接方式。

這次的model我是用四層CNN加上三層fully connected。第一層出去的channel是64層，之後經過Leaky ReLu, batch normalization, max pool(2,2)與dropout 25%。

第二層出去的channel是128層，之後經過Leaky ReLu, batch normalization, max pool(2,2)與dropout 30%。第三層出去的channel是512層，之後經過Leaky ReLu, batch normalization, max pool(2,2)與dropout 35%。第四層出去的channel是512層，之後經過Leaky ReLu, batch normalization, max pool(2,2)與dropout 40%。之後打參數攤平，連接到三層dense，第一層從512*3*3維到512維，之後經過ReLu, batch normalization, 與dropout 50%。第二層從512維到512維，之後經過ReLu, batch normalization, 與dropout 50%。第三層從512維到7維，最後給出分類結果。

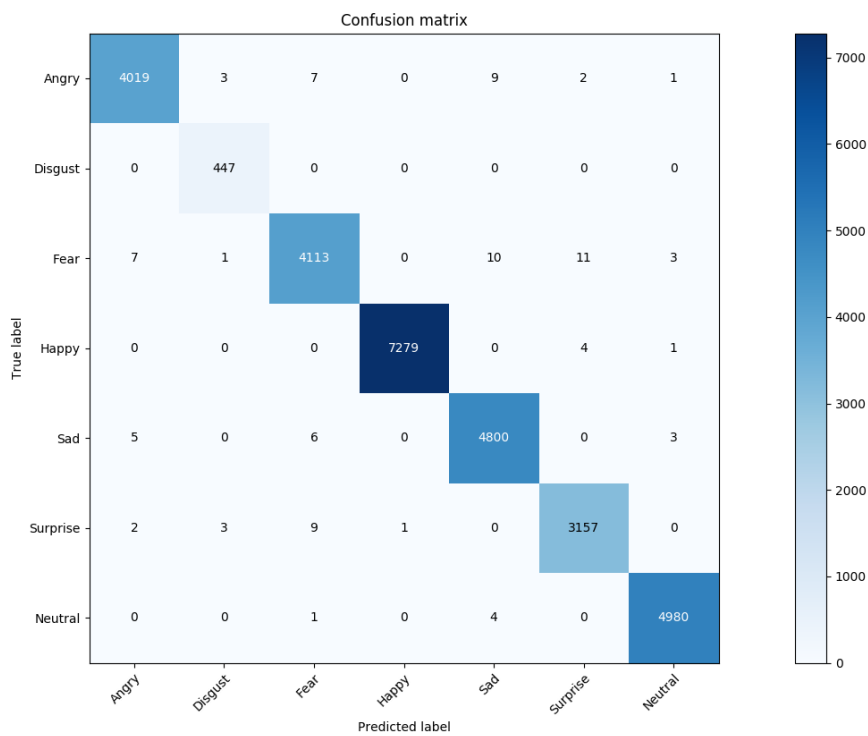
(1%) 請附上model的training/validation history (loss and accuracy)。



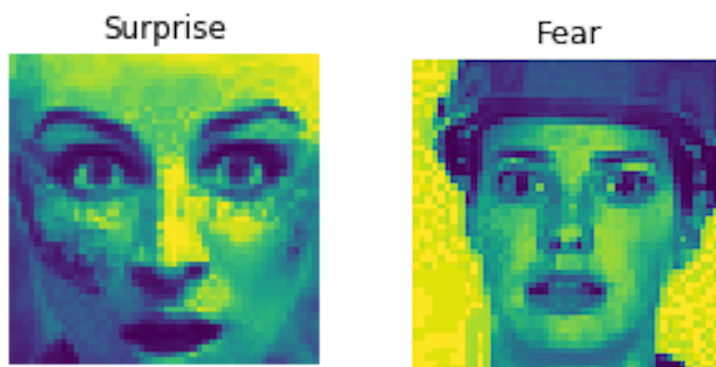
左圖藍線為training accuracy，橘色線為validation accuracy，可以觀察到training accuracy 持續上升，但是validation set從50個epoch後就上升很緩慢。

右圖藍線為training loss，橘色線為validation loss (loss為cross entropy)，validation set從100個epoch後就下降的不太明顯。

