```
In [1]: # Convolutional Neural Network
        # Installing Theano
        # pip install --upgrade --no-deps git+git://github.com/Theano/Theano.git
        # Installing Tensorflow
        # Install Tensorflow from the website: https://www.tensorflow.org/versions/r0.
        12/get started/os setup.html
        # Installing Keras
        # pip install --upgrade keras
        # Part 1 - Building the CNN
        # Importing the Keras libraries and packages
        import numpy as np
        import os
        import keras metrics
        from keras.models import Sequential
        from keras.layers import Convolution2D
        from keras.layers import MaxPooling2D
        from keras.layers import Flatten
        from keras.layers import Dense
        from keras.layers import Dropout
        from keras.layers import TimeDistributed
        from keras.layers import LSTM
        from keras.layers import Reshape
        import warnings
        warnings.filterwarnings('ignore')
        # Initialising the CNN
        classifier = Sequential()
        # Step 1 - Convolution
        classifier.add(Convolution2D(64, (3, 3), padding = 'same', input_shape = (128,
         128, 3), activation = 'relu'))
        # Step 2 - Pooling
        classifier.add(MaxPooling2D(pool size = (2, 2)))
        # Adding a second convolutional layer
        classifier.add(Convolution2D(64, (3, 3), padding = 'same', activation = 'relu'
        ))
        classifier.add(MaxPooling2D(pool size = (2, 2)))
        # Adding a third conolutional layer
        classifier.add(Convolution2D(64, (3, 3), padding = 'same', activation = 'relu'
        ))
        classifier.add(MaxPooling2D(pool size = (2, 2)))
        # Step 3 - Flattening
        classifier.add(Flatten())
        classifier.add(Dropout(rate = 0.5))
        # Step 4 - Full connection
```

```
classifier.add(Reshape((4*4, 1024)))
classifier.add(LSTM(units = 50, return_sequences = True, dropout = 0.5))
classifier.add(LSTM(units = 20, return_sequences = False, dropout = 0.5))
classifier.add(Dense(output_dim = 8, activation = 'softmax'))
classifier.summary()
```

Z:\Anaconda3\lib\site-packages\h5py__init__.py:36: FutureWarning: Conversion
of the second argument of issubdtype from `float` to `np.floating` is depreca
ted. In future, it will be treated as `np.float64 == np.dtype(float).type`.
 from ._conv import register_converters as _register_converters
Using TensorFlow backend.

Layer (type)	Output	Shape	Param #
conv2d_1 (Conv2D)	(None,	128, 128, 64)	1792
max_pooling2d_1 (MaxPooling2	(None,	64, 64, 64)	0
conv2d_2 (Conv2D)	(None,	64, 64, 64)	36928
max_pooling2d_2 (MaxPooling2	(None,	32, 32, 64)	0
conv2d_3 (Conv2D)	(None,	32, 32, 64)	36928
max_pooling2d_3 (MaxPooling2	(None,	16, 16, 64)	0
flatten_1 (Flatten)	(None,	16384)	0
dropout_1 (Dropout)	(None,	16384)	0
reshape_1 (Reshape)	(None,	16, 1024)	0
lstm_1 (LSTM)	(None,	16, 50)	215000
lstm_2 (LSTM)	(None,	20)	5680
dense_1 (Dense)	(None,	8)	168

Total params: 296,496 Trainable params: 296,496 Non-trainable params: 0

```
In [2]: # Compiling the CNN
    classifier.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metr
    ics = ['accuracy', keras_metrics.precision(), keras_metrics.recall()])
```

```
In [3]: # Part 2 - Fitting the CNN to the images
        from keras.preprocessing.image import ImageDataGenerator
        train datagen = ImageDataGenerator(rescale = 1./255,
                                            shear_range = 0.2,
                                            zoom range = 0.2,
                                            height shift range = 0.1,
                                            width shift range = 0.1,
                                            channel_shift_range = 10)
        test_datagen = ImageDataGenerator(rescale = 1./255)
        training_set = train_datagen.flow_from_directory('train/',
                                                          target_size = (128, 128),
                                                          batch_size = 32,
                                                          class_mode = 'categorical')
        test_set = test_datagen.flow_from_directory('test/',
                                                     target size = (128, 128),
                                                     batch size = 32,
                                                     class_mode = 'categorical')
```

Found 11880 images belonging to 8 classes. Found 3960 images belonging to 8 classes.

