D3: Query Answering Machine

Id	Category	Value	Description
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3	Project Name	***Feeling Artsy***	Extracting human emotions with CV techniques

Below are some general things I've tried before you see what's in this document:

1. I initially used 4 classes. The accuracy are the same as random guessing. I merged image classes to increase the sample size for each class.
2. I initially had only 9 features. The training outcomes are not so ideal. I used polynomial features of them.
3. I initially had very small estimators for ensemble, resulting in poor testing accuracy for Random Forest. I made the estimator larger.
4. I initially had a big gap for CNN. I reduced batch size and increased epochs.

In this section, I chose the following models for my classification task:

- kNN
- Random Forest
- Convolutional Neural Network

D3.1: Process Iterations

I first changed the kernal to DataPreparation kernal to migrate the prepared dataset to here.

In [112…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 805 entries, 0 to 804
Data columns (total 71 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   ID           805 non-null    object
 1   image        805 non-null    object
 2   red          805 non-null    object
 3   green        805 non-null    object
 4   blue         805 non-null    object
 5   rvar         805 non-null    float64
 6   gvar         805 non-null    float64
 7   bvar         805 non-null    float64
 8   rskew        805 non-null    float64
 9   gskew        805 non-null    float64
 10  bskew        805 non-null    float64
 11  rkurt        805 non-null    float64
 12  gkurt        805 non-null    float64
 13  bkurt        805 non-null    float64
 14  1            805 non-null    float64
 15  rvar         805 non-null    float64
 16  gvar         805 non-null    float64
 17  bvar         805 non-null    float64
 18  rskew        805 non-null    float64
 19  gskew        805 non-null    float64
 20  bskew        805 non-null    float64
 21  rkurt        805 non-null    float64
 22  gkurt        805 non-null    float64
 23  bkurt        805 non-null    float64
 24  rvar^2       805 non-null    float64
 25  rvar gvar    805 non-null    float64
 26  rvar bvar    805 non-null    float64
 27  rvar rskew   805 non-null    float64
 28  rvar gskew   805 non-null    float64
 29  rvar bskew   805 non-null    float64
 30  rvar rkurt   805 non-null    float64
 31  rvar gkurt   805 non-null    float64
 32  rvar bkurt   805 non-null    float64
 33  gvar^2       805 non-null    float64
 34  gvar bvar    805 non-null    float64
 35  gvar rskew   805 non-null    float64
 36  gvar gskew   805 non-null    float64
 37  gvar bskew   805 non-null    float64
 38  gvar rkurt   805 non-null    float64
 39  gvar gkurt   805 non-null    float64
 40  gvar bkurt   805 non-null    float64
 41  bvar^2       805 non-null    float64
 42  bvar rskew   805 non-null    float64
 43  bvar gskew   805 non-null    float64
 44  bvar bskew   805 non-null    float64
 45  bvar rkurt   805 non-null    float64
 46  bvar gkurt   805 non-null    float64
 47  bvar bkurt   805 non-null    float64
 48  rskew^2      805 non-null    float64
 49  rskew gskew  805 non-null    float64
 50  rskew bskew  805 non-null    float64
 51  rskew rkurt  805 non-null    float64
 52  rskew gkurt  805 non-null    float64
 53  rskew bkurt  805 non-null    float64
 54  gskew^2      805 non-null    float64
 55  gskew bskew  805 non-null    float64
 56  gskew rkurt  805 non-null    float64
 57  gskew gkurt  805 non-null    float64
 58  gskew bkurt  805 non-null    float64
```

```
 59  bskew^2      805 non-null    float64
 60  bskew rkurt  805 non-null    float64
 61  bskew gkurt  805 non-null    float64
 62  bskew bkurt  805 non-null    float64
 63  rkurt^2      805 non-null    float64
 64  rkurt gkurt  805 non-null    float64
 65  rkurt bkurt  805 non-null    float64
 66  gkurt^2      805 non-null    float64
 67  gkurt bkurt  805 non-null    float64
 68  bkurt^2      805 non-null    float64
 69  HOG          805 non-null    object
 70  label        805 non-null    int64
dtypes: float64(64), int64(1), object(6)
memory usage: 446.6+ KB
```

In [113…

```
hogdf = pd.DataFrame([np.hstack(i) for i in df['HOG']])
hogdf.shape,hogdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 805 entries, 0 to 804
Columns: 10000 entries, 0 to 9999
dtypes: float64(10000)
memory usage: 61.4 MB
```

Out[113]:

```
((805, 10000), None)
```

In [114…

```
# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)
```

Iteration 1: KNN

We humans often see emotions in images by relating them to similar images. For example, when looking at something with very bright colors, we might think it's happy because it relates to the fireworks we see.

As such, K Nearest Neighbors (KNN) model can be applied to perform this classification task. It is a non-parametric model that classifies data by considering its k closest neighbors. It falls under the supervised learning category, so our label can be useful.

Below I define some basic functions and import some libraries.

In [115…

```
from sklearn.model_selection import cross_validate
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
def learn_kNN_classifier(features_data, targets, neighbors, voting):
    '''Set up a K-NN classifier and fits it to the given training data.
       Return: learned classifier.'''

    classifier = KNeighborsClassifier(n_neighbors=neighbors,
                                      weights=voting
                                      )
    classifier.fit(features_data, targets)

    return classifier
```

Below I define features and labels for training

In [116…
```
features = pd.concat([df.iloc[:,5:69],hogdf],axis=1)
labels = df['label']
features.columns = features.columns.astype(str)
```

Below I use cross-validation to find the best k for kNN.

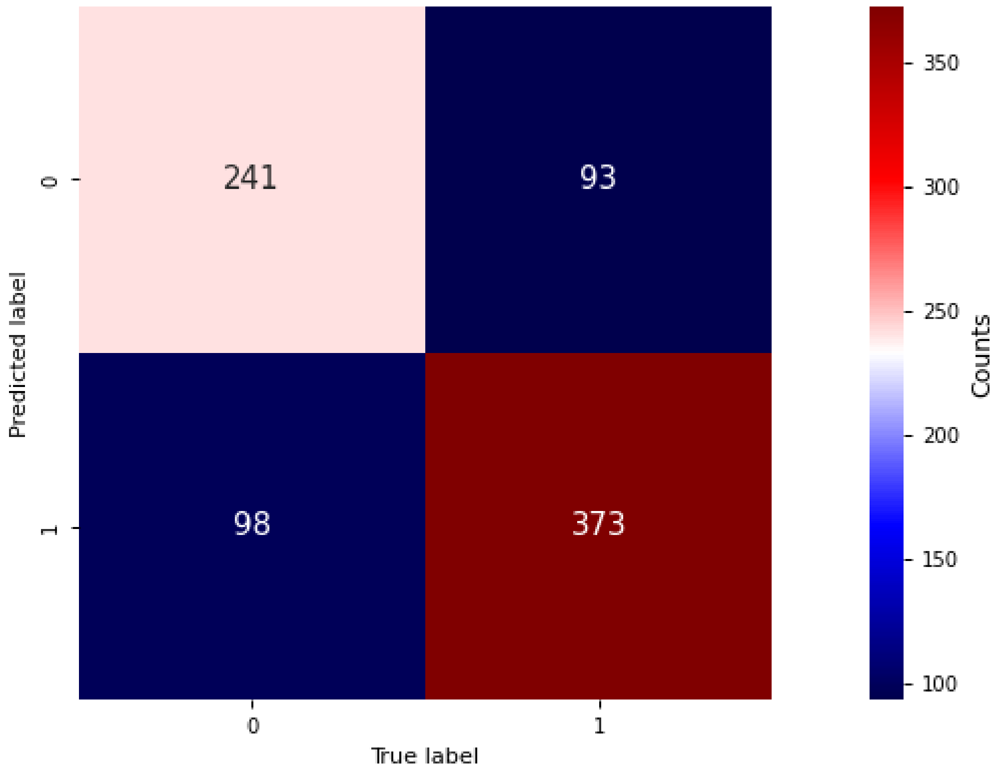
In [117…
```
from sklearn import metrics

k_fold = 10

for k in [2,3,4,5,6,7,8,9]:

    classifier = learn_kNN_classifier(features,
                                      labels,
                                      k,
                                      'uniform')