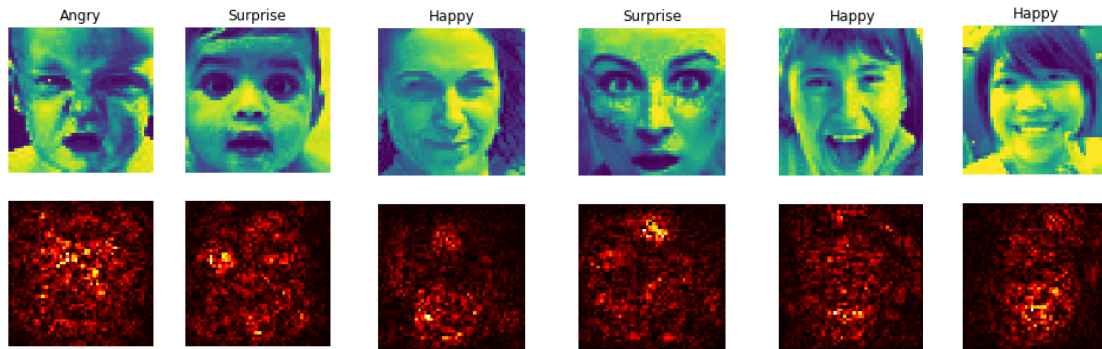
(1%) 畫出confusion matrix分析哪些類別的圖片容易使model搞混，並簡單說明。



由上圖可以看出 Sad & Fear, Surprise & Fear, Sad & Angry, Fear & Angry 是幾個比較容易搞混的類型。以分錯最多的 Surprise & Fear 為例，兩者都會瞪大眼睛和張嘴巴，連人看都不見得能區分，所以模型也容易搞混。



(1%) 畫出CNN model的saliency map，並簡單討論其現象。



上圖中saliency map的亮處代表我的模型focus圖片的部分。可以觀察到，model比較會focus在臉部，尤其五官處更明顯，例如第一張憤怒的圖著重在皺起的眉頭與眼睛，第二、四張驚訝的圖模型捕捉到瞪大的眼睛，第三、五、六張快樂的圖則著重在笑的嘴吧。

(1%) 畫出最後一層的filters最容易被哪些feature activate。

(3%)Refer to math problem

1. (output_channels, $\frac{W-k_1+p_1+S_1}{S_1}$, $\frac{H-k_2+p_2+S_2}{S_2}$)

2.

$$Q = F_2(F_1(u, \theta_1), \theta_2)$$

$$\text{where } \theta = \arg \min_{\theta} \frac{1}{N} \sum_{i=1}^N \ell(x_i, \theta)$$

$$\frac{\partial \ell}{\partial \hat{x}_i} = \frac{\partial \ell}{\partial y_i} = \gamma$$

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

$$\frac{\partial \ell}{\partial \mu_B} = \left(\sum_{i=1}^m \frac{\partial \ell}{\partial \hat{x}_i} \cdot \frac{-1}{\sqrt{\sigma_B^2 + \epsilon}} \right) + \frac{\partial \ell}{\partial \sigma_B^2} \sum_{i=1}^m \frac{-2(x_i - \mu_B)}{m}$$

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

$$\frac{\partial \ell}{\partial \gamma} = \sum_{i=1}^m \frac{\partial \ell}{\partial y_i} \cdot \hat{x}_i$$

$$\frac{\partial \ell}{\partial \beta} = \sum_{i=1}^m \frac{\partial \ell}{\partial y_i}$$

3.

$$\frac{\partial L_t}{\partial z_t} = \frac{-\partial y_t \log \hat{y}_t}{\partial z_t} = -y_t \frac{\partial \log \hat{y}_t}{\partial y_t} = -y_t \frac{1}{\hat{y}_t} \frac{\partial \hat{y}_t}{\partial z_t}$$

$$= -\frac{y_t}{\hat{y}_t} \frac{\partial \hat{y}_t}{\partial z_t} = -\frac{y_t}{\hat{y}_t} \hat{y}_t (1 - \hat{y}_t) = -y_t + y_t \hat{y}_t = \hat{y}_t - y_t$$