```
Epoch 1/100
c: 0.2082 - precision: 0.0000e+00 - recall: 0.0000e+00 - val loss: 1.8958 - v
al acc: 0.2358 - val precision: 0.0000e+00 - val recall: 0.0000e+00
Epoch 2/100
371/371 [============= ] - 2667s 7s/step - loss: 1.8522 - ac
c: 0.2806 - precision: 0.1188 - recall: 0.0047 - val loss: 1.6662 - val acc:
0.3714 - val precision: 0.6508 - val recall: 0.0487
Epoch 3/100
c: 0.3286 - precision: 0.5181 - recall: 0.0386 - val loss: 1.5928 - val acc:
0.3996 - val_precision: 0.6663 - val_recall: 0.0897
Epoch 4/100
c: 0.3507 - precision: 0.5503 - recall: 0.0613 - val loss: 1.5128 - val acc:
0.4359 - val_precision: 0.7229 - val_recall: 0.1422
Epoch 5/100
c: 0.3817 - precision: 0.6172 - recall: 0.1065 - val_loss: 1.4503 - val_acc:
0.4439 - val precision: 0.6817 - val recall: 0.2260
Epoch 6/100
c: 0.4062 - precision: 0.6256 - recall: 0.1494 - val loss: 1.3575 - val acc:
0.5008 - val_precision: 0.7080 - val_recall: 0.2429
Epoch 7/100
c: 0.4263 - precision: 0.6393 - recall: 0.1845 - val loss: 1.2864 - val acc:
0.5237 - val_precision: 0.7183 - val_recall: 0.3095
Epoch 8/100
c: 0.4549 - precision: 0.6554 - recall: 0.2257 - val_loss: 1.2898 - val_acc:
0.5265 - val precision: 0.7026 - val recall: 0.3149
Epoch 9/100
c: 0.4752 - precision: 0.6654 - recall: 0.2512 - val_loss: 1.2727 - val_acc:
0.5273 - val precision: 0.6915 - val recall: 0.3268
Epoch 10/100
c: 0.4906 - precision: 0.6828 - recall: 0.2837 - val loss: 1.1433 - val acc:
0.5800 - val_precision: 0.7657 - val_recall: 0.3843
Epoch 11/100
c: 0.4980 - precision: 0.6894 - recall: 0.3005 - val loss: 1.1008 - val acc:
0.6081 - val precision: 0.7498 - val recall: 0.4056
Epoch 12/100
c: 0.5190 - precision: 0.6901 - recall: 0.3191 - val_loss: 1.0338 - val_acc:
0.6241 - val_precision: 0.7704 - val_recall: 0.4506
Epoch 13/100
c: 0.5386 - precision: 0.7068 - recall: 0.3522 - val loss: 0.9604 - val acc:
0.6449 - val precision: 0.7755 - val recall: 0.4997
Epoch 14/100
c: 0.5513 - precision: 0.7125 - recall: 0.3716 - val_loss: 1.0064 - val_acc:
0.6372 - val precision: 0.7588 - val recall: 0.4991
Epoch 15/100
```

```
c: 0.5637 - precision: 0.7158 - recall: 0.3854 - val_loss: 0.9004 - val_acc:
0.6754 - val_precision: 0.8100 - val_recall: 0.5311
Epoch 16/100
c: 0.5697 - precision: 0.7179 - recall: 0.4089 - val loss: 0.9148 - val acc:
0.6705 - val precision: 0.7990 - val recall: 0.5225
Epoch 17/100
c: 0.5820 - precision: 0.7294 - recall: 0.4180 - val loss: 0.8941 - val acc:
0.6710 - val_precision: 0.7918 - val_recall: 0.5488
Epoch 18/100
c: 0.5956 - precision: 0.7328 - recall: 0.4434 - val_loss: 0.8375 - val_acc:
0.6957 - val precision: 0.8076 - val recall: 0.5770