    # if not specified either, K-Fold is the default CV method
    # and the cv argument specifies the number of foldings
    cv_results = cross_validate(classifier, features, labels,
                                cv=k_fold,
                                return_train_score=True)

    print('[{}-NN] Mean test score: {:.3f} (std: {:.3f})'
          '\nMean train score: {:.3f} (std: {:.3f})\n'.format(k,
                                                  np.mean(cv_results['test_score']),
                                                  np.std(cv_results['test_score']),
                                                  np.mean(cv_results['train_score'])
                                                  np.std(cv_results['train_score']))
```

```
[2-NN] Mean test score: 0.607 (std: 0.071)
Mean train score: 0.876 (std: 0.009)

[3-NN] Mean test score: 0.617 (std: 0.072)
Mean train score: 0.841 (std: 0.008)

[4-NN] Mean test score: 0.597 (std: 0.065)
Mean train score: 0.775 (std: 0.011)

[5-NN] Mean test score: 0.629 (std: 0.050)
Mean train score: 0.766 (std: 0.010)

[7-NN] Mean test score: 0.610 (std: 0.061)
Mean train score: 0.740 (std: 0.013)

[8-NN] Mean test score: 0.583 (std: 0.059)
Mean train score: 0.728 (std: 0.015)

[9-NN] Mean test score: 0.590 (std: 0.056)
Mean train score: 0.708 (std: 0.011)
```

The accuracies are a bit low. As k=5 has relatively the highest test and train scores, I would go with k=5 as the best one. Below is the confusion matrix.

In [118…
```
classifier = learn_kNN_classifier(features,
                                  labels,
                                  5,
                                  'uniform')
Y_pred = classifier.predict(features)

from sklearn.metrics import confusion_matrix
```

```
import seaborn as sns

def show_confusion_matrix(true_labels, learned_labels, class_names):

    cmat = confusion_matrix(true_labels, learned_labels)

    plt.figure(figsize=(14, 5))

    plt.tick_params(labelsize=8)


    hm = sns.heatmap(cmat.T, square=True, annot=True, fmt='d', cbar=True,
                     xticklabels=class_names,
                     yticklabels=class_names,
                     cmap="seismic",
                     annot_kws={"size":12}, cbar_kws={'label': 'Counts'})

    # this is to set the last axis of the figure, the colorbar in this case
    hm.figure.axes[-1].yaxis.label.set_size(10) # fontsize of bar label
    hm.figure.axes[-1].tick_params(labelsize=8) # fontsize of ticks labels

    #plt.ylim(10, 0)

    plt.xlabel('True label', fontsize=9)
    plt.ylabel('Predicted label', fontsize=9)

    plt.show()

show_confusion_matrix(labels, Y_pred, [0, 1])
```



And because the low accuracy in both training and testing, this suggest that the model is too weak, and I'll considering using a stronger model.

Recall that there were around 350 images with class 0 and 450 images with class 1. It's expected that the model does better at recognizing class 1 images.

In sum, KNN seems to be doing a decent job with maximum accuracy around 0.67. Can we do better with another classifier?

Iteration 2: Random Forest

Let's see what Random Forest does for us.

As we see form KNN (which was a weak model for the task), it's better to use ensemble method to increase the model complexity in order to achieve better performance.

Random Forest is such an ensemble method that uses a bunch of decision tree models. For a decision tree, each internal node contains a criteria for subdividing samples from its parents. On its leaves, there would be labels that correspond to outcomes. In this case, we use a classification tree.

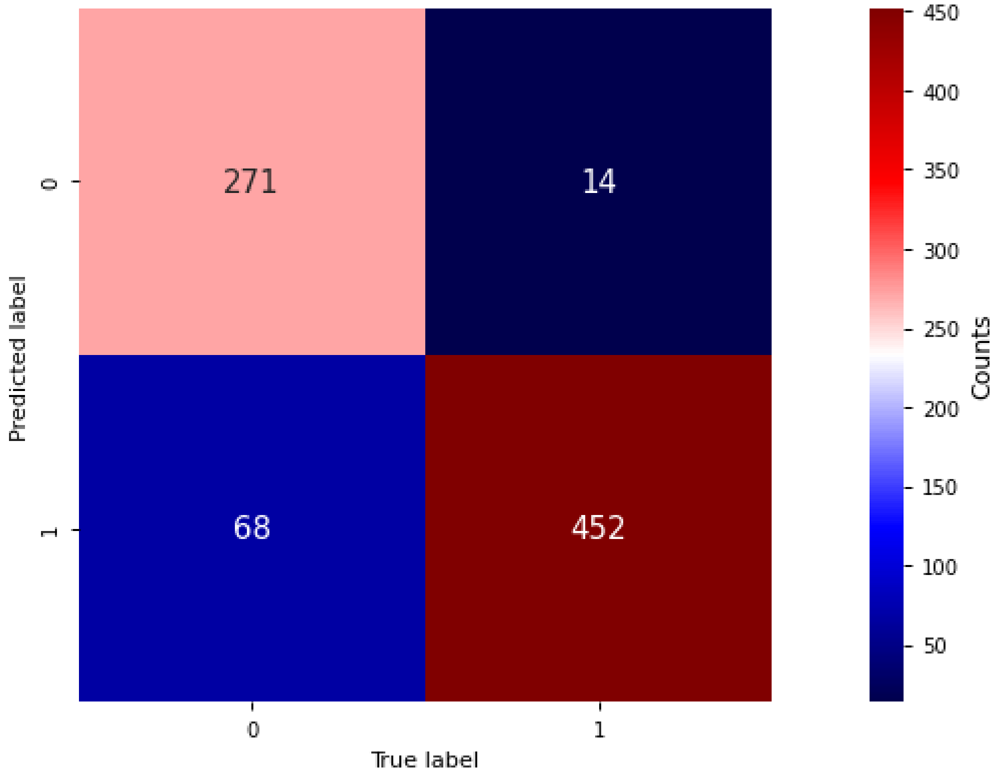
In [278…

```
from sklearn.tree import DecisionTreeClassifier

k_fold = 10
max_samples  = 0.3 # small sample size to reduce calculation
max_features = 0.7 # fewer features selected to increase diversity
n_estimators = 21 # that's how it's a forest

for depth in [5,7,9]:
    start = time.time()
    base = DecisionTreeClassifier(criterion='gini', max_depth=depth,
                                  random_state=15288)
    classifier = BaggingClassifier(base, n_estimators=n_estimators,
                              max_samples=max_samples, max_features=max_features,
                              random_state=15288)

    cv_results = cross_validate(classifier, features, labels,
                                cv=k_fold,
                                return_train_score=True)

    print('[Random Forest of depth {}] Mean test score: {:.3f} (std: {:.3f})'
          '\nMean train score: {:.3f} (std: {:.3f})'.format(depth,
                                                   np.mean(cv_results['test_score']),
                                                   np.std(cv_results['test_score']),
                                                   np.mean(cv_results['train_score'])
                                                   np.std(cv_results['train_score']))
    print('Time elapsed: {:.2f} seconds\n'.format(time.time()-start))
```

```
[Random Forest of depth 5] Mean test score: 0.614 (std: 0.047)
Mean train score: 0.880 (std: 0.014)
Time elapsed: 88.45 seconds

[Random Forest of depth 7] Mean test score: 0.647 (std: 0.036)
Mean train score: 0.894 (std: 0.009)
Time elapsed: 99.60 seconds

