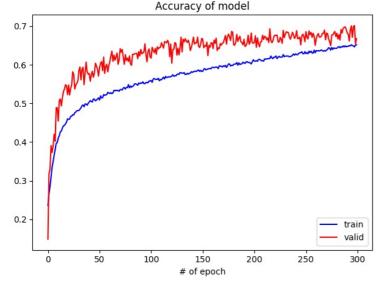
1. 大致 follow VGG16 的結構, 加入 batch normalization, 如下圖 Keras model.summary()

(type) Kaiti SC	0utput	Shape	A- A- A	Param # abc
1_conv1 (Conv2D)	(None,	48, 48,	<sup>2</sup> 64) <sup>A</sup> * <u>*</u>	640 <sup>A</sup> · A
_re_lu_1 (LeakyReLU)	(None,	48, 48,	64)	0
_c1 (BatchNormalization	(None,	48, 48,	64)	256
1_conv2 (Conv2D)	(None,	48, 48,	64)	36928
_re_lu_2 (LeakyReLU)	(None,	48, 48,	64)	of follow V
L_c2 (BatchNormalization	(None,	48, 48,	64) <sup>2</sup> .	256
1_pool (MaxPooling2D)	(None,	24, 24,	64)	0
<pre>&lt;2_conv1 (Conv2D)</pre>	(None,	24, 24,	128)	73856
/_re_lu_3 (LeakyReLU)	(None,	24, 24,	128)	0
_c1 (BatchNormalization	(None,	24, 24,	128)	512
2_conv2 (Conv2D)	(None,	24, 24,	128)	147584
re_lu_4 (LeakyReLU)	(None,	24, 24,	128)	0
_c2 (BatchNormalization	(None,	24, 24,	128)	512
:2_pool (MaxPooling2D)	(None,	12, 12,	128)	0
3_conv1 (Conv2D)	(None,	12, 12,	256)	295168
re_lu_5 (LeakyReLU)	(None,	12, 12,	256)	0
_c1 (BatchNormalization	(None,	12, 12,	256)	1024
3_conv2 (Conv2D)	(None,	12, 12,	256)	590080
re_lu_6 (LeakyReLU)	(None,	12, 12,	256)	0
c2 (BatchNormalization	(None,	12, 12,	256)	1024

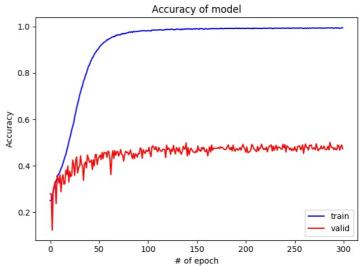
block3_conv3 (Conv2D) iti SC	(None,	12	, 1	2,	256) A~ A	590080 ab
leaky_re_lu_7 (LeakyReLU)	(None,	12	<sup>2</sup> 1	2,	256)	0 A + /
bn_b3_c3 (BatchNormalization	(None,	12	, 1	2,	256)	1024
block3_pool (MaxPooling2D)	(None,	6,	6,	25	 56)	0
block4_conv1 (Conv2D)	(None,	6,	6,	51	12)	1180160
leaky_re_lu_8 (LeakyReLU)	(None,	6,	6,	51	12)	follow \
bn_b4_c1 (BatchNormalization	(None,	6,	6,	51	l2) <sup>2</sup> .	2048
block4_conv2 (Conv2D)	(None,	6,	6,	51	12)	2359808
leaky_re_lu_9 (LeakyReLU)	(None,	6,	6,	51	 l2)	0
bn_b4_c2 (BatchNormalization	(None,	6,	6,	51	 l2)	2048
block4_conv3 (Conv2D)	(None,	6,	6,	51	 l2)	2359808
leaky_re_lu_10 (LeakyReLU)	(None,	6,	6,	51	12)	0
bn_b4_c3 (BatchNormalization	(None,	6,	6,	51	l2)	2048
block4_pool (MaxPooling2D)	(None,	3,	3,	51	 l2)	0
block5_conv1 (Conv2D)	(None,	3,	3,	51	 l2)	2359808
leaky_re_lu_11 (LeakyReLU)	(None,	3,	3,	51	12)	0
bn_b5_c1 (BatchNormalization	(None,	3,	3,	51	12)	2048
block5_conv2 (Conv2D)	(None,	3,	3,	51	12)	2359808
leaky_re_lu_12 (LeakyReLU)	(None,	3,	3,	51	12)	0
bn_b5_c2 (BatchNormalization	(None,	3,	3,	51	12)	2048
block5_conv3 (Conv2D)	(None,	3,	3,	51	L2)	2359808

leaky_re_lu_13 (LeakyReLU)	(None,	3, <sup>X</sup> 3,	512) A	* 2	0 A
bn_b5_c3 (BatchNormalization	(None,	3, 3,	512)		2048
block5_pool (MaxPooling2D)	(None,	1, 1,	512)	1	0
flatten (Flatten)	(None,	512)			0
fc1 (Dense)	(None,	4096)		我大	2101248
leaky_re_lu_14 (LeakyReLU)	(None,	4096)		2.	0
dropout_1 (Dropout)	(None,	4096)			0
fc2 (Dense)	(None,	4096)			1678131
leaky_re_lu_15 (LeakyReLU)	(None,	4096)			0
dropout_2 (Dropout)	(None,	4096)			0
fc3 (Dense)	(None,	1000)			4097000
leaky_re_lu_16 (LeakyReLU)	(None,	1000)			0
dropout_3 (Dropout)	(None,	1000)			0
predictions (Dense)	(None,	7)			7007
Total params: 37,716,999 Trainable params: 37,708,551 Non-trainable params: 8,448					