Epoch 19/100
c: 0.6028 - precision: 0.7252 - recall: 0.4474 - val_loss: 0.8249 - val_acc:
0.6959 - val precision: 0.7998 - val recall: 0.5875
Epoch 20/100
c: 0.6071 - precision: 0.7361 - recall: 0.4625 - val_loss: 0.8181 - val_acc:
0.6992 - val precision: 0.7862 - val recall: 0.5962
Epoch 21/100
c: 0.6106 - precision: 0.7370 - recall: 0.4666 - val_loss: 0.7737 - val_acc:
0.7157 - val_precision: 0.8043 - val_recall: 0.6290
Epoch 22/100
c: 0.6219 - precision: 0.7387 - recall: 0.4870 - val loss: 0.7216 - val acc:
0.7359 - val_precision: 0.8366 - val_recall: 0.6339
Epoch 23/100
c: 0.6218 - precision: 0.7381 - recall: 0.4859 - val loss: 0.7657 - val acc:
0.7137 - val precision: 0.8047 - val recall: 0.6167
Epoch 24/100
c: 0.6256 - precision: 0.7421 - recall: 0.4955 - val loss: 0.7382 - val acc:
0.7231 - val precision: 0.8015 - val recall: 0.6472
Epoch 25/100
c: 0.6314 - precision: 0.7472 - recall: 0.5085 - val loss: 0.6982 - val acc:
0.7435 - val_precision: 0.8241 - val_recall: 0.6601
Epoch 26/100
c: 0.6440 - precision: 0.7477 - recall: 0.5222 - val loss: 0.6512 - val acc:
0.7672 - val_precision: 0.8601 - val_recall: 0.6702
Epoch 27/100
c: 0.6483 - precision: 0.7504 - recall: 0.5350 - val_loss: 0.6796 - val_acc:
0.7545 - val precision: 0.8215 - val recall: 0.6679
Epoch 28/100
c: 0.6634 - precision: 0.7678 - recall: 0.5497 - val loss: 0.6054 - val acc:
0.7851 - val_precision: 0.8521 - val_recall: 0.7040
Epoch 29/100
```

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c: 0.6605 - precision: 0.7590 - recall: 0.5467 - val loss: 0.5856 - val acc:
0.8013 - val_precision: 0.8615 - val_recall: 0.7112
Epoch 30/100
c: 0.6660 - precision: 0.7627 - recall: 0.5588 - val loss: 0.5722 - val acc:
0.7950 - val_precision: 0.8555 - val_recall: 0.7205
Epoch 31/100
c: 0.6787 - precision: 0.7763 - recall: 0.5741 - val_loss: 0.5908 - val_acc:
0.7846 - val precision: 0.8381 - val recall: 0.7190
Epoch 32/100
c: 0.6754 - precision: 0.7639 - recall: 0.5744 - val loss: 0.5576 - val acc:
0.8063 - val_precision: 0.8669 - val_recall: 0.7303
Epoch 33/100
c: 0.6851 - precision: 0.7728 - recall: 0.5835 - val loss: 0.5804 - val acc:
0.7834 - val_precision: 0.8382 - val_recall: 0.7210
Epoch 34/100
c: 0.6849 - precision: 0.7748 - recall: 0.5895 - val_loss: 0.5643 - val_acc:
0.7957 - val precision: 0.8583 - val recall: 0.7285
Epoch 35/100
c: 0.6862 - precision: 0.7727 - recall: 0.5994 - val_loss: 0.4923 - val_acc:
0.8293 - val_precision: 0.8803 - val_recall: 0.7724
Epoch 36/100
c: 0.6974 - precision: 0.7789 - recall: 0.6055 - val loss: 0.5439 - val acc:
0.8093 - val precision: 0.8683 - val recall: 0.7472
Epoch 37/100