[Random Forest of depth 9] Mean test score: 0.624 (std: 0.042)
Mean train score: 0.899 (std: 0.006)
Time elapsed: 102.45 seconds
```

After some cross validation, max depth of 7 seems to be the most optimal. Let's see its confusion matrix.

In [279…
```
base = DecisionTreeClassifier(criterion='gini', max_depth=7,
                              random_state=15288)
classifier = BaggingClassifier(base, n_estimators=n_estimators,
                               max_samples=max_samples, max_features=max_features,
                               random_state=15288)
classifier.fit(features, labels)
Y_pred = classifier.predict(features)

show_confusion_matrix(labels, Y_pred, [0, 1])
```



For Random Forest, the confusion matrix looks a lot better than the kNN. However, the generalization error is around the same as that of kNN. Considering Decision Tree to be a more complex model than kNN, there might be risks of overfitting.

Iteration 3: CNN

From the previous two attempts, we often find the model to be too weak to identify the subtle emotions in images.

Let's see if the all-powerful CNN create miracles. Convolutional Neural Network is commonly used for image related tasks, so I think it could be useful here.

In [128…
```
import time
from time import process_time
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Flatten, Conv2D, MaxPooling2D
from keras.utils import np_utils
import tensorflow as tf
tf.random.set_seed(15288)
```

In [129…
```
model = Sequential()
```

```
# input layer
model.add(Conv2D(128,kernel_size=(7,7),input_shape=(100,100,3),activation='relu'))

# convolutional layer
model.add(Conv2D(64, kernel_size=(5,5), activation='relu'))
model.add(Conv2D(64, kernel_size=(3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(3,3)))
model.add(Dropout(0.2))

# flatten output of conv
model.add(Flatten())

# hidden layer
model.add(Dense(256, activation='relu'))
model.add(Dense(128, activation='relu'))
model.add(Dense(128, activation='relu'))
model.add(Dense(128, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.2))
# output layer
model.add(Dense(2, activation='softmax'))
model.summary()
```

```
Model: "sequential_13"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_51 (Conv2D)          (None, 94, 94, 128)       18944     
                                                                 
 conv2d_52 (Conv2D)          (None, 90, 90, 64)        204864    
                                                                 
 conv2d_53 (Conv2D)          (None, 88, 88, 64)        36928     
                                                                 
 max_pooling2d_17 (MaxPoolin  (None, 29, 29, 64)       0         
 g2D)                                                            
                                                                 
 dropout_31 (Dropout)        (None, 29, 29, 64)        0         
                                                                 
 flatten_13 (Flatten)        (None, 53824)             0         
                                                                 
 dense_73 (Dense)            (None, 256)               13779200  
                                                                 
 dense_74 (Dense)            (None, 128)               32896     
                                                                 
 dense_75 (Dense)            (None, 128)               16512     
                                                                 
 dense_76 (Dense)            (None, 128)               16512     
                                                                 
 dense_77 (Dense)            (None, 64)                8256      
                                                                 
 dropout_32 (Dropout)        (None, 64)                0         
                                                                 
 dense_78 (Dense)            (None, 2)                 130       
                                                                 
=================================================================
Total params: 14,114,242
Trainable params: 14,114,242
Non-trainable params: 0
_________________________________________________________________
```

14 million parameters! Let's see how the model performs.

In [130…

```
model.compile(loss='categorical_crossentropy',
              optimizer='adam', metrics=['accuracy'])
```

In [131…

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(df['image'], df['label'],
                                                    test_size=0.2, random_state=1528
img_shape = (100, 100, 3)

X_train = np.array([x.reshape(img_shape) for x in X_train])
X_test = np.array([x.reshape(img_shape) for x in X_test])
Y_train = np_utils.to_categorical(Y_train, 2)
Y_test = np_utils.to_categorical(Y_test, 2)
X_train.shape,X_test.shape,Y_train.shape,Y_test.shape
```

Out[131]:

```
((644, 100, 100, 3), (161, 100, 100, 3), (644, 2), (161, 2))
```

In [132…

```
# Train
batch_size = 64
epochs = 20

start_time = time.process_time()

training = model.fit(X_train, Y_train,
                     batch_size=batch_size,
                     epochs=epochs,
                     validation_data=(X_test,Y_test),
                     verbose=2)

print('\n\nTraining time: {:.3f} sec\n'.format(time.process_time() - start_time))

score = model.evaluate(X_test, Y_test, verbose=0)

print('Test score:', score[0])
print('Test accuracy:', score[1])
```

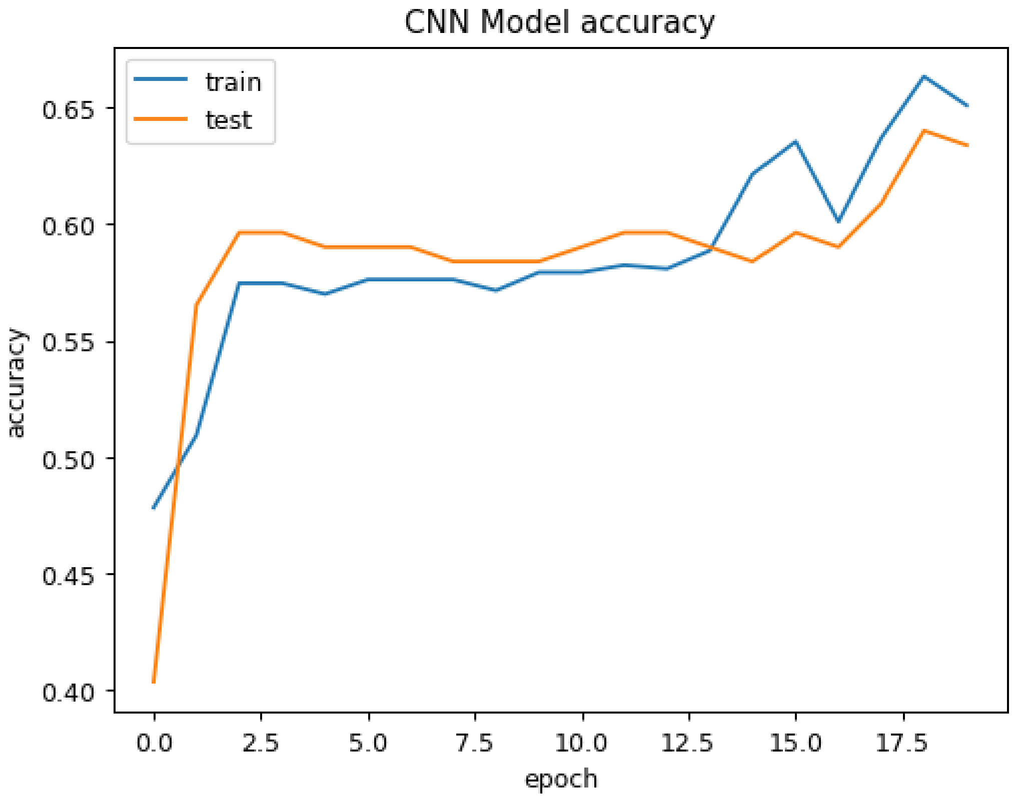
```
Epoch 1/20
11/11 - 22s - loss: 20.7779 - accuracy: 0.4783 - val_loss: 0.8017 - val_accuracy: 0.
4037 - 22s/epoch - 2s/step
Epoch 2/20
11/11 - 20s - loss: 0.7144 - accuracy: 0.5093 - val_loss: 0.6915 - val_accuracy: 0.5
652 - 20s/epoch - 2s/step
Epoch 3/20
11/11 - 19s - loss: 0.6889 - accuracy: 0.5745 - val_loss: 0.6839 - val_accuracy: 0.5
963 - 19s/epoch - 2s/step
Epoch 4/20
11/11 - 14s - loss: 0.6838 - accuracy: 0.5745 - val_loss: 0.6757 - val_accuracy: 0.5
963 - 14s/epoch - 1s/step
Epoch 5/20
11/11 - 14s - loss: 0.7055 - accuracy: 0.5699 - val_loss: 0.6769 - val_accuracy: 0.5
901 - 14s/epoch - 1s/step
Epoch 6/20
11/11 - 14s - loss: 0.6820 - accuracy: 0.5761 - val_loss: 0.6784 - val_accuracy: 0.5
901 - 14s/epoch - 1s/step
Epoch 7/20
11/11 - 14s - loss: 0.6804 - accuracy: 0.5761 - val_loss: 0.6774 - val_accuracy: 0.5
901 - 14s/epoch - 1s/step
Epoch 8/20
11/11 - 14s - loss: 0.6816 - accuracy: 0.5761 - val_loss: 0.6790 - val_accuracy: 0.5
839 - 14s/epoch - 1s/step
Epoch 9/20
11/11 - 14s - loss: 0.6829 - accuracy: 0.5714 - val_loss: 0.6801 - val_accuracy: 0.5
839 - 14s/epoch - 1s/step
Epoch 10/20
11/11 - 14s - loss: 0.6770 - accuracy: 0.5792 - val_loss: 0.6789 - val_accuracy: 0.5
839 - 14s/epoch - 1s/step
Epoch 11/20
11/11 - 14s - loss: 0.6713 - accuracy: 0.5792 - val_loss: 0.6763 - val_accuracy: 0.5
901 - 14s/epoch - 1s/step
Epoch 12/20
11/11 - 14s - loss: 0.6695 - accuracy: 0.5823 - val_loss: 0.6721 - val_accuracy: 0.5
963 - 14s/epoch - 1s/step
Epoch 13/20
11/11 - 14s - loss: 0.6514 - accuracy: 0.5807 - val_loss: 0.7392 - val_accuracy: 0.5
963 - 14s/epoch - 1s/step
Epoch 14/20
11/11 - 15s - loss: 0.6270 - accuracy: 0.5885 - val_loss: 0.6879 - val_accuracy: 0.5
901 - 15s/epoch - 1s/step
Epoch 15/20
11/11 - 14s - loss: 0.5871 - accuracy: 0.6211 - val_loss: 0.7100 - val_accuracy: 0.5
839 - 14s/epoch - 1s/step
Epoch 16/20
11/11 - 14s - loss: 0.5695 - accuracy: 0.6351 - val_loss: 0.8513 - val_accuracy: 0.5
963 - 14s/epoch - 1s/step
Epoch 17/20
11/11 - 14s - loss: 0.5831 - accuracy: 0.6009 - val_loss: 0.7351 - val_accuracy: 0.5
901 - 14s/epoch - 1s/step
Epoch 18/20
11/11 - 14s - loss: 0.5523 - accuracy: 0.6366 - val_loss: 0.8843 - val_accuracy: 0.6
087 - 14s/epoch - 1s/step
Epoch 19/20
11/11 - 14s - loss: 0.5244 - accuracy: 0.6630 - val_loss: 2.1778 - val_accuracy: 0.6
398 - 14s/epoch - 1s/step
Epoch 20/20
11/11 - 14s - loss: 0.5675 - accuracy: 0.6506 - val_loss: 0.7415 - val_accuracy: 0.6
335 - 14s/epoch - 1s/step


Training time: 5477.969 sec
```