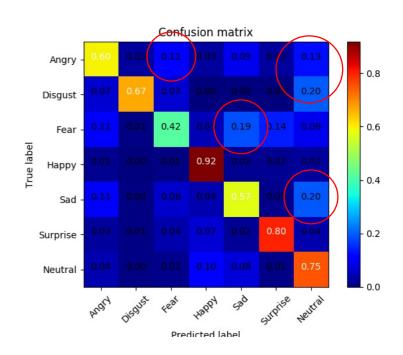


2. 若使用相同參數量的 fc model (模型結構如下圖), validation accuracy 就只能到 0.5 左右(右圖), 但 training accuracy 可以接近 1.0, 直觀來看因為 convolution 可以算是某種形式上的 regularization, 不會如 fully connected 這般 over fitting, 不過可以探討的點或許是加入 dropout 能讓兩者的 performance 接近多少。

performance based on 20-fold cross-validation 可以到 0.7 左右(如左圖), 有個比較特別值得注意的點是加入 batch normalization 之後, 模型的validation accuracy 總是比 training 還高,不過礙於時間因素,還沒能深入探討,猜測或許跟 training 的時候利用 Keras 所提供的 image data generator 來augment data 也有關係。



Layer (type)	0utput	Shape	Param #
dense_1 (Dense)	(None,	2000)	4610000
dense_2 (Dense)	(None,	2000)	4002000
dense_3 (Dense)	(None,	2000)	4002000
dense_4 (Dense)	(None,	2000)	4002000
dense_5 (Dense)	(None,	2000)	4002000
dense_6 (Dense)	(None,	2000)	4002000
dense_7 (Dense)	(None,	1000)	2001000
dense_8 (Dense)	(None,	1000)	1001000
dense_9 (Dense)	(None,	1000)	1001000
dense_10 (Dense)	(None,	1000)	1001000
dense_11 (Dense)	(None,	1000)	1001000
dense_12 (Dense)	(None,	1000)	1001000
dense_13 (Dense)	(None,	1000)	1001000
dense_14 (Dense)	(None,	1000)	1001000
dense_15 (Dense)	(None,	1000)	1001000
dense_16 (Dense)	(None,	1000)	1001000
dense_17 (Dense)	(None,	1000)	1001000
dense_18 (Dense)	(None,	1000)	1001000
dense_19 (Dense)	(None,	512)	512512
dense_20 (Dense)	(None,	128)	65664
dense_21 (Dense)	(None,	7)	903
activation_1 (Activation)	(None,	7)	0

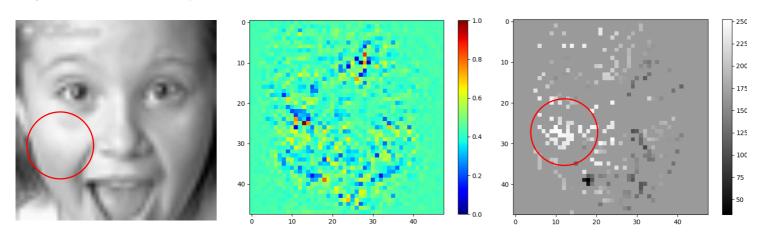


3.
20 fold 的 validation data 所畫出來的 confusion matrix 如上圖, Angry, Disgust 以及 Sad 容易跟 Neutral 混淆, 或許是因為這幾個表情都較為嚴肅, Fear 容易被判為 Sad 或Surprise 則可能是因為害怕通常伴隨著驚訝或是難過。

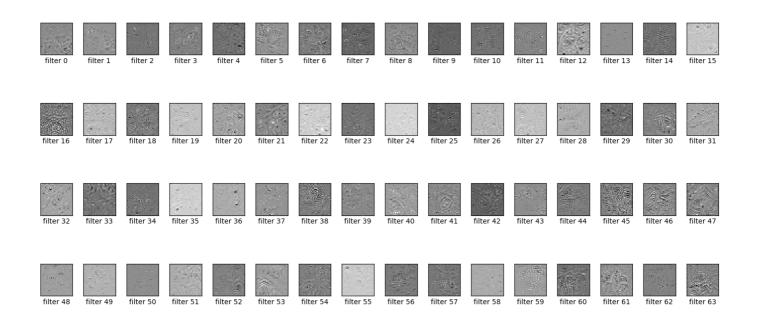
其實在 train 這 dataset 的過程有做了一些 survey, 發現許多結論都是人情緒大多時候是綜合的, 也就是為什麼要 classify 到單一情緒有時候是較為困難的, 而這也跟自己實際下去做的結果蠻吻合的。

4.

依據 neural network 的 gradient 把所有沒超過 0.5 的 pixel 改成 image mean 所畫出來的結果,不過跟我想像中可能會 focus 在眼睛嘴巴的情形似乎相差甚遠,不過可能的解釋是因為 Happy 常常引發笑,所以會 focus 在臉頰的部分。



5. 對第四次 pooing layer 做 gradient ascent 200 次得到的結果,但卻還沒有明顯的人臉樣。而第二層 pooling layer 的結果(下圖)卻有明顯的人臉輪廓,猜想可能跟從 random noise 進行 gradient ascent 有關。



過完第二次 pooling layer 得到的 feature map 畫出來的結果,可以看到很多像是人的臉,且有兩塊像眼睛以及一塊像嘴巴的白色區域。