c: 0.7034 - precision: 0.7811 - recall: 0.6140 - val loss: 0.5009 - val acc:
0.8189 - val precision: 0.8723 - val recall: 0.7636
Epoch 38/100
c: 0.7095 - precision: 0.7929 - recall: 0.6276 - val_loss: 0.4711 - val_acc:
0.8316 - val precision: 0.8720 - val recall: 0.7811
Epoch 39/100
c: 0.7110 - precision: 0.7841 - recall: 0.6258 - val loss: 0.4444 - val acc:
0.8505 - val precision: 0.8976 - val recall: 0.8058
Epoch 40/100
c: 0.7106 - precision: 0.7842 - recall: 0.6262 - val_loss: 0.5255 - val_acc:
0.8159 - val precision: 0.8649 - val recall: 0.7601
Epoch 41/100
c: 0.7179 - precision: 0.7920 - recall: 0.6377 - val loss: 0.4430 - val acc:
0.8477 - val_precision: 0.8878 - val_recall: 0.7949
Epoch 42/100
c: 0.7172 - precision: 0.7898 - recall: 0.6386 - val_loss: 0.4100 - val_acc:
0.8616 - val precision: 0.9047 - val recall: 0.8217
Epoch 43/100
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c: 0.7270 - precision: 0.7974 - recall: 0.6472 - val loss: 0.4818 - val acc:

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0.8335 - val precision: 0.8715 - val recall: 0.7934
Epoch 44/100
c: 0.7264 - precision: 0.7959 - recall: 0.6528 - val loss: 0.4663 - val acc:
0.8332 - val precision: 0.8733 - val recall: 0.7973
Epoch 45/100
c: 0.7182 - precision: 0.7875 - recall: 0.6441 - val loss: 0.4603 - val acc:
0.8439 - val_precision: 0.8846 - val_recall: 0.7954
Epoch 46/100
c: 0.7428 - precision: 0.8059 - recall: 0.6693 - val_loss: 0.3989 - val_acc:
0.8598 - val precision: 0.9021 - val recall: 0.8236
Epoch 47/100
c: 0.7414 - precision: 0.8046 - recall: 0.6723 - val loss: 0.4164 - val acc:
0.8472 - val precision: 0.8867 - val recall: 0.8106
Epoch 48/100
c: 0.7460 - precision: 0.8092 - recall: 0.6752 - val loss: 0.3828 - val acc:
0.8699 - val_precision: 0.9013 - val_recall: 0.8293
Epoch 49/100
c: 0.7475 - precision: 0.8090 - recall: 0.6778 - val loss: 0.3757 - val acc:
0.8728 - val_precision: 0.8993 - val_recall: 0.8349
Epoch 50/100
c: 0.7416 - precision: 0.8045 - recall: 0.6712 - val_loss: 0.3686 - val_acc:
0.8755 - val precision: 0.9083 - val recall: 0.8422
Epoch 51/100
c: 0.7536 - precision: 0.8151 - recall: 0.6856 - val loss: 0.4221 - val acc:
0.8507 - val_precision: 0.8771 - val_recall: 0.8245
Epoch 52/100
c: 0.7516 - precision: 0.8119 - recall: 0.6888 - val loss: 0.4660 - val acc:
0.8288 - val_precision: 0.8637 - val_recall: 0.7970
Epoch 53/100
c: 0.7531 - precision: 0.8117 - recall: 0.6869 - val_loss: 0.3474 - val_acc:
0.8858 - val precision: 0.9127 - val recall: 0.8553
Epoch 54/100
c: 0.7601 - precision: 0.8174 - recall: 0.6964 - val loss: 0.4196 - val acc:
0.8583 - val_precision: 0.8886 - val_recall: 0.8288