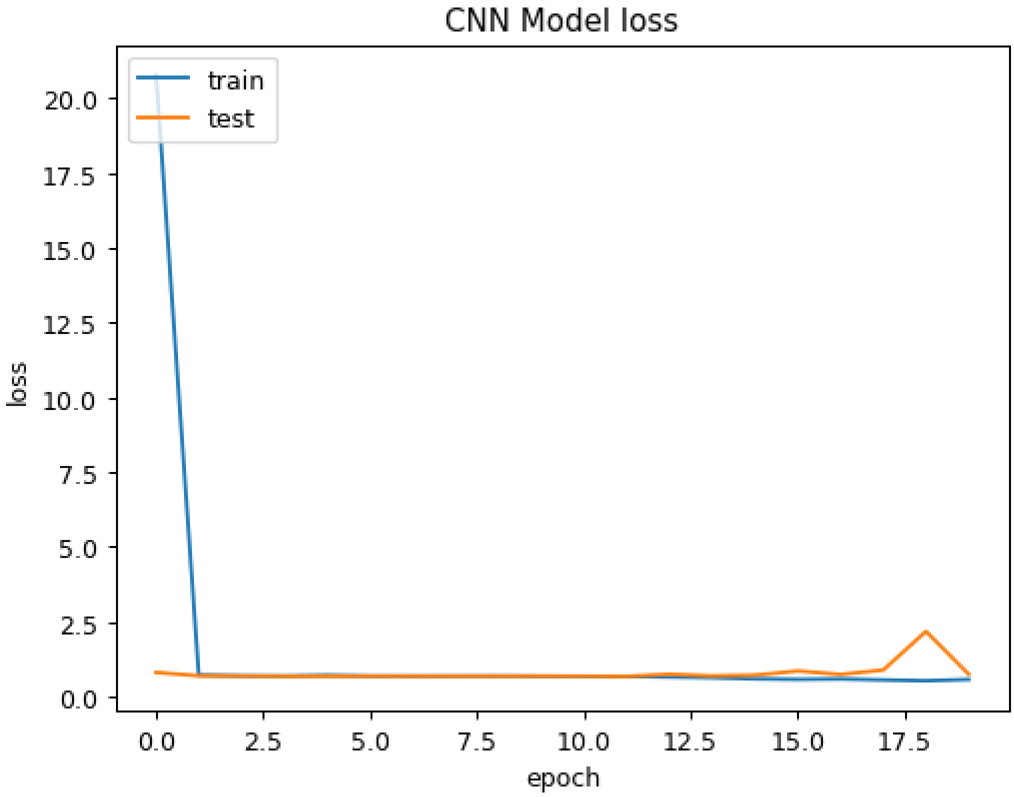
```
Test score: 0.7415297031402588
Test accuracy: 0.6335403919219971
```

In [133…

```
def show_learning_curves(learning_evolution, title=''):

    # list all data stored in the learning_evolution object
    print('Stored information:', [h for h in learning_evolution.history.keys()])

    # show evolution of accuracy
    plt.plot(learning_evolution.history['accuracy'])

    # show evolution of cross-validated accuracy
    if 'val_accuracy' in learning_evolution.history:
        plt.plot(learning_evolution.history['val_accuracy'])

    plt.title(title + ' Model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')

    plt.legend(['train', 'test'], loc='upper left')
    plt.show()

    # show evolution of loss
    plt.plot(learning_evolution.history['loss'])

     # show evolution of cross-validated loss
    if 'val_accuracy' in learning_evolution.history:
        plt.plot(learning_evolution.history['val_loss'])

    plt.title(title + ' Model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()

show_learning_curves(training, 'CNN')
```

```
Stored information: ['loss', 'accuracy', 'val_loss', 'val_accuracy']
```





The model seems to have needed more training time. It might be a good idea to increase the number of epochs.

In [134…

```
from keras.models import Model

def display_activation(activations, activation_index,
                       ncols = 5,
                       size=(12, 12), reshape=None):

    activation = activations[activation_index]

    print('Shape of layer: ', activation.shape)

    if len(activation.shape) > 2:
        total_fmaps = activation.shape[-1] # the last axis of the array
        nrows = int(np.ceil(total_fmaps / ncols))
    else:
        total_fmaps = 1
        nrows,ncols = (1,1)

    feature_map=0

    if (ncols, nrows) == (1,1):
        plt.yticks([], [])
        plt.xticks(fontsize=6)
        if reshape == None:
            plt.imshow(activation[0].reshape(-1,1).T) #cmap='gray')
        else:
            plt.imshow(activation[0].reshape(reshape).T)
        return

    #fig, subplot = plt.subplots(nrows, ncols, figsize=size)
    fig = plt.figure(figsize=size)
    fig.subplots_adjust(hspace=0.23, wspace=0.22)

    for row in range(nrows):
        for col in range(ncols):
```

```
            subplot = fig.add_subplot(nrows, ncols, feature_map+1)
            #subplot[row][col].imshow(activation[0, :, :, feature_map],
            #                         cmap='gray')
            #subplot[row][col].tick_params(labelsize = 3)
            subplot.imshow(activation[0, :, :, feature_map])# cmap='gray')
            subplot.tick_params(labelsize = 3)

            feature_map += 1
            if feature_map == total_fmaps:
                return
```

In [135…

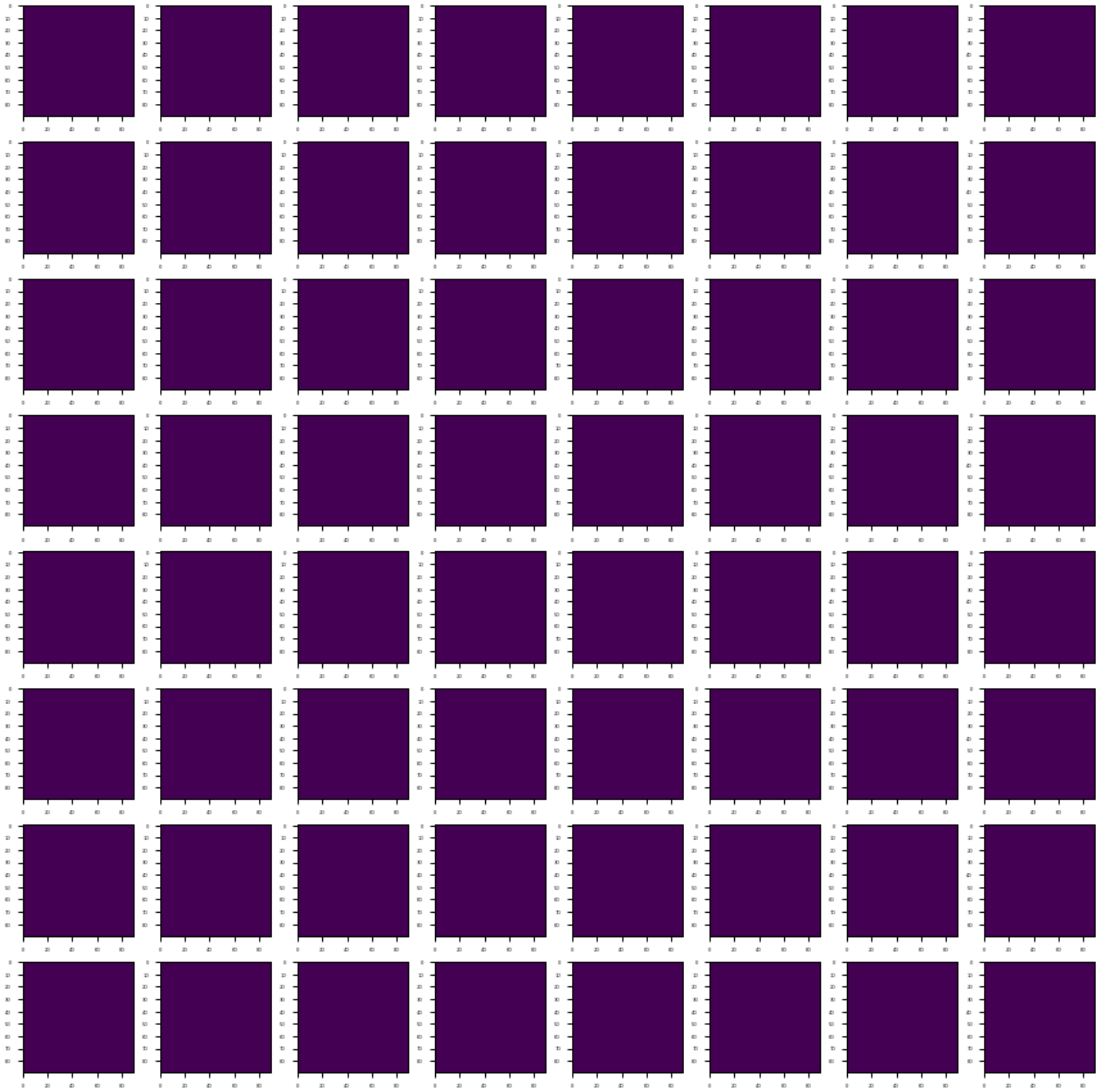
```
layer_outputs = [layer.output for layer in model.layers]

layer_names = [layer.name.split('_')[0] for layer in model.layers]

#print(layer_outputs)

activation_model = Model(inputs=model.input, outputs=layer_outputs)

img_index = 9

img_sample = X_train[img_index].reshape(1, *img_shape)

activations = activation_model.predict(img_sample)

for a,_ in enumerate(activations):
    print('Activation Layer [{}]: {} {}'.format(a, layer_names[a],
                                                activations[a].shape))
```

```
1/1 [==============================] - 0s 78ms/step
Activation Layer [0]: conv2d (1, 94, 94, 128)
Activation Layer [1]: conv2d (1, 90, 90, 64)
Activation Layer [2]: conv2d (1, 88, 88, 64)
Activation Layer [3]: max (1, 29, 29, 64)
Activation Layer [4]: dropout (1, 29, 29, 64)
Activation Layer [5]: flatten (1, 53824)
Activation Layer [6]: dense (1, 256)
Activation Layer [7]: dense (1, 128)
Activation Layer [8]: dense (1, 128)
Activation Layer [9]: dense (1, 128)
Activation Layer [10]: dense (1, 64)
Activation Layer [11]: dropout (1, 64)
Activation Layer [12]: dense (1, 2)
```

In [136…

```
print('Type of layer: ', layer_names[1])
display_activation(activations, 1, 8)
```

```
Type of layer:  conv2d
Shape of layer:  (1, 90, 90, 64)
```



Many of these feature maps don't have anything... Maybe we can reduce the model?

In [357…

```
model = Sequential()

# input + convolutional layer
model.add(Conv2D(128,kernel_size=(7,7),input_shape=(100,100,3),activation='relu'))
model.add(Dropout(0.2))
model.add(Conv2D(64, kernel_size=(5,5), activation='relu'))
model.add(Dropout(0.2))
model.add(Conv2D(32, kernel_size=(3,3), activation='relu'))
model.add(Dropout(0.2))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(32, kernel_size=(7,7), activation='relu'))
model.add(Dropout(0.2))
model.add(Conv2D(16, kernel_size=(5,5), activation='relu'))
model.add(Dropout(0.2))
model.add(Conv2D(16, kernel_size=(3,3), activation='relu'))
model.add(Dropout(0.2))
model.add(MaxPooling2D(pool_size=(2,2)))

# flatten + dense + output layers
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(2, activation='softmax'))
model.summary()
```

```
Model: "sequential_85"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_347 (Conv2D)         (None, 94, 94, 128)       18944     
                                                                 
 dropout_295 (Dropout)       (None, 94, 94, 128)       0         
                                                                 
 conv2d_348 (Conv2D)         (None, 90, 90, 64)        204864    
                                                                 
 dropout_296 (Dropout)       (None, 90, 90, 64)        0         
                                                                 
 conv2d_349 (Conv2D)         (None, 88, 88, 32)        18464     
                                                                 
 dropout_297 (Dropout)       (None, 88, 88, 32)        0         
                                                                 
 max_pooling2d_123 (MaxPooli  (None, 44, 44, 32)       0         
 ng2D)                                                           
                                                                 
 conv2d_350 (Conv2D)         (None, 38, 38, 32)        50208     
                                                                 
 dropout_298 (Dropout)       (None, 38, 38, 32)        0         
                                                                 
 conv2d_351 (Conv2D)         (None, 34, 34, 16)        12816     
                                                                 
 dropout_299 (Dropout)       (None, 34, 34, 16)        0         
                                                                 
 conv2d_352 (Conv2D)         (None, 32, 32, 16)        2320      
                                                                 
 dropout_300 (Dropout)       (None, 32, 32, 16)        0         
                                                                 
 max_pooling2d_124 (MaxPooli  (None, 16, 16, 16)       0         
 ng2D)                                                           
                                                                 
 flatten_81 (Flatten)        (None, 4096)              0         
                                                                 
 dense_330 (Dense)           (None, 64)                262208    
                                                                 
 dense_331 (Dense)           (None, 2)                 130       
                                                                 
=================================================================
Total params: 569,954
Trainable params: 569,954
Non-trainable params: 0
_________________________________________________________________
```

Much fewer parameters! Let's see how it performs.