Epoch 55/100
c: 0.7587 - precision: 0.8152 - recall: 0.6977 - val loss: 0.3367 - val acc:
0.8825 - val_precision: 0.9120 - val_recall: 0.8578
Epoch 56/100
c: 0.7551 - precision: 0.8134 - recall: 0.6986 - val_loss: 0.3325 - val_acc:
0.8883 - val_precision: 0.9177 - val_recall: 0.8641
Epoch 57/100
c: 0.7668 - precision: 0.8242 - recall: 0.7055 - val_loss: 0.4184 - val_acc:
0.8516 - val_precision: 0.8762 - val_recall: 0.8278
```

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Epoch 58/100
c: 0.7636 - precision: 0.8182 - recall: 0.7073 - val loss: 0.3445 - val acc:
0.8825 - val_precision: 0.9037 - val_recall: 0.8575
Epoch 59/100
c: 0.7657 - precision: 0.8178 - recall: 0.7093 - val loss: 0.3016 - val acc:
0.8980 - val_precision: 0.9183 - val_recall: 0.8803
Epoch 60/100
c: 0.7700 - precision: 0.8230 - recall: 0.7178 - val loss: 0.3611 - val acc:
0.8720 - val_precision: 0.8962 - val_recall: 0.8503
Epoch 61/100
c: 0.7635 - precision: 0.8215 - recall: 0.7132 - val loss: 0.2889 - val acc:
0.9080 - val_precision: 0.9293 - val_recall: 0.8871
Epoch 62/100
c: 0.7732 - precision: 0.8268 - recall: 0.7191 - val loss: 0.2999 - val acc:
0.9015 - val precision: 0.9220 - val recall: 0.8770
Epoch 63/100
c: 0.7749 - precision: 0.8240 - recall: 0.7186 - val loss: 0.2917 - val acc:
0.9006 - val_precision: 0.9257 - val_recall: 0.8768
Epoch 64/100
c: 0.7754 - precision: 0.8281 - recall: 0.7229 - val loss: 0.2877 - val acc:
0.9046 - val_precision: 0.9247 - val_recall: 0.8839
Epoch 65/100
c: 0.7758 - precision: 0.8271 - recall: 0.7246 - val_loss: 0.2914 - val_acc:
0.9033 - val_precision: 0.9229 - val_recall: 0.8823
Epoch 66/100
c: 0.7785 - precision: 0.8281 - recall: 0.7303 - val loss: 0.2847 - val acc:
0.9061 - val_precision: 0.9234 - val_recall: 0.8798
Epoch 67/100
c: 0.7812 - precision: 0.8313 - recall: 0.7282 - val loss: 0.2922 - val acc:
0.8989 - val_precision: 0.9195 - val_recall: 0.8800
Epoch 68/100
c: 0.7827 - precision: 0.8326 - recall: 0.7340 - val_loss: 0.3095 - val_acc:
0.8917 - val precision: 0.9134 - val recall: 0.8735
Epoch 69/100
c: 0.7850 - precision: 0.8336 - recall: 0.7348 - val_loss: 0.2782 - val_acc:
0.9017 - val precision: 0.9203 - val recall: 0.8869
Epoch 70/100
c: 0.7867 - precision: 0.8330 - recall: 0.7354 - val loss: 0.2837 - val acc:
0.9023 - val precision: 0.9239 - val recall: 0.8869
Epoch 71/100
c: 0.7902 - precision: 0.8391 - recall: 0.7412 - val_loss: 0.3112 - val_acc:
0.8937 - val_precision: 0.9127 - val_recall: 0.8762
Epoch 72/100
```

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c: 0.7882 - precision: 0.8365 - recall: 0.7423 - val_loss: 0.2508 - val_acc:
0.9180 - val_precision: 0.9328 - val_recall: 0.8973
Epoch 73/100
c: 0.7937 - precision: 0.8397 - recall: 0.7485 - val_loss: 0.2546 - val_acc:
0.9124 - val precision: 0.9299 - val recall: 0.8944
Epoch 74/100
c: 0.7883 - precision: 0.8371 - recall: 0.7439 - val loss: 0.2555 - val acc:
0.9104 - val precision: 0.9303 - val recall: 0.8953
Epoch 75/100
c: 0.7918 - precision: 0.8401 - recall: 0.7473 - val_loss: 0.2571 - val_acc:
0.9149 - val precision: 0.9302 - val recall: 0.8950
Epoch 76/100
c: 0.7969 - precision: 0.8414 - recall: 0.7490 - val loss: 0.2613 - val acc:
0.9085 - val precision: 0.9290 - val recall: 0.8929
Epoch 77/100
c: 0.7989 - precision: 0.8429 - recall: 0.7536 - val_loss: 0.2425 - val_acc:
0.9197 - val precision: 0.9380 - val recall: 0.9048
Epoch 78/100
c: 0.8040 - precision: 0.8486 - recall: 0.7580 - val_loss: 0.2166 - val_acc:
0.9280 - val_precision: 0.9434 - val_recall: 0.9134
Epoch 79/100
c: 0.7993 - precision: 0.8432 - recall: 0.7541 - val loss: 0.2472 - val acc:
0.9220 - val_precision: 0.9354 - val_recall: 0.9063
Epoch 80/100
c: 0.8037 - precision: 0.8400 - recall: 0.7620 - val loss: 0.2310 - val acc:
0.9287 - val precision: 0.9434 - val recall: 0.9090
Epoch 81/100
c: 0.8060 - precision: 0.8494 - recall: 0.7645 - val loss: 0.2527 - val acc:
0.9170 - val precision: 0.9341 - val recall: 0.8975
Epoch 82/100
c: 0.8026 - precision: 0.8462 - recall: 0.7623 - val loss: 0.2836 - val acc:
0.9035 - val_precision: 0.9224 - val_recall: 0.8858
Epoch 83/100
c: 0.8048 - precision: 0.8490 - recall: 0.7644 - val loss: 0.2626 - val acc:
0.9111 - val_precision: 0.9287 - val_recall: 0.8979
Epoch 84/100
c: 0.8133 - precision: 0.8536 - recall: 0.7686 - val_loss: 0.2419 - val_acc:
0.9204 - val precision: 0.9337 - val recall: 0.9055
Epoch 85/100
c: 0.8004 - precision: 0.8413 - recall: 0.7570 - val loss: 0.2470 - val acc:
0.9184 - val_precision: 0.9352 - val_recall: 0.9047
Epoch 86/100
```

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c: 0.8083 - precision: 0.8503 - recall: 0.7656 - val loss: 0.2454 - val acc:
0.9174 - val_precision: 0.9302 - val_recall: 0.9018
Epoch 87/100
c: 0.8160 - precision: 0.8562 - recall: 0.7785 - val loss: 0.2238 - val acc:
0.9259 - val_precision: 0.9377 - val_recall: 0.9121
Epoch 88/100
c: 0.8091 - precision: 0.8529 - recall: 0.7681 - val_loss: 0.2325 - val_acc:
0.9187 - val precision: 0.9352 - val recall: 0.9040
Epoch 89/100
c: 0.8115 - precision: 0.8526 - recall: 0.7723 - val loss: 0.2044 - val acc:
0.9326 - val_precision: 0.9448 - val_recall: 0.9238
Epoch 90/100
c: 0.8122 - precision: 0.8507 - recall: 0.7730 - val loss: 0.2157 - val acc:
0.9291 - val_precision: 0.9409 - val_recall: 0.9157
Epoch 91/100
c: 0.8103 - precision: 0.8509 - recall: 0.7748 - val_loss: 0.2566 - val_acc:
0.9080 - val precision: 0.9241 - val recall: 0.8949
Epoch 92/100
c: 0.8151 - precision: 0.8544 - recall: 0.7733 - val_loss: 0.2435 - val_acc:
0.9230 - val_precision: 0.9350 - val_recall: 0.9064
Epoch 93/100
c: 0.8138 - precision: 0.8525 - recall: 0.7779 - val loss: 0.2037 - val acc:
0.9341 - val precision: 0.9478 - val recall: 0.9212
Epoch 94/100
c: 0.8170 - precision: 0.8540 - recall: 0.7811 - val loss: 0.2309 - val acc:
0.9225 - val precision: 0.9380 - val recall: 0.9087
Epoch 95/100
c: 0.8170 - precision: 0.8557 - recall: 0.7811 - val_loss: 0.2030 - val_acc:
0.9326 - val precision: 0.9441 - val recall: 0.9210
Epoch 96/100
c: 0.8197 - precision: 0.8569 - recall: 0.7808 - val loss: 0.1956 - val acc:
0.9358 - val precision: 0.9490 - val recall: 0.9262
Epoch 97/100
c: 0.8137 - precision: 0.8498 - recall: 0.7771 - val loss: 0.2430 - val acc:
0.9217 - val precision: 0.9337 - val recall: 0.9101
Epoch 98/100
c: 0.8245 - precision: 0.8604 - recall: 0.7880 - val loss: 0.2188 - val acc:
0.9238 - val_precision: 0.9357 - val_recall: 0.9099
Epoch 99/100
c: 0.8164 - precision: 0.8552 - recall: 0.7820 - val_loss: 0.2282 - val_acc:
0.9242 - val precision: 0.9348 - val recall: 0.9131
Epoch 100/100
```

c: 0.8221 - precision: 0.8589 - recall: 0.7844 - val_loss: 0.1977 - val_acc:
0.9354 - val_precision: 0.9498 - val_recall: 0.9251

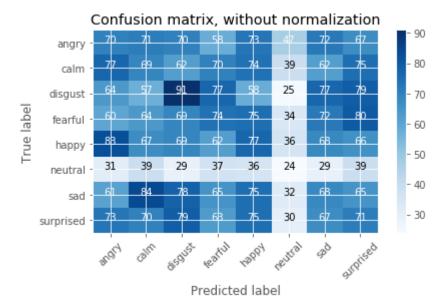
- In [5]: test_steps_per_epoch = np.math.ceil(test_set.samples / test_set.batch_size)
 predictions = classifier.predict_generator(test_set, steps=test_steps_per_epoc
 h)
 predicted_classes = np.argmax(predictions, axis=1)
- In [6]: true_classes = test_set.classes
 class_labels = list(test_set.class_indices.keys())
- In [7]: import sklearn.metrics as metrics
 report = metrics.classification_report(true_classes, predicted_classes, target
 _names=class_labels)
 print(report)

	precision	recall	f1-score	support
angry	0.13	0.13	0.13	528
calm	0.13	0.13	0.13	528
disgust	0.17	0.17	0.17	528
fearful	0.15	0.14	0.14	528
happy	0.14	0.15	0.14	528
neutral	0.09	0.09	0.09	264
sad	0.13	0.13	0.13	528
surprised	0.13	0.13	0.13	528
avg / total	0.14	0.14	0.14	3960

```
In [10]:
         import matplotlib.pyplot as plt
         import itertools
         def plot_confusion_matrix(cm, classes,
                                    normalize=False,
                                    title='Confusion matrix',
                                    cmap=plt.cm.Blues):
              This function prints and plots the confusion matrix.