In [358…

```
adam = tf.keras.optimizers.Adam(learning_rate=0.0005)
model.compile(loss='categorical_crossentropy',
              optimizer=adam, metrics=['accuracy'])
```

In [359…

```
from numpy.random import seed
seed(15288)
# Train
batch_size = 32
epochs = 50

start_time = time.process_time()

training = model.fit(X_train, Y_train,
                     batch_size=batch_size,
```

```
                    epochs=epochs,
                    validation_data=(X_test,Y_test),
                    verbose=2)

print('\n\nTraining time: {:.3f} sec\n'.format(time.process_time() - start_time))

score = model.evaluate(X_test, Y_test, verbose=0)

print('Test score:', score[0])
print('Test accuracy:', score[1])
```

```
Epoch 1/50
21/21 - 16s - loss: 11.5805 - accuracy: 0.4907 - val_loss: 0.6843 - val_accuracy: 0.
6273 - 16s/epoch - 752ms/step
Epoch 2/50
21/21 - 16s - loss: 0.7973 - accuracy: 0.4922 - val_loss: 0.6818 - val_accuracy: 0.6
087 - 16s/epoch - 739ms/step
Epoch 3/50
21/21 - 16s - loss: 0.7170 - accuracy: 0.5683 - val_loss: 0.6696 - val_accuracy: 0.6
398 - 16s/epoch - 754ms/step
Epoch 4/50
21/21 - 16s - loss: 0.7072 - accuracy: 0.5839 - val_loss: 0.6679 - val_accuracy: 0.6
584 - 16s/epoch - 747ms/step
Epoch 5/50
21/21 - 16s - loss: 0.6754 - accuracy: 0.5963 - val_loss: 0.6755 - val_accuracy: 0.6
025 - 16s/epoch - 747ms/step
Epoch 6/50
21/21 - 16s - loss: 0.6770 - accuracy: 0.5978 - val_loss: 0.6712 - val_accuracy: 0.6
211 - 16s/epoch - 741ms/step
Epoch 7/50
21/21 - 16s - loss: 0.6715 - accuracy: 0.6320 - val_loss: 0.6660 - val_accuracy: 0.6
211 - 16s/epoch - 755ms/step
Epoch 8/50
21/21 - 16s - loss: 0.6490 - accuracy: 0.6227 - val_loss: 0.6647 - val_accuracy: 0.6
398 - 16s/epoch - 747ms/step
Epoch 9/50
21/21 - 16s - loss: 0.6416 - accuracy: 0.6444 - val_loss: 0.6572 - val_accuracy: 0.5
963 - 16s/epoch - 748ms/step
Epoch 10/50
21/21 - 16s - loss: 0.6264 - accuracy: 0.6537 - val_loss: 0.6509 - val_accuracy: 0.6
149 - 16s/epoch - 751ms/step
Epoch 11/50
21/21 - 16s - loss: 0.6373 - accuracy: 0.6413 - val_loss: 0.6615 - val_accuracy: 0.5
963 - 16s/epoch - 751ms/step
Epoch 12/50
21/21 - 16s - loss: 0.6030 - accuracy: 0.6786 - val_loss: 0.6277 - val_accuracy: 0.6
522 - 16s/epoch - 745ms/step
Epoch 13/50
21/21 - 16s - loss: 0.6453 - accuracy: 0.6429 - val_loss: 0.6559 - val_accuracy: 0.6
087 - 16s/epoch - 750ms/step
Epoch 14/50
21/21 - 16s - loss: 0.6135 - accuracy: 0.6553 - val_loss: 0.6435 - val_accuracy: 0.6
398 - 16s/epoch - 742ms/step
Epoch 15/50
21/21 - 16s - loss: 0.6507 - accuracy: 0.6087 - val_loss: 0.6492 - val_accuracy: 0.6
273 - 16s/epoch - 753ms/step
Epoch 16/50
21/21 - 16s - loss: 0.6452 - accuracy: 0.6335 - val_loss: 0.6545 - val_accuracy: 0.6
211 - 16s/epoch - 750ms/step
Epoch 17/50
21/21 - 16s - loss: 0.5832 - accuracy: 0.6879 - val_loss: 0.6917 - val_accuracy: 0.6
025 - 16s/epoch - 751ms/step
Epoch 18/50
21/21 - 16s - loss: 0.6892 - accuracy: 0.6413 - val_loss: 0.6538 - val_accuracy: 0.6
025 - 16s/epoch - 747ms/step
Epoch 19/50
21/21 - 16s - loss: 0.6391 - accuracy: 0.6568 - val_loss: 0.6571 - val_accuracy: 0.6
087 - 16s/epoch - 758ms/step
Epoch 20/50
21/21 - 16s - loss: 0.6041 - accuracy: 0.6615 - val_loss: 0.6341 - val_accuracy: 0.6
025 - 16s/epoch - 749ms/step
Epoch 21/50
21/21 - 16s - loss: 0.5691 - accuracy: 0.6755 - val_loss: 0.6277 - val_accuracy: 0.6
025 - 16s/epoch - 777ms/step
Epoch 22/50
```

```
21/21 - 16s - loss: 0.5777 - accuracy: 0.6863 - val_loss: 0.6263 - val_accuracy: 0.6
460 - 16s/epoch - 764ms/step
Epoch 23/50
21/21 - 16s - loss: 0.5616 - accuracy: 0.7081 - val_loss: 0.5826 - val_accuracy: 0.6
335 - 16s/epoch - 747ms/step
Epoch 24/50
21/21 - 16s - loss: 0.5539 - accuracy: 0.7050 - val_loss: 0.5941 - val_accuracy: 0.6
335 - 16s/epoch - 751ms/step
Epoch 25/50
21/21 - 16s - loss: 0.5585 - accuracy: 0.7500 - val_loss: 0.6371 - val_accuracy: 0.5
963 - 16s/epoch - 748ms/step
Epoch 26/50
21/21 - 16s - loss: 0.5064 - accuracy: 0.7453 - val_loss: 0.5900 - val_accuracy: 0.6
770 - 16s/epoch - 758ms/step
Epoch 27/50
21/21 - 16s - loss: 0.5116 - accuracy: 0.7391 - val_loss: 0.5814 - val_accuracy: 0.6
832 - 16s/epoch - 745ms/step
Epoch 28/50
21/21 - 16s - loss: 0.4659 - accuracy: 0.7609 - val_loss: 0.6272 - val_accuracy: 0.6
584 - 16s/epoch - 742ms/step
Epoch 29/50
21/21 - 16s - loss: 0.5259 - accuracy: 0.7360 - val_loss: 0.5490 - val_accuracy: 0.6
832 - 16s/epoch - 746ms/step
Epoch 30/50
21/21 - 16s - loss: 0.4758 - accuracy: 0.7702 - val_loss: 0.5421 - val_accuracy: 0.7
019 - 16s/epoch - 749ms/step
Epoch 31/50
21/21 - 16s - loss: 0.4239 - accuracy: 0.7873 - val_loss: 0.5602 - val_accuracy: 0.6
957 - 16s/epoch - 742ms/step
Epoch 32/50
21/21 - 16s - loss: 0.3873 - accuracy: 0.7857 - val_loss: 0.6235 - val_accuracy: 0.6
708 - 16s/epoch - 749ms/step
Epoch 33/50
21/21 - 16s - loss: 0.4003 - accuracy: 0.7780 - val_loss: 0.5872 - val_accuracy: 0.7
267 - 16s/epoch - 742ms/step
Epoch 34/50
21/21 - 16s - loss: 0.3681 - accuracy: 0.8043 - val_loss: 0.6274 - val_accuracy: 0.6
957 - 16s/epoch - 747ms/step
Epoch 35/50
21/21 - 16s - loss: 0.3512 - accuracy: 0.8292 - val_loss: 0.6185 - val_accuracy: 0.6
522 - 16s/epoch - 743ms/step
Epoch 36/50
21/21 - 16s - loss: 0.3842 - accuracy: 0.8059 - val_loss: 0.5662 - val_accuracy: 0.7
329 - 16s/epoch - 745ms/step
Epoch 37/50
21/21 - 16s - loss: 0.3715 - accuracy: 0.8106 - val_loss: 0.6782 - val_accuracy: 0.6
832 - 16s/epoch - 746ms/step
Epoch 38/50
21/21 - 16s - loss: 0.3418 - accuracy: 0.8261 - val_loss: 0.6930 - val_accuracy: 0.6
584 - 16s/epoch - 744ms/step
Epoch 39/50
21/21 - 16s - loss: 0.3546 - accuracy: 0.8307 - val_loss: 0.7460 - val_accuracy: 0.6
584 - 16s/epoch - 743ms/step
Epoch 40/50
21/21 - 16s - loss: 0.3193 - accuracy: 0.8339 - val_loss: 0.7596 - val_accuracy: 0.6
957 - 16s/epoch - 744ms/step
Epoch 41/50
21/21 - 16s - loss: 0.2700 - accuracy: 0.8680 - val_loss: 0.9553 - val_accuracy: 0.6
708 - 16s/epoch - 747ms/step
Epoch 42/50
21/21 - 16s - loss: 0.4999 - accuracy: 0.7655 - val_loss: 0.6841 - val_accuracy: 0.6
460 - 16s/epoch - 742ms/step
Epoch 43/50
21/21 - 16s - loss: 0.3984 - accuracy: 0.7997 - val_loss: 0.5775 - val_accuracy: 0.7
```