             Normalization can be applied by setting normalize=True.
             if normalize:
                  cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]*100
                 print("Normalized confusion matrix")
             else:
                 print('Confusion matrix, without normalization')
             print(cm)
             plt.imshow(cm, interpolation='nearest', cmap=cmap, aspect = 'auto')
             plt.title(title)
             plt.colorbar()
             tick_marks = np.arange(len(classes))
             plt.xticks(tick marks, classes, rotation=45)
             plt.yticks(tick_marks, classes)
             fmt = '.2f' if normalize else 'd'
             thresh = cm.max() / 2.
             for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                  plt.text(j, i, format(cm[i, j], fmt),
                           horizontalalignment="center",
                           color="white" if cm[i, j] > thresh else "black")
             plt.tight layout()
             plt.ylabel('True label')
             plt.xlabel('Predicted label')
         # Compute confusion matrix
         cnf matrix = metrics.confusion matrix(true classes, predicted classes)
         np.set printoptions(precision=4)
         # Plot non-normalized confusion matrix
         plt.figure()
         plot confusion matrix(cnf matrix, classes=class labels,
                                title='Confusion matrix, without normalization')
         plt.savefig("non_normalized_confusion_matrix_cnn_lstm.png")
         plt.show()
         # Plot normalized confusion matrix
         plt.figure()
         plot confusion matrix(cnf matrix, classes=class labels, normalize=True,
                                title='Normalized confusion matrix')
         plt.savefig("normalized confusion matrix cnn lstm.png")
         plt.show()
```

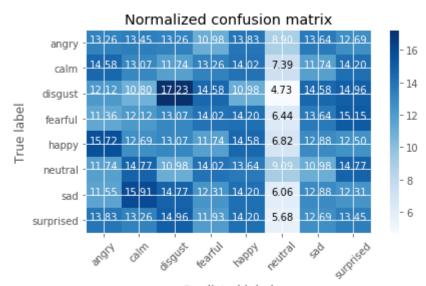
Confusion matrix, without normalization

[[70 71 70 58 73 47 72 67] [77 69 62 70 74 39 62 75] [64 57 91 77 58 25 77 79] [60 64 69 74 75 34 72 80] [83 67 69 62 77 36 68 66] [31 39 29 37 36 24 29 39] [61 84 78 65 75 32 68 65] [73 70 79 63 75 30 67 71]]



Normalized confusion matrix

[[13.2576 13.447 13.2576 10.9848 13.8258 8.9015 13.6364 12.6894]
[14.5833 13.0682 11.7424 13.2576 14.0152 7.3864 11.7424 14.2045]
[12.1212 10.7955 17.2348 14.5833 10.9848 4.7348 14.5833 14.9621]
[11.3636 12.1212 13.0682 14.0152 14.2045 6.4394 13.6364 15.1515]
[15.7197 12.6894 13.0682 11.7424 14.5833 6.8182 12.8788 12.5]
[11.7424 14.7727 10.9848 14.0152 13.6364 9.0909 10.9848 14.7727]
[11.553 15.9091 14.7727 12.3106 14.2045 6.0606 12.8788 12.3106]
[13.8258 13.2576 14.9621 11.9318 14.2045 5.6818 12.6894 13.447]]



```
In [11]: import matplotlib.pyplot as plt
    plt.style.use("ggplot")
    plt.figure()
    N = 100
    plt.plot(np.arange(0, N), results.history["loss"], label="train_loss")
    plt.plot(np.arange(0, N), results.history["val_loss"], label="val_loss")
    plt.plot(np.arange(0, N), results.history["acc"], label="train_acc")
    plt.plot(np.arange(0, N), results.history["val_acc"], label="val_acc")
    plt.title("Training Loss and Accuracy")
    plt.xlabel("Epoch #")
    plt.ylabel("Loss/Accuracy")
    plt.legend(loc="upper left")
    plt.savefig("plot_cnn_lstm.png")
```