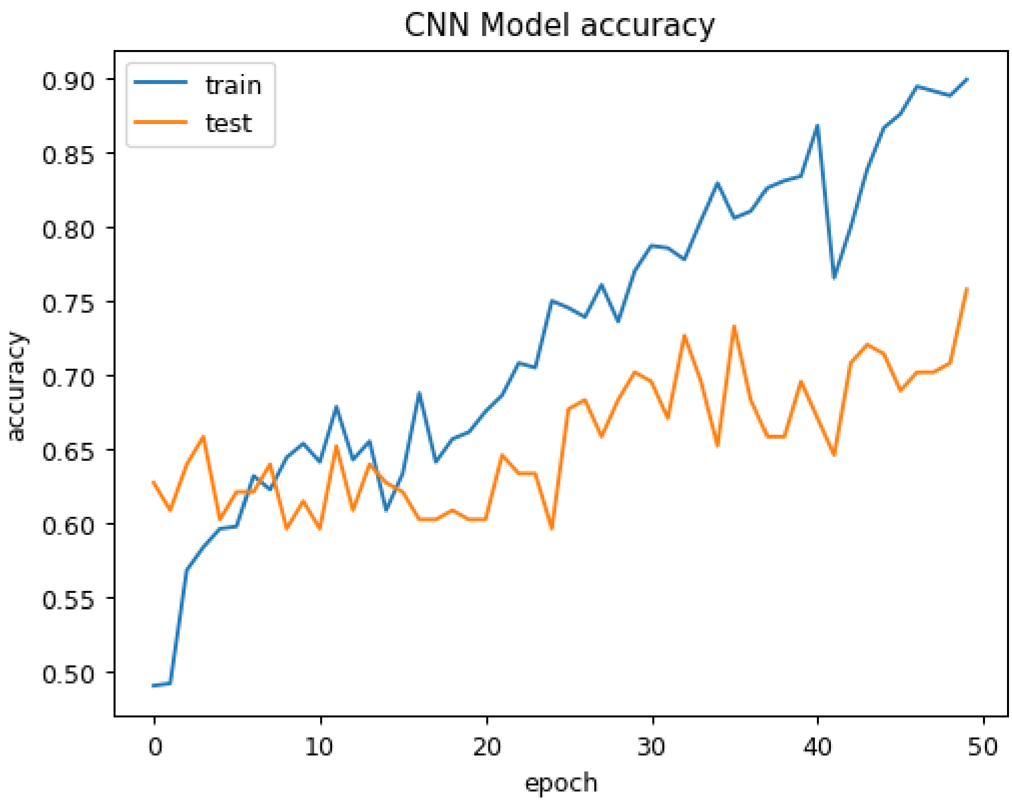
```
081 - 16s/epoch - 746ms/step
Epoch 44/50
21/21 - 16s - loss: 0.3138 - accuracy: 0.8385 - val_loss: 0.5805 - val_accuracy: 0.7
205 - 16s/epoch - 753ms/step
Epoch 45/50
21/21 - 16s - loss: 0.2634 - accuracy: 0.8665 - val_loss: 0.6384 - val_accuracy: 0.7
143 - 16s/epoch - 753ms/step
Epoch 46/50
21/21 - 16s - loss: 0.2396 - accuracy: 0.8758 - val_loss: 0.7045 - val_accuracy: 0.6
894 - 16s/epoch - 747ms/step
Epoch 47/50
21/21 - 16s - loss: 0.2257 - accuracy: 0.8944 - val_loss: 0.8371 - val_accuracy: 0.7
019 - 16s/epoch - 767ms/step
Epoch 48/50
21/21 - 16s - loss: 0.2460 - accuracy: 0.8913 - val_loss: 0.6724 - val_accuracy: 0.7
019 - 16s/epoch - 756ms/step
Epoch 49/50
21/21 - 16s - loss: 0.2096 - accuracy: 0.8882 - val_loss: 1.2223 - val_accuracy: 0.7
081 - 16s/epoch - 751ms/step
Epoch 50/50
21/21 - 16s - loss: 0.2503 - accuracy: 0.8991 - val_loss: 0.5224 - val_accuracy: 0.7
578 - 16s/epoch - 743ms/step


Training time: 14056.797 sec

Test score: 0.5224094986915588
Test accuracy: 0.7577639818191528
```

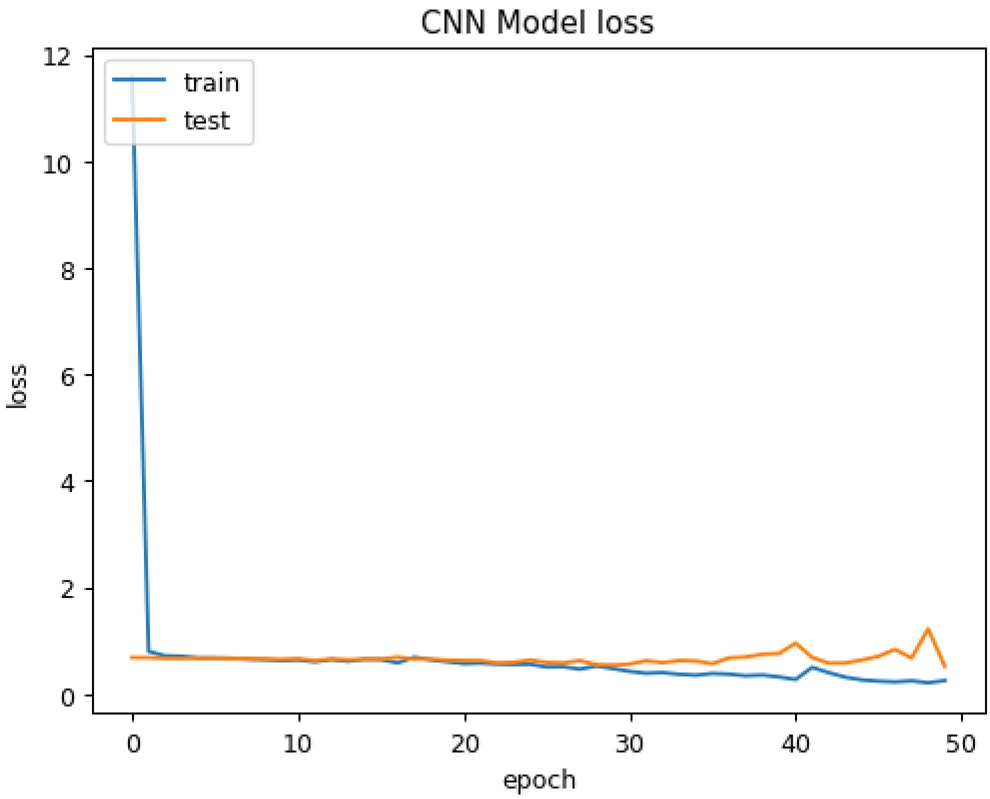
Wow! Testing accuracy is over 75%! CNN is magic indeed!

In [360…

```
show_learning_curves(training, 'CNN')
```

```
Stored information: ['loss', 'accuracy', 'val_loss', 'val_accuracy']
```





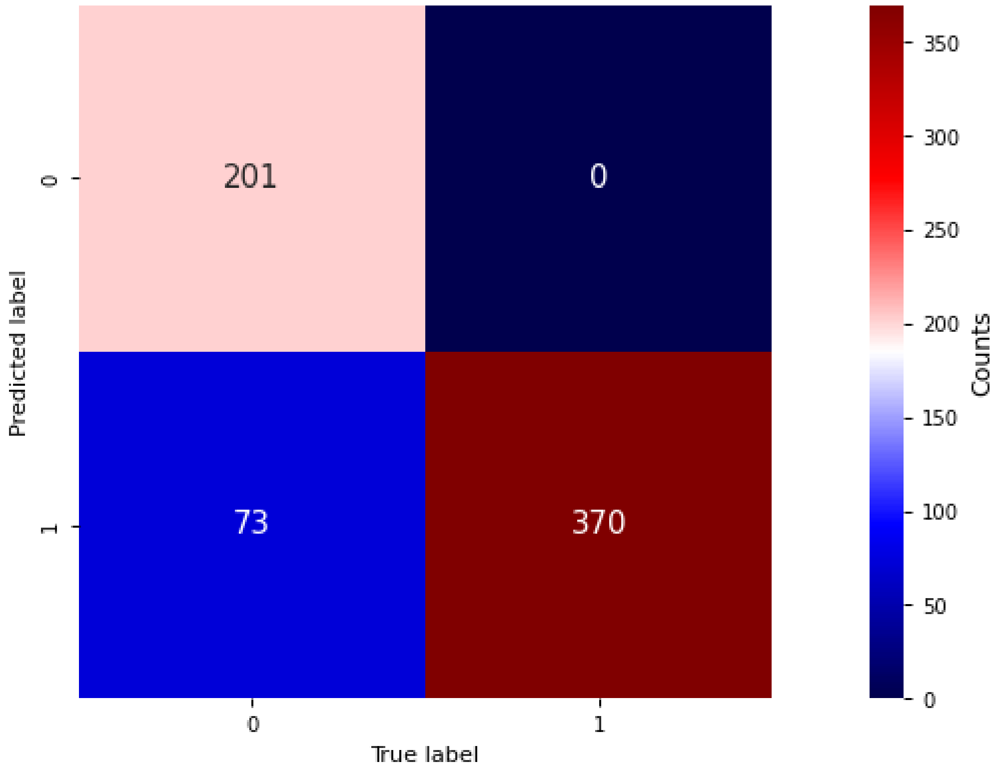
The training curves look a bit stepwise? After 10 epochs, both training and testing accuracy begins to stablize, but the testing error starts to increase. There might be an overfitting happening. However, it is reasonable to say that CNN performed around 10% better than random forest.

Let's see its performance on training data!

In [361…

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

Y_prediction = model.predict(X_train)

# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_prediction, axis = 1)

# Convert test data to one hot vectors
Y_true = np.argmax(Y_train, axis = 1)

show_confusion_matrix(Y_true, Y_pred_classes, [0, 1])
```

```
21/21 [==============================] - 3s 134ms/step
```

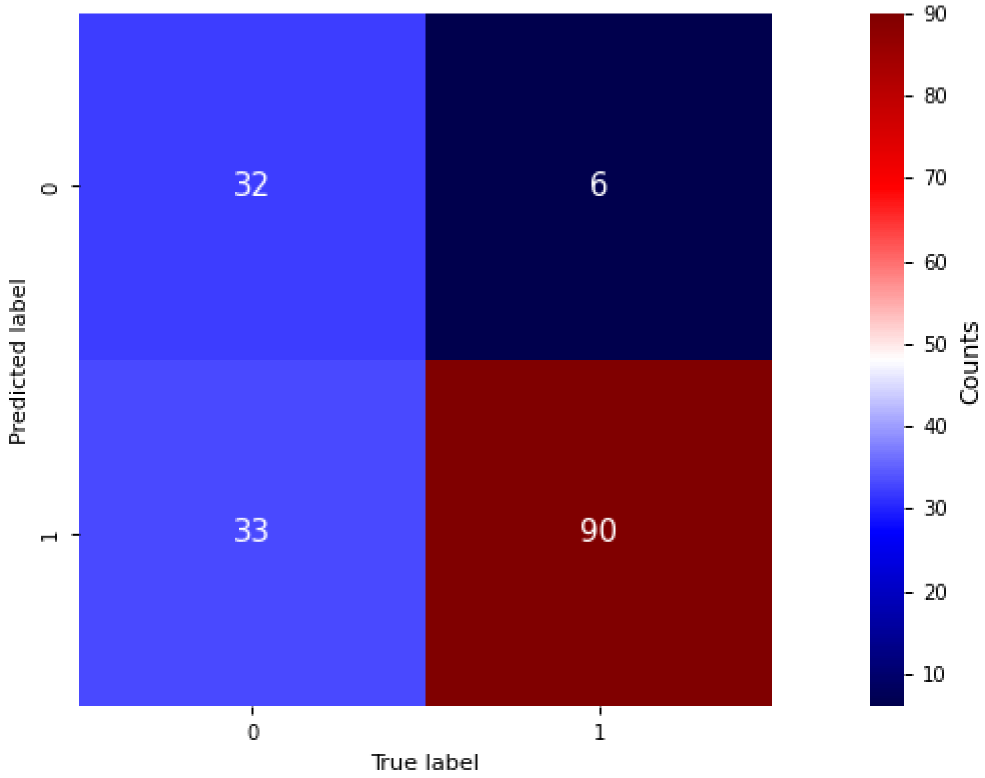


How about for testing data?

In [362…

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

Y_prediction = model.predict(X_test)

# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_prediction, axis = 1)

# Convert test data to one hot vectors
Y_true = np.argmax(Y_test, axis = 1)

show_confusion_matrix(Y_true, Y_pred_classes, [0, 1])
```

```
6/6 [==============================] - 1s 116ms/step
```



Not bad! We see that it rarely misclassify negative images as positive images, but sometimes misclassify positive images as negative ones.

Final words

Id	Model	Parameters	Training accuracy	Testing accuracy
1	kNN	neighbors=5, weights='distance'	0.740	0.629
2	Random Forest	max_depth=7, criterion='gini', n_estimators = 21	0.894	0.647
3	CNN	(see model summary above, epoch 49)	0.899	0.758

Clearly, CNN is the most optimal model for our task. Let's use it in the app!

In [ ]: