

Exercise Instructions:

The goal of this challenge is to train a model that can identify whether a work of art was created by Pablo Picasso or Vincent van Gogh. The dataset provided has a total of 2,000 images. Half of the images were created by Picasso and the other half were created by van Gogh.

The two main goals of this project are to:

1. Create a model and train it OR finetune a pre-trained model
2. Optimize a hyperparameter for the network that you've chosen to use -- Please show the experiments that you used to perform this optimization

Your submission should include:

- A description of what you did
- Why you made the design choices you made
- Analysis and explanation of model performance
- A Jupyter notebook is preferred, but raw code with an accompanying document describing your methods is fine.

```
In [1]: # First import some basic packages
import os
import numpy as np
from shutil import copyfile
import matplotlib.pyplot as plt

# Set randomization seeds constant across training conditions
# this is important for reproducible results and testing influence of different hyperparameters later
from numpy.random import seed
import tensorflow as tf
from tensorflow import set_random_seed
import random as rn
from keras import backend as K

seed(1)
set_random_seed(2)
rn.seed(3)

Using TensorFlow backend.
```

First do some preprocessing to load the dataset and prepare for the input to our neural networks

```
In [2]: # First go through the artist folders and rename to something consistent across files and artists

artist_dir = '/home/arthur/Data/Artists/'

vg_filenames = os.listdir(artist_dir + '/vanGogh')
p_filenames = os.listdir(artist_dir + '/Picasso')

print(str(len(vg_filenames)) + ' Files For VanGogh')
print(str(len(p_filenames)) + ' Files For Picasso')

# Rename the files in each folder
# for ind, filename in enumerate(vg_filenames):
#     file_pre = artist_dir + '/vanGogh/'
#     os.rename(file_pre + filename, file_pre + 'vg_' + str(ind).zfill(4) + '.jpg')

# for ind, filename in enumerate(p_filenames):
#     file_pre = artist_dir + '/Picasso/'
#     os.rename(file_pre + filename, file_pre + 'p_' + str(ind).zfill(4) + '.jpg')

866 Files For VanGogh
1125 Files For Picasso
```

So we don't have even numbers of images for both artists - I want to make sure I use even numbers of samples for the training dataset, but not as concerned about the test set.

Lets start with 500 images for each class for training (1000 total), 200 for validation set (400 total), and the remaining images will be used for the test set

```
In [3]: # We are going to use an image generator during training so we copy the images
# in to training, validation, and test folders to be able to pass them to the model for training

vg_filenames = os.listdir(artist_dir + 'vanGogh/')
p_filenames = os.listdir(artist_dir + 'Picasso/')

vg_filenames.sort()
p_filenames.sort()

vg_train_files = vg_filenames[:500]
vg_val_files = vg_filenames[500:700]
vg_test_files = vg_filenames[700:len(vg_filenames)]

p_train_files = p_filenames[:500]
p_val_files = p_filenames[500:700]
p_test_files = p_filenames[700:len(p_filenames)]

# Copy images to respective directory
# for filename in vg_train_files:
#     vg_dst = artist_dir + 'train_data/vangogh/' + filename
#     vg_src = artist_dir + 'vanGogh/' + filename
#     copyfile(vg_src, vg_dst)

# for filename in vg_val_files:
#     vg_dst = artist_dir + 'val_data/vangogh/' + filename
#     vg_src = artist_dir + 'vanGogh/' + filename
#     copyfile(vg_src, vg_dst)

# for filename in vg_test_files:
#     vg_dst = artist_dir + 'test_data/vangogh/' + filename
#     vg_src = artist_dir + 'vanGogh/' + filename
#     copyfile(vg_src, vg_dst)

# for filename in p_train_files:
#     p_dst = artist_dir + 'train_data/picasso/' + filename
#     p_src = artist_dir + 'Picasso/' + filename
#     copyfile(p_src, p_dst)

# for filename in p_val_files:
#     p_dst = artist_dir + 'val_data/picasso/' + filename
#     p_src = artist_dir + 'Picasso/' + filename
#     copyfile(p_src, p_dst)

# for filename in p_test_files:
#     p_dst = artist_dir + 'test_data/picasso/' + filename
#     p_src = artist_dir + 'Picasso/' + filename
#     copyfile(p_src, p_dst)
```

Now we can build our basic CNN to extract painting features and try to classify the images based on the artist

```
In [4]: import keras
from keras import layers
from keras import models
from keras import optimizers

# 3x3 Conv and 2x2 MaxPool typically work well for CNN architectures (we can stack a few of these layers for our first CNN)
# 5x5 might also be a good one to try, but we could miss some granularity

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))

model.summary()

model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=2e-4),
              metrics=['acc'])
```

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_1 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_2 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_3 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_3 (MaxPooling2D)	(None, 17, 17, 128)	0
flatten_1 (Flatten)	(None, 36992)	0
dense_1 (Dense)	(None, 512)	18940416
dense_2 (Dense)	(None, 1)	513
Total params: 19,034,177		
Trainable params: 19,034,177		
Non-trainable params: 0		

The CNN model constructed above is relatively simple, but has enough conv and maxpool layers that it should be able to extract features across multiple spatial scales.

During model compilation we set the loss to 'binary_crossentropy' which is well suited for binary classification and we are using an optimizer called RMSprop which is an optimized gradient descent algorithm. Another good option for an adaptive optimizer is 'adam'. The learning rate of 2e-4 is a decent starting point but anywhere in a range of 1e-3 to 1e-5 might be good to try, but smaller learning rates can drastically increase training time...

```
In [5]: from keras.preprocessing.image import ImageDataGenerator

# Create a generator for preprocessing the images on the fly during training

# Rescale images to be from 0 -> 1
train_datagen = ImageDataGenerator(rescale=1./255)
val_datagen = ImageDataGenerator(rescale=1./255)

train_dir = artist_dir + 'train_data/'
val_dir = artist_dir + 'val_data/'

# The generators also reshape the images to a constant 150x150 size for the model input
# 150x150 is a decent size for training quickly while still preserving some finer features of the paintings
# Keras uses PIL backend to resize/interpolate images
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(150, 150),
    batch_size=20,
    class_mode='binary')

val_generator = val_datagen.flow_from_directory(
    val_dir,
    target_size=(150, 150),
    batch_size=20,
    class_mode='binary')
```

Found 1000 images belonging to 2 classes.
Found 400 images belonging to 2 classes.

With the image generators we set a couple additional parameters for training the CNN. We are using a target size of 150x150 for the input images, meaning we will have to resize the paintings to fit the square shape. This can be problematic because it will induce stretching or squishing of rectangular images to fit the square, though it is a decent method to start. An alternative would be maintaining the aspect ratios of the images and then padding (adding zeros) around the images to reach the desired input shape, but this zero-padding can be problematic for training.

We also set the class mode at this stage which tells the generator how to assign labels to our folders with images. Since we are just trying to decide between two artists we set the mode to binary. Lastly we set the batch size at this step - this is a balance between large batches that feed the most data in to the network but require increasing amounts of memory and small batches that only allow the model to see small parts of the data at a time and may take longer to train. 20 is an ok place to start, we could try going up to 30/40/50 if our GPU has enough memory, but the dataset is relatively small so training time at this stage isn't really an issue.

```
In [6]: history = model.fit_generator(
    train_generator,
    steps_per_epoch=100, # how many batches we process in a single epoch
    epochs=20, # how many complete iterations over the dataset
    validation_data=val_generator,
    validation_steps=50,
    workers=12) # adding workers lets keras use multiple CPU threads which drastically speeds up image preprocessing
```

```
Epoch 1/20
100/100 [=====] - 11s 110ms/step - loss: 0.6531 - acc: 0.6545 - val_loss: 0.4991 - val_acc: 0.7550
Epoch 2/20
100/100 [=====] - 8s 80ms/step - loss: 0.4827 - acc: 0.7685 - val_loss: 0.5481 - val_acc: 0.7200
Epoch 3/20
100/100 [=====] - 8s 80ms/step - loss: 0.3796 - acc: 0.8340 - val_loss: 0.4854 - val_acc: 0.7730
Epoch 4/20
100/100 [=====] - 8s 84ms/step - loss: 0.3047 - acc: 0.8715 - val_loss: 0.5113 - val_acc: 0.7400
Epoch 5/20
100/100 [=====] - 8s 82ms/step - loss: 0.2305 - acc: 0.9190 - val_loss: 0.5497 - val_acc: 0.7500
Epoch 6/20
100/100 [=====] - 8s 84ms/step - loss: 0.1621 - acc: 0.9415 - val_loss: 0.5320 - val_acc: 0.7770
Epoch 7/20
100/100 [=====] - 8s 80ms/step - loss: 0.1092 - acc: 0.9635 - val_loss: 0.6228 - val_acc: 0.7970
Epoch 8/20
100/100 [=====] - 8s 83ms/step - loss: 0.0952 - acc: 0.9700 - val_loss: 0.7959 - val_acc: 0.7360
Epoch 9/20
100/100 [=====] - 8s 82ms/step - loss: 0.0715 - acc: 0.9765 - val_loss: 0.6205 - val_acc: 0.7850
Epoch 10/20
100/100 [=====] - 8s 84ms/step - loss: 0.0422 - acc: 0.9915 - val_loss: 1.7232 - val_acc: 0.6570
Epoch 11/20
100/100 [=====] - 8s 83ms/step - loss: 0.0494 - acc: 0.9865 - val_loss: 0.8191 - val_acc: 0.7830
Epoch 12/20
100/100 [=====] - 8s 82ms/step - loss: 0.0304 - acc: 0.9920 - val_loss: 1.0876 - val_acc: 0.7490
Epoch 13/20
100/100 [=====] - 8s 83ms/step - loss: 0.0477 - acc: 0.9900 - val_loss: 0.9381 - val_acc: 0.7770
Epoch 14/20
100/100 [=====] - 8s 84ms/step - loss: 0.0130 - acc: 0.9955 - val_loss: 1.4101 - val_acc: 0.7380
Epoch 15/20
100/100 [=====] - 8s 83ms/step - loss: 0.0513 - acc: 0.9880 - val_loss: 1.0642 - val_acc: 0.7800
Epoch 16/20
100/100 [=====] - 8s 82ms/step - loss: 0.0406 - acc: 0.9880 - val_loss: 0.9914 - val_acc: 0.7670
Epoch 17/20
100/100 [=====] - 9s 85ms/step - loss: 0.0176 - acc: 0.9950 - val_loss: 1.1573 - val_acc: 0.7750
Epoch 18/20
100/100 [=====] - 8s 84ms/step - loss: 0.0323 - acc: 0.9935 - val_loss: 1.2088 - val_acc: 0.7930
Epoch 19/20
100/100 [=====] - 8s 81ms/step - loss: 0.0145 - acc: 0.9955 - val_loss: 1.4403 - val_acc: 0.7780
Epoch 20/20
100/100 [=====] - 8s 84ms/step - loss: 0.0089 - acc: 0.9975 - val_loss: 1.4622 - val_acc: 0.7980
```

In [7]: *# Lets make a plotting function to be able to visualize our training curves for our different models*

```
def plot_training(training_history):
    acc = training_history.history['acc']
    val_acc = training_history.history['val_acc']
    loss = training_history.history['loss']
    val_loss = training_history.history['val_loss']

    epochs = range(len(acc))

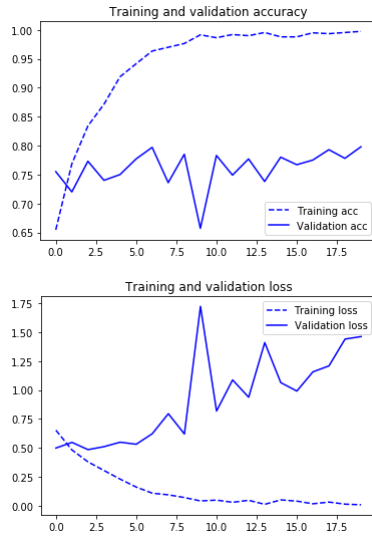
    plt.plot(epochs, acc, 'b--', label='Training acc')
    plt.plot(epochs, val_acc, 'b', label='Validation acc')
    plt.title('Training and validation accuracy')
    plt.legend()

    plt.figure()

    plt.plot(epochs, loss, 'b--', label='Training loss')
    plt.plot(epochs, val_loss, 'b', label='Validation loss')
    plt.title('Training and validation loss')
    plt.legend()

    plt.show()

plot_training(history)
```



In [8]: *# Save model*
 model.save('Artists_v1.h5')

```

In [9]: from sklearn.metrics import confusion_matrix
        from sklearn.metrics import f1_score

        # Finally, how well do we classify on our test set?

        # Confusion Matrix Plot (plotting code from SKlearn examples)
        # https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html#sphx-glr-auto-examples-model-selection-plot-confusion-matrix-py
        def plot_confusion_matrix(y_true, y_pred, classes,
                                   normalize=True,
                                   title=None,
                                   cmap=plt.cm.Blues):
            """
            This function prints and plots the confusion matrix.
            Normalization can be applied by setting 'normalize=True'.
            """
            if not title:
                if normalize:
                    title = 'Normalized confusion matrix'
                else:
                    title = 'Confusion matrix, without normalization'

            # Compute confusion matrix
            cm = confusion_matrix(y_true, y_pred)

            if normalize:
                cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                print("Normalized confusion matrix")
            else:
                print('Confusion matrix, without normalization')

            fig, ax = plt.subplots()
            im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
            ax.figure.colorbar(im, ax=ax)
            # We want to show all ticks...
            ax.set(xticks=np.arange(cm.shape[1]),
                   yticks=np.arange(cm.shape[0]),
                   # ... and label them with the respective list entries
                   xticklabels=classes, yticklabels=classes,
                   title=title,
                   ylabel='True label',
                   xlabel='Predicted label')

            # Rotate the tick labels and set their alignment.
            plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
                     rotation_mode="anchor")

            # Loop over data dimensions and create text annotations.
            fmt = '.2f' if normalize else 'd'
            thresh = cm.max() / 2.
            for i in range(cm.shape[0]):
                for j in range(cm.shape[1]):
                    ax.text(j, i, format(cm[i, j], fmt),
                            ha="center", va="center",
                            color="white" if cm[i, j] > thresh else "black")
            fig.tight_layout()
            return ax

        # Display performance metrics from (Also uses confusion matrix function from Sklearn)
        def perf_eval(test_dir, model):

            test_datagen = ImageDataGenerator(rescale=1./255)

            test_generator = test_datagen.flow_from_directory(
                test_dir,
                target_size=(150, 150),
                batch_size=1,
                class_mode='binary')

            pred_label = []
            actual_label = []
            count = 591
            batch_size = 1

            i = 0
            for inputs_batch, labels_batch in test_generator:
                pred_label.append(round(model.predict(inputs_batch).tolist()[0][0]))
                actual_label.append(round(labels_batch.tolist()[0][0]))
                i += 1
                if i * batch_size >= count:
                    break

            pc, pm, vgm, vgc = confusion_matrix(actual_label, pred_label).ravel()

            print('Test Classification Results:')
            print(' Pred. VanGogh Correct - ' + str(vgc))
            print(' Pred. Picasso Correct - ' + str(pc))
            print(' Pred. VanGogh Miss - ' + str(vgm))
            print(' Pred. Picasso Miss - ' + str(pm))

            print()

            total_accuracy = (vgc + pc) / len(pred_label)
            vg_accuracy = vgc / (vgc + vgm)
            p_accuracy = pc / (pc + pm)

            f1 = f1_score(actual_label, pred_label, labels=['Picasso', 'VanGogh'])

            print('Test Accuracy: ' + str(total_accuracy))
            print('VanGogh Accuracy: ' + str(vg_accuracy))
            print('Picasso Accuracy: ' + str(p_accuracy))
            print('F1 Score: ' + str(f1))
            print()

            plot_confusion_matrix(actual_label, pred_label, classes=['Picasso', 'VanGogh'])

        test_dir = artist_dir + 'test_data/'
        perf_eval(test_dir, model)

```

Found 591 images belonging to 2 classes.

Test Classification Results:

Pred. VanGogh Correct - 127

Pred. Picasso Correct - 337

Pred. VanGogh Miss - 39

Pred. Picasso Miss - 88

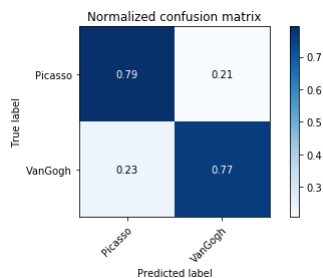
Test Accuracy: 0.7851099830795262

VanGogh Accuracy: 0.7650602409638554

Picasso Accuracy: 0.7929411764705883

F1 Score: 0.6666666666666666

Normalized confusion matrix



So we have an initial model that can predict the artist with ~78% test accuracy

A further breakdown of the classification results above shows the model is slightly skewed as we are better classifying Picasso paintings (80%) compared to VanGogh (75%). Another useful classification metric is the F1 score, which is a weighted average of precision and recall (1 is the best, 0 the worst). We get an F1 score of 0.66 for the current classification results.

But we are starting to overfit pretty early in training (the validation accuracy plateaus and loss increases as the training accuracy approaches 1...). We see our best validation accuracy at only the second epoch

Perhaps the best way to improve the model and reduce overfitting is to get more data. Unfortunately we can't get any more paintings from the artists, but fortunately there are lots of other ways to regularize and improve our models accuracy - to name a few:

1. We could augment the incoming images to create similar, but different paintings to add to the training data.
2. We can add dropout to one or a few of the layers
3. We could try to use a smaller CNN
4. We might use a pre-trained CNN architecture (VGG, ResNet, etc)

Lets first try training the same NN architecture with **image augmentation** to see if we can get test accuracy above 78%

Image augmentation artificially provides more training data by manipulating the training images in a variety of ways like rotating, stretching, zooming, or flipping the images.

```
In [10]: # only augment the training dataset
train_datagen_wAug = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40, # this will rotate the image within a range of 40deg
    width_shift_range=0.2, # the next two will stretch/compress the images
    height_shift_range=0.2,
    shear_range=0.2, # will shear the image
    zoom_range=0.2, # zoom in on image
    horizontal_flip=True,) # can flip the image along the horizontal axis

# Validation set remains the same
val_datagen = ImageDataGenerator(rescale=1./255)

train_dir = artist_dir + 'train_data/'
val_dir = artist_dir + 'val_data/'

train_generator_wAug = train_datagen_wAug.flow_from_directory(
    train_dir,
    target_size=(150, 150),
    batch_size=20,
    class_mode='binary')

val_generator = val_datagen.flow_from_directory(
    val_dir,
    target_size=(150, 150),
    batch_size=20,
    class_mode='binary')
```

Found 1000 images belonging to 2 classes.

Found 400 images belonging to 2 classes.

In [11]: *# Create another model (model_wAug) and see how data augmentation helps with overfitting and test accuracy*

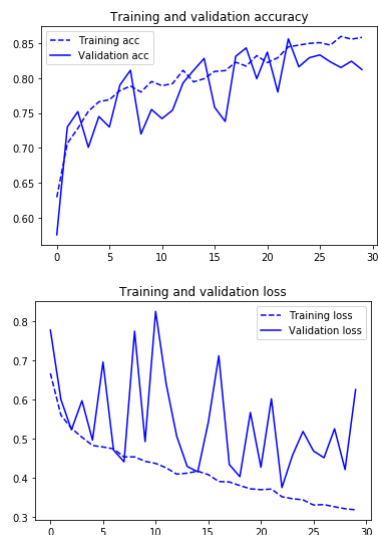
```
model_wAug = models.Sequential()
model_wAug.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 3)))
model_wAug.add(layers.MaxPooling2D((2, 2)))
model_wAug.add(layers.Conv2D(64, (3, 3), activation='relu'))
model_wAug.add(layers.MaxPooling2D((2, 2)))
model_wAug.add(layers.Conv2D(128, (3, 3), activation='relu'))
model_wAug.add(layers.MaxPooling2D((2, 2)))
model_wAug.add(layers.Flatten())
model_wAug.add(layers.Dense(512, activation='relu'))
model_wAug.add(layers.Dense(1, activation='sigmoid'))

model_wAug.compile(loss='binary_crossentropy',
                    optimizer=optimizers.RMSprop(lr=2e-4),
                    metrics=['acc'])

# Let this model train a bit longer since it shouldn't overfit as quickly
history_wAug = model_wAug.fit_generator(
    train_generator_wAug,
    steps_per_epoch=100,
    epochs=30, # increased epochs from 20 to 30 for this model
    validation_data=val_generator,
    validation_steps=50,
    workers=12) # also added workers to reduce up CPU bottleneck
```

Epoch 1/30
100/100 [=====] - 10s 102ms/step - loss: 0.6662 - acc: 0.6295 - val_loss: 0.7766 - val_acc: 0.5760
Epoch 2/30
100/100 [=====] - 9s 93ms/step - loss: 0.5593 - acc: 0.7065 - val_loss: 0.5994 - val_acc: 0.7300
Epoch 3/30
100/100 [=====] - 9s 91ms/step - loss: 0.5258 - acc: 0.7280 - val_loss: 0.5220 - val_acc: 0.7520
Epoch 4/30
100/100 [=====] - 9s 85ms/step - loss: 0.5029 - acc: 0.7525 - val_loss: 0.5962 - val_acc: 0.7010
Epoch 5/30
100/100 [=====] - 9s 91ms/step - loss: 0.4821 - acc: 0.7660 - val_loss: 0.4958 - val_acc: 0.7450
Epoch 6/30
100/100 [=====] - 9s 90ms/step - loss: 0.4780 - acc: 0.7690 - val_loss: 0.6950 - val_acc: 0.7300
Epoch 7/30
100/100 [=====] - 9s 93ms/step - loss: 0.4734 - acc: 0.7820 - val_loss: 0.4703 - val_acc: 0.7900
Epoch 8/30
100/100 [=====] - 9s 89ms/step - loss: 0.4526 - acc: 0.7885 - val_loss: 0.4403 - val_acc: 0.8110
Epoch 9/30
100/100 [=====] - 9s 90ms/step - loss: 0.4529 - acc: 0.7800 - val_loss: 0.7737 - val_acc: 0.7200
Epoch 10/30
100/100 [=====] - 9s 90ms/step - loss: 0.4416 - acc: 0.7950 - val_loss: 0.4917 - val_acc: 0.7550
Epoch 11/30
100/100 [=====] - 9s 91ms/step - loss: 0.4361 - acc: 0.7890 - val_loss: 0.8245 - val_acc: 0.7420
Epoch 12/30
100/100 [=====] - 9s 89ms/step - loss: 0.4250 - acc: 0.7920 - val_loss: 0.6395 - val_acc: 0.7540
Epoch 13/30
100/100 [=====] - 9s 91ms/step - loss: 0.4087 - acc: 0.8110 - val_loss: 0.5060 - val_acc: 0.7930
Epoch 14/30
100/100 [=====] - 9s 89ms/step - loss: 0.4113 - acc: 0.7945 - val_loss: 0.4284 - val_acc: 0.8110
Epoch 15/30
100/100 [=====] - 10s 95ms/step - loss: 0.4163 - acc: 0.7990 - val_loss: 0.4146 - val_acc: 0.8280
Epoch 16/30
100/100 [=====] - 9s 93ms/step - loss: 0.4075 - acc: 0.8095 - val_loss: 0.5406 - val_acc: 0.7580
Epoch 17/30
100/100 [=====] - 9s 92ms/step - loss: 0.3900 - acc: 0.8105 - val_loss: 0.7108 - val_acc: 0.7380
Epoch 18/30
100/100 [=====] - 9s 91ms/step - loss: 0.3887 - acc: 0.8225 - val_loss: 0.4334 - val_acc: 0.8310
Epoch 19/30
100/100 [=====] - 9s 90ms/step - loss: 0.3796 - acc: 0.8170 - val_loss: 0.4023 - val_acc: 0.8430
Epoch 20/30
100/100 [=====] - 9s 92ms/step - loss: 0.3713 - acc: 0.8320 - val_loss: 0.5663 - val_acc: 0.7990
Epoch 21/30
100/100 [=====] - 9s 89ms/step - loss: 0.3690 - acc: 0.8220 - val_loss: 0.4265 - val_acc: 0.8370
Epoch 22/30
100/100 [=====] - 9s 93ms/step - loss: 0.3707 - acc: 0.8290 - val_loss: 0.6012 - val_acc: 0.7800
Epoch 23/30
100/100 [=====] - 9s 90ms/step - loss: 0.3510 - acc: 0.8445 - val_loss: 0.3745 - val_acc: 0.8560
Epoch 24/30
100/100 [=====] - 10s 95ms/step - loss: 0.3460 - acc: 0.8470 - val_loss: 0.4567 - val_acc: 0.8160
Epoch 25/30
100/100 [=====] - 9s 90ms/step - loss: 0.3431 - acc: 0.8495 - val_loss: 0.5178 - val_acc: 0.8290
Epoch 26/30
100/100 [=====] - 9s 90ms/step - loss: 0.3299 - acc: 0.8505 - val_loss: 0.4678 - val_acc: 0.8330
Epoch 27/30
100/100 [=====] - 9s 92ms/step - loss: 0.3310 - acc: 0.8470 - val_loss: 0.4507 - val_acc: 0.8230
Epoch 28/30
100/100 [=====] - 9s 91ms/step - loss: 0.3254 - acc: 0.8595 - val_loss: 0.5246 - val_acc: 0.8150
Epoch 29/30
100/100 [=====] - 9s 92ms/step - loss: 0.3204 - acc: 0.8555 - val_loss: 0.4204 - val_acc: 0.8240
Epoch 30/30
100/100 [=====] - 9s 90ms/step - loss: 0.3177 - acc: 0.8580 - val_loss: 0.6248 - val_acc: 0.8120

```
In [12]: plot_training(history_wAug)
```



Looking at the training curves tell us a few things:

1. We are no longer over-fitting (well maybe slightly...)! training and validation accuracy now closely follow each other across all epochs
2. We see peak validation accuracy and minimum loss around epoch 20. Could possibly end training earlier for best results

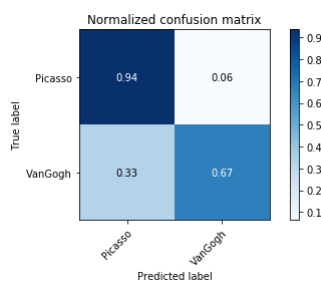
Lets check performance on the test set:

```
In [13]: perf_eval(test_dir, model_wAug)
```

```
Found 591 images belonging to 2 classes.
Test Classification Results:
Pred. VanGogh Correct - 111
Pred. Picasso Correct - 398
Pred. VanGogh Miss - 55
Pred. Picasso Miss - 27
```

```
Test Accuracy: 0.8612521150592216
VanGogh Accuracy: 0.6686746987951807
Picasso Accuracy: 0.9364785882352942
F1 Score: 0.730263157894737
```

Normalized confusion matrix



```
In [14]: # Save model
model_wAug.save('Artists_vlwAug.h5')
```

Now Test Accuracy Increases to ~86% with image augmentation

Great! But this is a little misleading... with the confusion matrix we can see that the model does a great job classifying Picasso paintings, but now tends to incorrectly classify nearly 1/3 of VanGogh paintings as Picasso...

Perhaps some hyperparameter adjustments can improve these shortcomings.

Hyperparameter Tuning

A couple hyperparameters that can have significant results in model training and performance include:

- learning rate
- hidden layers
- batch size

Lets give hidden layers a try - testing its impact by training multiple models with varying numbers of layers

In [15]: *# Hidden Layer Testing - Try using different numbers of hidden layers to improve performance*

```
# Function to return CNN model with number of hidden layers based on num_layers input
def HL_Depth_Test(num_layers):
    model_HL_Test = models.Sequential()
    model_HL_Test.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 3)))
    model_HL_Test.add(layers.MaxPooling2D((2, 2)))
    model_HL_Test.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model_HL_Test.add(layers.MaxPooling2D((2, 2)))
    # Lets preserve early layers and adjust how many final layers are included
    for i in range(num_layers):
        model_HL_Test.add(layers.Conv2D(128, (3, 3), activation='relu'))
        model_HL_Test.add(layers.MaxPooling2D((2, 2)))

    model_HL_Test.add(layers.Flatten())
    model_HL_Test.add(layers.Dense(512, activation='relu'))
    model_HL_Test.add(layers.Dense(1, activation='sigmoid'))

    model_HL_Test.compile(loss='binary_crossentropy',
                          optimizer=optimizers.RMSprop(lr=2e-4),
                          metrics=['acc'])

    return model_HL_Test
```

In [16]: *# Check to make sure function is working*

```
model_HL1 = HL_Depth_Test(2)
model_HL1.summary()
```

Layer (type)	Output Shape	Param #
=====		
conv2d_7 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_7 (MaxPooling2	(None, 74, 74, 32)	0
conv2d_8 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_8 (MaxPooling2	(None, 36, 36, 64)	0
conv2d_9 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_9 (MaxPooling2	(None, 17, 17, 128)	0
conv2d_10 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_10 (MaxPooling	(None, 7, 7, 128)	0
flatten_3 (Flatten)	(None, 6272)	0
dense_5 (Dense)	(None, 512)	3211776
dense_6 (Dense)	(None, 1)	513
=====		
Total params: 3,453,121		
Trainable params: 3,453,121		
Non-trainable params: 0		

In [17]: *# Try using between 0 and 2 final hidden layers (1 is the same as the original model)*

```
n_layers = [0, 1, 2]

history_results = []
model_results = []

for add_layers in n_layers:
    print(str(add_layers) + ' : training condition')
    temp_model = HL_Depth_Test(add_layers)
    temp_history = temp_model.fit_generator(
        train_generator_wAug,
        steps_per_epoch=100,
        epochs=30,
        validation_data=val_generator,
        validation_steps=50,
        workers=12)
    history_results.append(temp_history)
    model_results.append(temp_model)

# save each model
temp_model.save('Artists_HLtest_' + str(add_layers) + '.h5')
```

```
0 : training condition
Epoch 1/30
100/100 [=====] - 11s 110ms/step - loss: 0.7757 - acc: 0.6160 - val_loss: 0.5278 - val_acc: 0.7270
Epoch 2/30
100/100 [=====] - 9s 92ms/step - loss: 0.5418 - acc: 0.7140 - val_loss: 0.4797 - val_acc: 0.7750
Epoch 3/30
100/100 [=====] - 9s 91ms/step - loss: 0.4991 - acc: 0.7455 - val_loss: 0.4703 - val_acc: 0.7730
Epoch 4/30
100/100 [=====] - 9s 93ms/step - loss: 0.4805 - acc: 0.7620 - val_loss: 0.5798 - val_acc: 0.7480
Epoch 5/30
100/100 [=====] - 9s 91ms/step - loss: 0.4814 - acc: 0.7590 - val_loss: 0.4689 - val_acc: 0.7980
Epoch 6/30
100/100 [=====] - 9s 93ms/step - loss: 0.4570 - acc: 0.7780 - val_loss: 0.5527 - val_acc: 0.7500
Epoch 7/30
100/100 [=====] - 9s 92ms/step - loss: 0.4480 - acc: 0.7800 - val_loss: 0.4808 - val_acc: 0.7860
Epoch 8/30
100/100 [=====] - 10s 95ms/step - loss: 0.4497 - acc: 0.7795 - val_loss: 0.4472 - val_acc: 0.7960
Epoch 9/30
100/100 [=====] - 9s 93ms/step - loss: 0.4245 - acc: 0.7850 - val_loss: 0.5267 - val_acc: 0.7660
Epoch 10/30
100/100 [=====] - 10s 98ms/step - loss: 0.4296 - acc: 0.7965 - val_loss: 0.5542 - val_acc: 0.7720
Epoch 11/30
100/100 [=====] - 10s 96ms/step - loss: 0.4202 - acc: 0.7955 - val_loss: 0.4136 - val_acc: 0.8090
Epoch 12/30
100/100 [=====] - 9s 94ms/step - loss: 0.4150 - acc: 0.7960 - val_loss: 0.6241 - val_acc: 0.7480
Epoch 13/30
100/100 [=====] - 9s 91ms/step - loss: 0.3892 - acc: 0.8090 - val_loss: 0.8786 - val_acc: 0.7170
Epoch 14/30
100/100 [=====] - 9s 88ms/step - loss: 0.3996 - acc: 0.8100 - val_loss: 0.6436 - val_acc: 0.7460
Epoch 15/30
100/100 [=====] - 9s 92ms/step - loss: 0.3765 - acc: 0.8160 - val_loss: 0.5808 - val_acc: 0.7780
Epoch 16/30
100/100 [=====] - 9s 90ms/step - loss: 0.3809 - acc: 0.8160 - val_loss: 0.4338 - val_acc: 0.8290
Epoch 17/30
100/100 [=====] - 9s 92ms/step - loss: 0.3749 - acc: 0.8235 - val_loss: 0.5880 - val_acc: 0.7750
Epoch 18/30
100/100 [=====] - 9s 95ms/step - loss: 0.3725 - acc: 0.8295 - val_loss: 0.5342 - val_acc: 0.7890
Epoch 19/30
100/100 [=====] - 9s 93ms/step - loss: 0.3730 - acc: 0.8270 - val_loss: 0.6164 - val_acc: 0.7790
Epoch 20/30
100/100 [=====] - 10s 97ms/step - loss: 0.3416 - acc: 0.8490 - val_loss: 0.7204 - val_acc: 0.7510
Epoch 21/30
100/100 [=====] - 9s 92ms/step - loss: 0.3546 - acc: 0.8445 - val_loss: 0.4842 - val_acc: 0.8210
Epoch 22/30
100/100 [=====] - 9s 93ms/step - loss: 0.3488 - acc: 0.8445 - val_loss: 0.5401 - val_acc: 0.7980
Epoch 23/30
100/100 [=====] - 9s 87ms/step - loss: 0.3451 - acc: 0.8375 - val_loss: 0.4199 - val_acc: 0.8410
Epoch 24/30
100/100 [=====] - 9s 94ms/step - loss: 0.3361 - acc: 0.8450 - val_loss: 0.4022 - val_acc: 0.8480
Epoch 25/30
100/100 [=====] - 10s 97ms/step - loss: 0.3109 - acc: 0.8610 - val_loss: 0.4734 - val_acc: 0.8110
Epoch 26/30
100/100 [=====] - 9s 88ms/step - loss: 0.3318 - acc: 0.8525 - val_loss: 0.9398 - val_acc: 0.7250
Epoch 27/30
100/100 [=====] - 9s 94ms/step - loss: 0.3303 - acc: 0.8560 - val_loss: 0.4274 - val_acc: 0.8370
Epoch 28/30
100/100 [=====] - 9s 91ms/step - loss: 0.3077 - acc: 0.8615 - val_loss: 0.4745 - val_acc: 0.8370
Epoch 29/30
100/100 [=====] - 9s 92ms/step - loss: 0.3253 - acc: 0.8545 - val_loss: 0.3515 - val_acc: 0.8560
Epoch 30/30
100/100 [=====] - 9s 93ms/step - loss: 0.3073 - acc: 0.8570 - val_loss: 0.4083 - val_acc: 0.8440
1 : training condition
Epoch 1/30
100/100 [=====] - 10s 105ms/step - loss: 0.6659 - acc: 0.6365 - val_loss: 0.5542 - val_acc: 0.7150
Epoch 2/30
100/100 [=====] - 9s 91ms/step - loss: 0.5631 - acc: 0.7010 - val_loss: 0.4959 - val_acc: 0.7510
Epoch 3/30
100/100 [=====] - 9s 91ms/step - loss: 0.5195 - acc: 0.7405 - val_loss: 0.4888 - val_acc: 0.7920
Epoch 4/30
100/100 [=====] - 9s 92ms/step - loss: 0.5039 - acc: 0.7510 - val_loss: 0.5033 - val_acc: 0.7370
Epoch 5/30
100/100 [=====] - 9s 88ms/step - loss: 0.4862 - acc: 0.7705 - val_loss: 0.7475 - val_acc: 0.6880
Epoch 6/30
100/100 [=====] - 9s 92ms/step - loss: 0.4836 - acc: 0.7605 - val_loss: 0.4999 - val_acc: 0.7730
Epoch 7/30
100/100 [=====] - 9s 93ms/step - loss: 0.4694 - acc: 0.7800 - val_loss: 0.4934 - val_acc: 0.7890
Epoch 8/30
100/100 [=====] - 9s 93ms/step - loss: 0.4336 - acc: 0.7915 - val_loss: 0.7910 - val_acc: 0.6890
Epoch 9/30
100/100 [=====] - 9s 90ms/step - loss: 0.4424 - acc: 0.7910 - val_loss: 0.4298 - val_acc: 0.8010
Epoch 10/30
100/100 [=====] - 9s 92ms/step - loss: 0.4342 - acc: 0.7910 - val_loss: 0.5571 - val_acc: 0.7530
Epoch 11/30
100/100 [=====] - 9s 92ms/step - loss: 0.4182 - acc: 0.7925 - val_loss: 0.4335 - val_acc: 0.8190
Epoch 12/30
100/100 [=====] - 9s 90ms/step - loss: 0.4165 - acc: 0.8060 - val_loss: 0.4205 - val_acc: 0.8120
Epoch 13/30
100/100 [=====] - 9s 90ms/step - loss: 0.4053 - acc: 0.8115 - val_loss: 0.6468 - val_acc: 0.7340
Epoch 14/30
100/100 [=====] - 9s 90ms/step - loss: 0.4124 - acc: 0.8175 - val_loss: 0.3975 - val_acc: 0.8410
Epoch 15/30
100/100 [=====] - 9s 90ms/step - loss: 0.3998 - acc: 0.8085 - val_loss: 0.4305 - val_acc: 0.8310
Epoch 16/30
100/100 [=====] - 9s 93ms/step - loss: 0.3711 - acc: 0.8270 - val_loss: 0.5603 - val_acc: 0.7760
Epoch 17/30
100/100 [=====] - 9s 94ms/step - loss: 0.3861 - acc: 0.8205 - val_loss: 0.4381 - val_acc: 0.8300
Epoch 18/30
100/100 [=====] - 9s 91ms/step - loss: 0.3689 - acc: 0.8325 - val_loss: 0.8742 - val_acc: 0.7290
Epoch 19/30
100/100 [=====] - 9s 92ms/step - loss: 0.3778 - acc: 0.8205 - val_loss: 0.6093 - val_acc: 0.7720
Epoch 20/30
100/100 [=====] - 9s 89ms/step - loss: 0.3506 - acc: 0.8405 - val_loss: 0.4122 - val_acc: 0.8150
Epoch 21/30
100/100 [=====] - 9s 92ms/step - loss: 0.3538 - acc: 0.8460 - val_loss: 0.4626 - val_acc: 0.8150
Epoch 22/30
100/100 [=====] - 9s 91ms/step - loss: 0.3370 - acc: 0.8375 - val_loss: 0.4273 - val_acc: 0.8350
Epoch 23/30
100/100 [=====] - 9s 89ms/step - loss: 0.3477 - acc: 0.8365 - val_loss: 0.4037 - val_acc: 0.8510
Epoch 24/30
100/100 [=====] - 9s 91ms/step - loss: 0.3319 - acc: 0.8480 - val_loss: 0.3906 - val_acc: 0.8530
Epoch 25/30
100/100 [=====] - 9s 89ms/step - loss: 0.3219 - acc: 0.8455 - val_loss: 0.4570 - val_acc: 0.8170
Epoch 26/30
100/100 [=====] - 9s 92ms/step - loss: 0.3472 - acc: 0.8495 - val_loss: 0.4105 - val_acc: 0.8300
```

```
Epoch 27/30
100/100 [=====] - 9s 89ms/step - loss: 0.3213 - acc: 0.8560 - val_loss: 0.4490 - val_acc: 0.8340
Epoch 28/30
100/100 [=====] - 9s 91ms/step - loss: 0.3099 - acc: 0.8605 - val_loss: 0.5080 - val_acc: 0.8090
Epoch 29/30
100/100 [=====] - 9s 90ms/step - loss: 0.3184 - acc: 0.8615 - val_loss: 0.6616 - val_acc: 0.8010
Epoch 30/30
100/100 [=====] - 9s 92ms/step - loss: 0.2963 - acc: 0.8725 - val_loss: 0.4521 - val_acc: 0.8580
2 : training condition
Epoch 1/30
100/100 [=====] - 11s 105ms/step - loss: 0.6510 - acc: 0.6155 - val_loss: 0.5851 - val_acc: 0.6880
Epoch 2/30
100/100 [=====] - 9s 90ms/step - loss: 0.5559 - acc: 0.7065 - val_loss: 0.6068 - val_acc: 0.7020
Epoch 3/30
100/100 [=====] - 9s 87ms/step - loss: 0.5470 - acc: 0.7210 - val_loss: 0.5248 - val_acc: 0.7130
Epoch 4/30
100/100 [=====] - 9s 93ms/step - loss: 0.5073 - acc: 0.7530 - val_loss: 0.9569 - val_acc: 0.6870
Epoch 5/30
100/100 [=====] - 9s 89ms/step - loss: 0.4992 - acc: 0.7625 - val_loss: 0.5676 - val_acc: 0.7610
Epoch 6/30
100/100 [=====] - 9s 90ms/step - loss: 0.4896 - acc: 0.7625 - val_loss: 0.4905 - val_acc: 0.7720
Epoch 7/30
100/100 [=====] - 9s 89ms/step - loss: 0.4617 - acc: 0.7805 - val_loss: 0.5352 - val_acc: 0.7450
Epoch 8/30
100/100 [=====] - 9s 90ms/step - loss: 0.4728 - acc: 0.7750 - val_loss: 0.5447 - val_acc: 0.7460
Epoch 9/30
100/100 [=====] - 9s 88ms/step - loss: 0.4636 - acc: 0.7740 - val_loss: 0.4513 - val_acc: 0.7880
Epoch 10/30
100/100 [=====] - 9s 90ms/step - loss: 0.4380 - acc: 0.7890 - val_loss: 0.5343 - val_acc: 0.7760
Epoch 11/30
100/100 [=====] - 9s 92ms/step - loss: 0.4454 - acc: 0.7855 - val_loss: 0.4482 - val_acc: 0.8060
Epoch 12/30
100/100 [=====] - 9s 91ms/step - loss: 0.4278 - acc: 0.7845 - val_loss: 0.6148 - val_acc: 0.7530
Epoch 13/30
100/100 [=====] - 9s 92ms/step - loss: 0.4196 - acc: 0.8035 - val_loss: 0.8359 - val_acc: 0.7120
Epoch 14/30
100/100 [=====] - 9s 88ms/step - loss: 0.4196 - acc: 0.8065 - val_loss: 0.4375 - val_acc: 0.8050
Epoch 15/30
100/100 [=====] - 9s 91ms/step - loss: 0.4222 - acc: 0.7940 - val_loss: 0.5229 - val_acc: 0.7830
Epoch 16/30
100/100 [=====] - 9s 90ms/step - loss: 0.4268 - acc: 0.8020 - val_loss: 0.4982 - val_acc: 0.8000
Epoch 17/30
100/100 [=====] - 9s 94ms/step - loss: 0.4027 - acc: 0.8095 - val_loss: 0.6058 - val_acc: 0.7890
Epoch 18/30
100/100 [=====] - 9s 92ms/step - loss: 0.3955 - acc: 0.8190 - val_loss: 0.4778 - val_acc: 0.8160
Epoch 19/30
100/100 [=====] - 9s 90ms/step - loss: 0.3774 - acc: 0.8185 - val_loss: 0.6816 - val_acc: 0.7800
Epoch 20/30
100/100 [=====] - 9s 93ms/step - loss: 0.3988 - acc: 0.8170 - val_loss: 0.4334 - val_acc: 0.8070
Epoch 21/30
100/100 [=====] - 10s 95ms/step - loss: 0.3754 - acc: 0.8195 - val_loss: 1.0113 - val_acc: 0.7490
Epoch 22/30
100/100 [=====] - 9s 90ms/step - loss: 0.3832 - acc: 0.8225 - val_loss: 0.5708 - val_acc: 0.8010
Epoch 23/30
100/100 [=====] - 9s 89ms/step - loss: 0.3566 - acc: 0.8355 - val_loss: 0.7469 - val_acc: 0.7690
Epoch 24/30
100/100 [=====] - 9s 90ms/step - loss: 0.3862 - acc: 0.8190 - val_loss: 0.6496 - val_acc: 0.7690
Epoch 25/30
100/100 [=====] - 9s 93ms/step - loss: 0.3456 - acc: 0.8390 - val_loss: 0.5884 - val_acc: 0.7700
Epoch 26/30
100/100 [=====] - 9s 90ms/step - loss: 0.3622 - acc: 0.8345 - val_loss: 0.5916 - val_acc: 0.7860
Epoch 27/30
100/100 [=====] - 9s 88ms/step - loss: 0.3481 - acc: 0.8380 - val_loss: 0.4899 - val_acc: 0.8280
Epoch 28/30
100/100 [=====] - 9s 94ms/step - loss: 0.3452 - acc: 0.8470 - val_loss: 0.4576 - val_acc: 0.8120
Epoch 29/30
100/100 [=====] - 9s 90ms/step - loss: 0.3521 - acc: 0.8420 - val_loss: 0.8449 - val_acc: 0.7470
Epoch 30/30
100/100 [=====] - 9s 88ms/step - loss: 0.3290 - acc: 0.8525 - val_loss: 0.5237 - val_acc: 0.8120
```

```
In [18]: # Plot training history from different LR conditions
def plot_HL_acc(history_list, HL_vals):

    for i, training_history in enumerate(history_list):
        acc = training_history.history['acc']
        val_acc = training_history.history['val_acc']
        loss = training_history.history['loss']
        val_loss = training_history.history['val_loss']

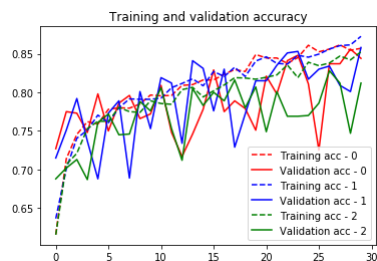
        epochs = range(len(acc))
        colors = ['r', 'b', 'g']

        plt.plot(epochs, acc, colors[i] + '--', label='Training acc - ' + str(n_layers[i]))
        plt.plot(epochs, val_acc, colors[i], label='Validation acc - ' + str(n_layers[i]))
        plt.title('Training and validation accuracy')
        plt.legend()

    plt.show()

# Calculate model performance on test dataset
def perf_HL_eval(model_list):
    for i, model_HL in enumerate(model_list):
        print('Total Hidden Layers - ' + str(n_layers[i] + 2)) # we preserve the first two hidden layers
        perf_eval(test_dir, model_HL)
        print()

plot_HL_acc(history_results, n_layers)
perf_HL_eval(model_results)
```



Total Hidden Layers - 2
 Found 591 images belonging to 2 classes.
 Test Classification Results:
 Pred. VanGogh Correct - 141
 Pred. Picasso Correct - 352
 Pred. VanGogh Miss - 25
 Pred. Picasso Miss - 73

Test Accuracy: 0.8341793570219966
 VanGogh Accuracy: 0.8493975903614458
 Picasso Accuracy: 0.8282352941176471
 F1 Score: 0.7421052631578947

Normalized confusion matrix

Total Hidden Layers - 3
 Found 591 images belonging to 2 classes.
 Test Classification Results:
 Pred. VanGogh Correct - 141
 Pred. Picasso Correct - 339
 Pred. VanGogh Miss - 25
 Pred. Picasso Miss - 86

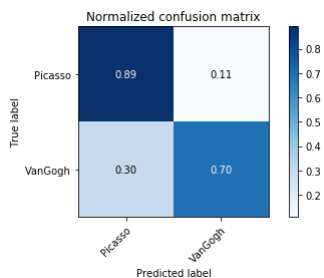
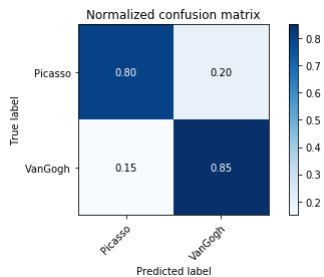
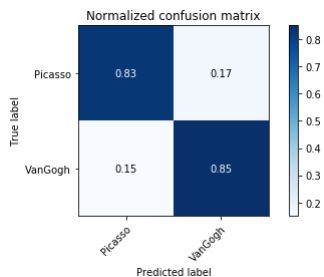
Test Accuracy: 0.8121827411167513
 VanGogh Accuracy: 0.8493975903614458
 Picasso Accuracy: 0.7976470588235294
 F1 Score: 0.717557251908397

Normalized confusion matrix

Total Hidden Layers - 4
 Found 591 images belonging to 2 classes.
 Test Classification Results:
 Pred. VanGogh Correct - 116
 Pred. Picasso Correct - 379
 Pred. VanGogh Miss - 50
 Pred. Picasso Miss - 46

Test Accuracy: 0.8375634517766497
 VanGogh Accuracy: 0.6987951807228916
 Picasso Accuracy: 0.8917647058823529
 F1 Score: 0.7073170731707318

Normalized confusion matrix



Looking at the training curves, it seems like the model with 1 additional layer (blue lines - same as the original model) is able to train the best over the 30 epochs.

But then looking at the classification results tells a slightly different story. The model with nearly the highest test accuracy and best F1 score is our first model (83% and 0.74). This model is also the most balanced with minimal bias in predicting Picasso vs VanGogh in the test set.

The 3rd model with the most layers has slightly higher test accuracy than the others, but has a bias towards classifying Picasso over VanGogh...

An important consideration when designing experiments for developing and tuning the model parameters is the initial weights that are randomly initialized each time we train our model. Depending on how the weights are initialized, you will see the model train and perform differently. When trying to evaluate how different parameters influence model training (such as learning rate, or number/size of hidden layers, etc) the best experiment would use a single initialization seed for the weights so that they are random, but held constant for the different hyperparameter conditions.

An even better experiment would use several random initialization seeds to run for each condition so we not only get a comparable measure of performance for the given conditions, but can also determine the sensitivity of the conditions to the initialized weights.

Using multiple cores with the keras image generators can impact reproducibility so this could also be set to only use a single worker to improve consistency

While the results above demonstrates a basic deep CNN that can perform pretty well in classifying the artist of provided paintings

Though I am still wondering how much better a pre-trained CNN might perform - How about ResNet50?

```
In [19]: # Lets load ResNet50 from keras and create a base model with pre-trained weights from the ImageNet dataset

from keras.applications.resnet50 import ResNet50
from keras.preprocessing import image
from keras.applications.resnet50 import preprocess_input, decode_predictions
import numpy as np

base_model = ResNet50(weights='imagenet',
                      include_top=False, # We remove the classification layers since we want to replace with our own
                      input_shape=(150,150,3))

base_model.summary()
```



```
/home/arthur/anaconda3/envs/tf-gpu/lib/python3.6/site-packages/keras_applications/resnet50.py:265: UserWarning: The output shape of `ResNet50(include_top=False)` has been changed since Keras 2.2.0.  
warnings.warn('The output shape of `ResNet50(include_top=False)` ')
```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 150, 150, 3)	0	
conv1_pad (ZeroPadding2D)	(None, 156, 156, 3)	0	input_1[0][0]
conv1 (Conv2D)	(None, 75, 75, 64)	9472	conv1_pad[0][0]
bn_conv1 (BatchNormalization)	(None, 75, 75, 64)	256	conv1[0][0]
activation_1 (Activation)	(None, 75, 75, 64)	0	bn_conv1[0][0]
pool1_pad (ZeroPadding2D)	(None, 77, 77, 64)	0	activation_1[0][0]
max_pooling2d_20 (MaxPooling2D)	(None, 38, 38, 64)	0	pool1_pad[0][0]
res2a_branch2a (Conv2D)	(None, 38, 38, 64)	4160	max_pooling2d_20[0][0]
bn2a_branch2a (BatchNormalization)	(None, 38, 38, 64)	256	res2a_branch2a[0][0]
activation_2 (Activation)	(None, 38, 38, 64)	0	bn2a_branch2a[0][0]
res2a_branch2b (Conv2D)	(None, 38, 38, 64)	36928	activation_2[0][0]
bn2a_branch2b (BatchNormalization)	(None, 38, 38, 64)	256	res2a_branch2b[0][0]
activation_3 (Activation)	(None, 38, 38, 64)	0	bn2a_branch2b[0][0]
res2a_branch2c (Conv2D)	(None, 38, 38, 256)	16640	activation_3[0][0]
res2a_branch1 (Conv2D)	(None, 38, 38, 256)	16640	max_pooling2d_20[0][0]
bn2a_branch2c (BatchNormalization)	(None, 38, 38, 256)	1024	res2a_branch2c[0][0]
bn2a_branch1 (BatchNormalization)	(None, 38, 38, 256)	1024	res2a_branch1[0][0]
add_1 (Add)	(None, 38, 38, 256)	0	bn2a_branch2c[0][0] bn2a_branch1[0][0]
activation_4 (Activation)	(None, 38, 38, 256)	0	add_1[0][0]
res2b_branch2a (Conv2D)	(None, 38, 38, 64)	16448	activation_4[0][0]
bn2b_branch2a (BatchNormalization)	(None, 38, 38, 64)	256	res2b_branch2a[0][0]
activation_5 (Activation)	(None, 38, 38, 64)	0	bn2b_branch2a[0][0]
res2b_branch2b (Conv2D)	(None, 38, 38, 64)	36928	activation_5[0][0]
bn2b_branch2b (BatchNormalization)	(None, 38, 38, 64)	256	res2b_branch2b[0][0]
activation_6 (Activation)	(None, 38, 38, 64)	0	bn2b_branch2b[0][0]
res2b_branch2c (Conv2D)	(None, 38, 38, 256)	16640	activation_6[0][0]
bn2b_branch2c (BatchNormalization)	(None, 38, 38, 256)	1024	res2b_branch2c[0][0]
add_2 (Add)	(None, 38, 38, 256)	0	bn2b_branch2c[0][0] activation_4[0][0]
activation_7 (Activation)	(None, 38, 38, 256)	0	add_2[0][0]
res2c_branch2a (Conv2D)	(None, 38, 38, 64)	16448	activation_7[0][0]
bn2c_branch2a (BatchNormalization)	(None, 38, 38, 64)	256	res2c_branch2a[0][0]
activation_8 (Activation)	(None, 38, 38, 64)	0	bn2c_branch2a[0][0]
res2c_branch2b (Conv2D)	(None, 38, 38, 64)	36928	activation_8[0][0]
bn2c_branch2b (BatchNormalization)	(None, 38, 38, 64)	256	res2c_branch2b[0][0]
activation_9 (Activation)	(None, 38, 38, 64)	0	bn2c_branch2b[0][0]
res2c_branch2c (Conv2D)	(None, 38, 38, 256)	16640	activation_9[0][0]
bn2c_branch2c (BatchNormalization)	(None, 38, 38, 256)	1024	res2c_branch2c[0][0]
add_3 (Add)	(None, 38, 38, 256)	0	bn2c_branch2c[0][0] activation_7[0][0]
activation_10 (Activation)	(None, 38, 38, 256)	0	add_3[0][0]
res3a_branch2a (Conv2D)	(None, 19, 19, 128)	32896	activation_10[0][0]
bn3a_branch2a (BatchNormalization)	(None, 19, 19, 128)	512	res3a_branch2a[0][0]
activation_11 (Activation)	(None, 19, 19, 128)	0	bn3a_branch2a[0][0]
res3a_branch2b (Conv2D)	(None, 19, 19, 128)	147584	activation_11[0][0]
bn3a_branch2b (BatchNormalization)	(None, 19, 19, 128)	512	res3a_branch2b[0][0]
activation_12 (Activation)	(None, 19, 19, 128)	0	bn3a_branch2b[0][0]
res3a_branch2c (Conv2D)	(None, 19, 19, 512)	66048	activation_12[0][0]
res3a_branch1 (Conv2D)	(None, 19, 19, 512)	131584	activation_10[0][0]
bn3a_branch2c (BatchNormalization)	(None, 19, 19, 512)	2048	res3a_branch2c[0][0]
bn3a_branch1 (BatchNormalization)	(None, 19, 19, 512)	2048	res3a_branch1[0][0]
add_4 (Add)	(None, 19, 19, 512)	0	bn3a_branch2c[0][0] bn3a_branch1[0][0]
activation_13 (Activation)	(None, 19, 19, 512)	0	add_4[0][0]
res3b_branch2a (Conv2D)	(None, 19, 19, 128)	65664	activation_13[0][0]
bn3b_branch2a (BatchNormalization)	(None, 19, 19, 128)	512	res3b_branch2a[0][0]
activation_14 (Activation)	(None, 19, 19, 128)	0	bn3b_branch2a[0][0]

res3b_branch2b (Conv2D)	(None, 19, 19, 128)	147584	activation_14[0][0]
bn3b_branch2b (BatchNormalizati	(None, 19, 19, 128)	512	res3b_branch2b[0][0]
activation_15 (Activation)	(None, 19, 19, 128)	0	bn3b_branch2b[0][0]
res3b_branch2c (Conv2D)	(None, 19, 19, 512)	66048	activation_15[0][0]
bn3b_branch2c (BatchNormalizati	(None, 19, 19, 512)	2048	res3b_branch2c[0][0]
add_5 (Add)	(None, 19, 19, 512)	0	bn3b_branch2c[0][0] activation_13[0][0]
activation_16 (Activation)	(None, 19, 19, 512)	0	add_5[0][0]
res3c_branch2a (Conv2D)	(None, 19, 19, 128)	65664	activation_16[0][0]
bn3c_branch2a (BatchNormalizati	(None, 19, 19, 128)	512	res3c_branch2a[0][0]
activation_17 (Activation)	(None, 19, 19, 128)	0	bn3c_branch2a[0][0]
res3c_branch2b (Conv2D)	(None, 19, 19, 128)	147584	activation_17[0][0]
bn3c_branch2b (BatchNormalizati	(None, 19, 19, 128)	512	res3c_branch2b[0][0]
activation_18 (Activation)	(None, 19, 19, 128)	0	bn3c_branch2b[0][0]
res3c_branch2c (Conv2D)	(None, 19, 19, 512)	66048	activation_18[0][0]
bn3c_branch2c (BatchNormalizati	(None, 19, 19, 512)	2048	res3c_branch2c[0][0]
add_6 (Add)	(None, 19, 19, 512)	0	bn3c_branch2c[0][0] activation_16[0][0]
activation_19 (Activation)	(None, 19, 19, 512)	0	add_6[0][0]
res3d_branch2a (Conv2D)	(None, 19, 19, 128)	65664	activation_19[0][0]
bn3d_branch2a (BatchNormalizati	(None, 19, 19, 128)	512	res3d_branch2a[0][0]
activation_20 (Activation)	(None, 19, 19, 128)	0	bn3d_branch2a[0][0]
res3d_branch2b (Conv2D)	(None, 19, 19, 128)	147584	activation_20[0][0]
bn3d_branch2b (BatchNormalizati	(None, 19, 19, 128)	512	res3d_branch2b[0][0]
activation_21 (Activation)	(None, 19, 19, 128)	0	bn3d_branch2b[0][0]
res3d_branch2c (Conv2D)	(None, 19, 19, 512)	66048	activation_21[0][0]
bn3d_branch2c (BatchNormalizati	(None, 19, 19, 512)	2048	res3d_branch2c[0][0]
add_7 (Add)	(None, 19, 19, 512)	0	bn3d_branch2c[0][0] activation_19[0][0]
activation_22 (Activation)	(None, 19, 19, 512)	0	add_7[0][0]
res4a_branch2a (Conv2D)	(None, 10, 10, 256)	131328	activation_22[0][0]
bn4a_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4a_branch2a[0][0]
activation_23 (Activation)	(None, 10, 10, 256)	0	bn4a_branch2a[0][0]
res4a_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_23[0][0]
bn4a_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4a_branch2b[0][0]
activation_24 (Activation)	(None, 10, 10, 256)	0	bn4a_branch2b[0][0]
res4a_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_24[0][0]
res4a_branch1 (Conv2D)	(None, 10, 10, 1024)	525312	activation_22[0][0]
bn4a_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4a_branch2c[0][0]
bn4a_branch1 (BatchNormalizatio	(None, 10, 10, 1024)	4096	res4a_branch1[0][0]
add_8 (Add)	(None, 10, 10, 1024)	0	bn4a_branch2c[0][0] bn4a_branch1[0][0]
activation_25 (Activation)	(None, 10, 10, 1024)	0	add_8[0][0]
res4b_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_25[0][0]
bn4b_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4b_branch2a[0][0]
activation_26 (Activation)	(None, 10, 10, 256)	0	bn4b_branch2a[0][0]
res4b_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_26[0][0]
bn4b_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4b_branch2b[0][0]
activation_27 (Activation)	(None, 10, 10, 256)	0	bn4b_branch2b[0][0]
res4b_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_27[0][0]
bn4b_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4b_branch2c[0][0]
add_9 (Add)	(None, 10, 10, 1024)	0	bn4b_branch2c[0][0] activation_25[0][0]
activation_28 (Activation)	(None, 10, 10, 1024)	0	add_9[0][0]
res4c_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_28[0][0]
bn4c_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4c_branch2a[0][0]
activation_29 (Activation)	(None, 10, 10, 256)	0	bn4c_branch2a[0][0]
res4c_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_29[0][0]
bn4c_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4c_branch2b[0][0]
activation_30 (Activation)	(None, 10, 10, 256)	0	bn4c_branch2b[0][0]

res4c_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_30[0][0]
bn4c_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4c_branch2c[0][0]
add_10 (Add)	(None, 10, 10, 1024)	0	bn4c_branch2c[0][0] activation_28[0][0]
activation_31 (Activation)	(None, 10, 10, 1024)	0	add_10[0][0]
res4d_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_31[0][0]
bn4d_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4d_branch2a[0][0]
activation_32 (Activation)	(None, 10, 10, 256)	0	bn4d_branch2a[0][0]
res4d_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_32[0][0]
bn4d_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4d_branch2b[0][0]
activation_33 (Activation)	(None, 10, 10, 256)	0	bn4d_branch2b[0][0]
res4d_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_33[0][0]
bn4d_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4d_branch2c[0][0]
add_11 (Add)	(None, 10, 10, 1024)	0	bn4d_branch2c[0][0] activation_31[0][0]
activation_34 (Activation)	(None, 10, 10, 1024)	0	add_11[0][0]
res4e_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_34[0][0]
bn4e_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4e_branch2a[0][0]
activation_35 (Activation)	(None, 10, 10, 256)	0	bn4e_branch2a[0][0]
res4e_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_35[0][0]
bn4e_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4e_branch2b[0][0]
activation_36 (Activation)	(None, 10, 10, 256)	0	bn4e_branch2b[0][0]
res4e_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_36[0][0]
bn4e_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4e_branch2c[0][0]
add_12 (Add)	(None, 10, 10, 1024)	0	bn4e_branch2c[0][0] activation_34[0][0]
activation_37 (Activation)	(None, 10, 10, 1024)	0	add_12[0][0]
res4f_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_37[0][0]
bn4f_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4f_branch2a[0][0]
activation_38 (Activation)	(None, 10, 10, 256)	0	bn4f_branch2a[0][0]
res4f_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_38[0][0]
bn4f_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4f_branch2b[0][0]
activation_39 (Activation)	(None, 10, 10, 256)	0	bn4f_branch2b[0][0]
res4f_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_39[0][0]
bn4f_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4f_branch2c[0][0]
add_13 (Add)	(None, 10, 10, 1024)	0	bn4f_branch2c[0][0] activation_37[0][0]
activation_40 (Activation)	(None, 10, 10, 1024)	0	add_13[0][0]
res5a_branch2a (Conv2D)	(None, 5, 5, 512)	524800	activation_40[0][0]
bn5a_branch2a (BatchNormalizati	(None, 5, 5, 512)	2048	res5a_branch2a[0][0]
activation_41 (Activation)	(None, 5, 5, 512)	0	bn5a_branch2a[0][0]
res5a_branch2b (Conv2D)	(None, 5, 5, 512)	2359808	activation_41[0][0]
bn5a_branch2b (BatchNormalizati	(None, 5, 5, 512)	2048	res5a_branch2b[0][0]
activation_42 (Activation)	(None, 5, 5, 512)	0	bn5a_branch2b[0][0]
res5a_branch2c (Conv2D)	(None, 5, 5, 2048)	1050624	activation_42[0][0]
res5a_branch1 (Conv2D)	(None, 5, 5, 2048)	2099200	activation_40[0][0]
bn5a_branch2c (BatchNormalizati	(None, 5, 5, 2048)	8192	res5a_branch2c[0][0]
bn5a_branch1 (BatchNormalizatio	(None, 5, 5, 2048)	8192	res5a_branch1[0][0]
add_14 (Add)	(None, 5, 5, 2048)	0	bn5a_branch2c[0][0] bn5a_branch1[0][0]
activation_43 (Activation)	(None, 5, 5, 2048)	0	add_14[0][0]
res5b_branch2a (Conv2D)	(None, 5, 5, 512)	1049088	activation_43[0][0]
bn5b_branch2a (BatchNormalizati	(None, 5, 5, 512)	2048	res5b_branch2a[0][0]
activation_44 (Activation)	(None, 5, 5, 512)	0	bn5b_branch2a[0][0]
res5b_branch2b (Conv2D)	(None, 5, 5, 512)	2359808	activation_44[0][0]
bn5b_branch2b (BatchNormalizati	(None, 5, 5, 512)	2048	res5b_branch2b[0][0]
activation_45 (Activation)	(None, 5, 5, 512)	0	bn5b_branch2b[0][0]
res5b_branch2c (Conv2D)	(None, 5, 5, 2048)	1050624	activation_45[0][0]
bn5b_branch2c (BatchNormalizati	(None, 5, 5, 2048)	8192	res5b_branch2c[0][0]
add_15 (Add)	(None, 5, 5, 2048)	0	bn5b_branch2c[0][0]

activation_43[0][0]			
activation_46 (Activation)	(None, 5, 5, 2048)	0	add_15[0][0]
res5c_branch2a (Conv2D)	(None, 5, 5, 512)	1049088	activation_46[0][0]
bn5c_branch2a (BatchNormalizati	(None, 5, 5, 512)	2048	res5c_branch2a[0][0]
activation_47 (Activation)	(None, 5, 5, 512)	0	bn5c_branch2a[0][0]
res5c_branch2b (Conv2D)	(None, 5, 5, 512)	2359808	activation_47[0][0]
bn5c_branch2b (BatchNormalizati	(None, 5, 5, 512)	2048	res5c_branch2b[0][0]
activation_48 (Activation)	(None, 5, 5, 512)	0	bn5c_branch2b[0][0]
res5c_branch2c (Conv2D)	(None, 5, 5, 2048)	1050624	activation_48[0][0]
bn5c_branch2c (BatchNormalizati	(None, 5, 5, 2048)	8192	res5c_branch2c[0][0]
add_16 (Add)	(None, 5, 5, 2048)	0	bn5c_branch2c[0][0] activation_46[0][0]
activation_49 (Activation)	(None, 5, 5, 2048)	0	add_16[0][0]
=====			
Total params: 23,587,712			
Trainable params: 23,534,592			
Non-trainable params: 53,120			

We want to freeze the feature extraction layers from ResNet50, but will run in to trouble if we also freeze the batch norm layers...

So we need to cycle through and selectively make the batch norm layers trainable

```
In [20]: # go through the base model (ResNet50) layers
for layer in base_model.layers:
    layer.trainable = False
    if isinstance(layer, keras.layers.normalization.BatchNormalization): # make sure the batch_norm layers in ResNet are still trainable
        layer.trainable = True

base_model.summary()
```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 150, 150, 3)	0	
conv1_pad (ZeroPadding2D)	(None, 156, 156, 3)	0	input_1[0][0]
conv1 (Conv2D)	(None, 75, 75, 64)	9472	conv1_pad[0][0]
bn_conv1 (BatchNormalization)	(None, 75, 75, 64)	256	conv1[0][0]
activation_1 (Activation)	(None, 75, 75, 64)	0	bn_conv1[0][0]
pool1_pad (ZeroPadding2D)	(None, 77, 77, 64)	0	activation_1[0][0]
max_pooling2d_20 (MaxPooling2D)	(None, 38, 38, 64)	0	pool1_pad[0][0]
res2a_branch2a (Conv2D)	(None, 38, 38, 64)	4160	max_pooling2d_20[0][0]
bn2a_branch2a (BatchNormalization)	(None, 38, 38, 64)	256	res2a_branch2a[0][0]
activation_2 (Activation)	(None, 38, 38, 64)	0	bn2a_branch2a[0][0]
res2a_branch2b (Conv2D)	(None, 38, 38, 64)	36928	activation_2[0][0]
bn2a_branch2b (BatchNormalization)	(None, 38, 38, 64)	256	res2a_branch2b[0][0]
activation_3 (Activation)	(None, 38, 38, 64)	0	bn2a_branch2b[0][0]
res2a_branch2c (Conv2D)	(None, 38, 38, 256)	16640	activation_3[0][0]
res2a_branch1 (Conv2D)	(None, 38, 38, 256)	16640	max_pooling2d_20[0][0]
bn2a_branch2c (BatchNormalization)	(None, 38, 38, 256)	1024	res2a_branch2c[0][0]
bn2a_branch1 (BatchNormalization)	(None, 38, 38, 256)	1024	res2a_branch1[0][0]
add_1 (Add)	(None, 38, 38, 256)	0	bn2a_branch2c[0][0] bn2a_branch1[0][0]
activation_4 (Activation)	(None, 38, 38, 256)	0	add_1[0][0]
res2b_branch2a (Conv2D)	(None, 38, 38, 64)	16448	activation_4[0][0]
bn2b_branch2a (BatchNormalization)	(None, 38, 38, 64)	256	res2b_branch2a[0][0]
activation_5 (Activation)	(None, 38, 38, 64)	0	bn2b_branch2a[0][0]
res2b_branch2b (Conv2D)	(None, 38, 38, 64)	36928	activation_5[0][0]
bn2b_branch2b (BatchNormalization)	(None, 38, 38, 64)	256	res2b_branch2b[0][0]
activation_6 (Activation)	(None, 38, 38, 64)	0	bn2b_branch2b[0][0]
res2b_branch2c (Conv2D)	(None, 38, 38, 256)	16640	activation_6[0][0]
bn2b_branch2c (BatchNormalization)	(None, 38, 38, 256)	1024	res2b_branch2c[0][0]
add_2 (Add)	(None, 38, 38, 256)	0	bn2b_branch2c[0][0] activation_4[0][0]
activation_7 (Activation)	(None, 38, 38, 256)	0	add_2[0][0]
res2c_branch2a (Conv2D)	(None, 38, 38, 64)	16448	activation_7[0][0]
bn2c_branch2a (BatchNormalization)	(None, 38, 38, 64)	256	res2c_branch2a[0][0]
activation_8 (Activation)	(None, 38, 38, 64)	0	bn2c_branch2a[0][0]
res2c_branch2b (Conv2D)	(None, 38, 38, 64)	36928	activation_8[0][0]
bn2c_branch2b (BatchNormalization)	(None, 38, 38, 64)	256	res2c_branch2b[0][0]
activation_9 (Activation)	(None, 38, 38, 64)	0	bn2c_branch2b[0][0]
res2c_branch2c (Conv2D)	(None, 38, 38, 256)	16640	activation_9[0][0]
bn2c_branch2c (BatchNormalization)	(None, 38, 38, 256)	1024	res2c_branch2c[0][0]
add_3 (Add)	(None, 38, 38, 256)	0	bn2c_branch2c[0][0] activation_7[0][0]
activation_10 (Activation)	(None, 38, 38, 256)	0	add_3[0][0]
res3a_branch2a (Conv2D)	(None, 19, 19, 128)	32896	activation_10[0][0]
bn3a_branch2a (BatchNormalization)	(None, 19, 19, 128)	512	res3a_branch2a[0][0]
activation_11 (Activation)	(None, 19, 19, 128)	0	bn3a_branch2a[0][0]
res3a_branch2b (Conv2D)	(None, 19, 19, 128)	147584	activation_11[0][0]
bn3a_branch2b (BatchNormalization)	(None, 19, 19, 128)	512	res3a_branch2b[0][0]
activation_12 (Activation)	(None, 19, 19, 128)	0	bn3a_branch2b[0][0]
res3a_branch2c (Conv2D)	(None, 19, 19, 512)	66048	activation_12[0][0]
res3a_branch1 (Conv2D)	(None, 19, 19, 512)	131584	activation_10[0][0]
bn3a_branch2c (BatchNormalization)	(None, 19, 19, 512)	2048	res3a_branch2c[0][0]
bn3a_branch1 (BatchNormalization)	(None, 19, 19, 512)	2048	res3a_branch1[0][0]
add_4 (Add)	(None, 19, 19, 512)	0	bn3a_branch2c[0][0] bn3a_branch1[0][0]
activation_13 (Activation)	(None, 19, 19, 512)	0	add_4[0][0]
res3b_branch2a (Conv2D)	(None, 19, 19, 128)	65664	activation_13[0][0]
bn3b_branch2a (BatchNormalization)	(None, 19, 19, 128)	512	res3b_branch2a[0][0]
activation_14 (Activation)	(None, 19, 19, 128)	0	bn3b_branch2a[0][0]

res3b_branch2b (Conv2D)	(None, 19, 19, 128)	147584	activation_14[0][0]
bn3b_branch2b (BatchNormalizati	(None, 19, 19, 128)	512	res3b_branch2b[0][0]
activation_15 (Activation)	(None, 19, 19, 128)	0	bn3b_branch2b[0][0]
res3b_branch2c (Conv2D)	(None, 19, 19, 512)	66048	activation_15[0][0]
bn3b_branch2c (BatchNormalizati	(None, 19, 19, 512)	2048	res3b_branch2c[0][0]
add_5 (Add)	(None, 19, 19, 512)	0	bn3b_branch2c[0][0] activation_13[0][0]
activation_16 (Activation)	(None, 19, 19, 512)	0	add_5[0][0]
res3c_branch2a (Conv2D)	(None, 19, 19, 128)	65664	activation_16[0][0]
bn3c_branch2a (BatchNormalizati	(None, 19, 19, 128)	512	res3c_branch2a[0][0]
activation_17 (Activation)	(None, 19, 19, 128)	0	bn3c_branch2a[0][0]
res3c_branch2b (Conv2D)	(None, 19, 19, 128)	147584	activation_17[0][0]
bn3c_branch2b (BatchNormalizati	(None, 19, 19, 128)	512	res3c_branch2b[0][0]
activation_18 (Activation)	(None, 19, 19, 128)	0	bn3c_branch2b[0][0]
res3c_branch2c (Conv2D)	(None, 19, 19, 512)	66048	activation_18[0][0]
bn3c_branch2c (BatchNormalizati	(None, 19, 19, 512)	2048	res3c_branch2c[0][0]
add_6 (Add)	(None, 19, 19, 512)	0	bn3c_branch2c[0][0] activation_16[0][0]
activation_19 (Activation)	(None, 19, 19, 512)	0	add_6[0][0]
res3d_branch2a (Conv2D)	(None, 19, 19, 128)	65664	activation_19[0][0]
bn3d_branch2a (BatchNormalizati	(None, 19, 19, 128)	512	res3d_branch2a[0][0]
activation_20 (Activation)	(None, 19, 19, 128)	0	bn3d_branch2a[0][0]
res3d_branch2b (Conv2D)	(None, 19, 19, 128)	147584	activation_20[0][0]
bn3d_branch2b (BatchNormalizati	(None, 19, 19, 128)	512	res3d_branch2b[0][0]
activation_21 (Activation)	(None, 19, 19, 128)	0	bn3d_branch2b[0][0]
res3d_branch2c (Conv2D)	(None, 19, 19, 512)	66048	activation_21[0][0]
bn3d_branch2c (BatchNormalizati	(None, 19, 19, 512)	2048	res3d_branch2c[0][0]
add_7 (Add)	(None, 19, 19, 512)	0	bn3d_branch2c[0][0] activation_19[0][0]
activation_22 (Activation)	(None, 19, 19, 512)	0	add_7[0][0]
res4a_branch2a (Conv2D)	(None, 10, 10, 256)	131328	activation_22[0][0]
bn4a_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4a_branch2a[0][0]
activation_23 (Activation)	(None, 10, 10, 256)	0	bn4a_branch2a[0][0]
res4a_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_23[0][0]
bn4a_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4a_branch2b[0][0]
activation_24 (Activation)	(None, 10, 10, 256)	0	bn4a_branch2b[0][0]
res4a_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_24[0][0]
res4a_branch1 (Conv2D)	(None, 10, 10, 1024)	525312	activation_22[0][0]
bn4a_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4a_branch2c[0][0]
bn4a_branch1 (BatchNormalizatio	(None, 10, 10, 1024)	4096	res4a_branch1[0][0]
add_8 (Add)	(None, 10, 10, 1024)	0	bn4a_branch2c[0][0] bn4a_branch1[0][0]
activation_25 (Activation)	(None, 10, 10, 1024)	0	add_8[0][0]
res4b_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_25[0][0]
bn4b_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4b_branch2a[0][0]
activation_26 (Activation)	(None, 10, 10, 256)	0	bn4b_branch2a[0][0]
res4b_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_26[0][0]
bn4b_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4b_branch2b[0][0]
activation_27 (Activation)	(None, 10, 10, 256)	0	bn4b_branch2b[0][0]
res4b_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_27[0][0]
bn4b_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4b_branch2c[0][0]
add_9 (Add)	(None, 10, 10, 1024)	0	bn4b_branch2c[0][0] activation_25[0][0]
activation_28 (Activation)	(None, 10, 10, 1024)	0	add_9[0][0]
res4c_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_28[0][0]
bn4c_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4c_branch2a[0][0]
activation_29 (Activation)	(None, 10, 10, 256)	0	bn4c_branch2a[0][0]
res4c_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_29[0][0]
bn4c_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4c_branch2b[0][0]
activation_30 (Activation)	(None, 10, 10, 256)	0	bn4c_branch2b[0][0]

res4c_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_30[0][0]
bn4c_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4c_branch2c[0][0]
add_10 (Add)	(None, 10, 10, 1024)	0	bn4c_branch2c[0][0] activation_28[0][0]
activation_31 (Activation)	(None, 10, 10, 1024)	0	add_10[0][0]
res4d_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_31[0][0]
bn4d_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4d_branch2a[0][0]
activation_32 (Activation)	(None, 10, 10, 256)	0	bn4d_branch2a[0][0]
res4d_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_32[0][0]
bn4d_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4d_branch2b[0][0]
activation_33 (Activation)	(None, 10, 10, 256)	0	bn4d_branch2b[0][0]
res4d_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_33[0][0]
bn4d_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4d_branch2c[0][0]
add_11 (Add)	(None, 10, 10, 1024)	0	bn4d_branch2c[0][0] activation_31[0][0]
activation_34 (Activation)	(None, 10, 10, 1024)	0	add_11[0][0]
res4e_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_34[0][0]
bn4e_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4e_branch2a[0][0]
activation_35 (Activation)	(None, 10, 10, 256)	0	bn4e_branch2a[0][0]
res4e_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_35[0][0]
bn4e_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4e_branch2b[0][0]
activation_36 (Activation)	(None, 10, 10, 256)	0	bn4e_branch2b[0][0]
res4e_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_36[0][0]
bn4e_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4e_branch2c[0][0]
add_12 (Add)	(None, 10, 10, 1024)	0	bn4e_branch2c[0][0] activation_34[0][0]
activation_37 (Activation)	(None, 10, 10, 1024)	0	add_12[0][0]
res4f_branch2a (Conv2D)	(None, 10, 10, 256)	262400	activation_37[0][0]
bn4f_branch2a (BatchNormalizati	(None, 10, 10, 256)	1024	res4f_branch2a[0][0]
activation_38 (Activation)	(None, 10, 10, 256)	0	bn4f_branch2a[0][0]
res4f_branch2b (Conv2D)	(None, 10, 10, 256)	590080	activation_38[0][0]
bn4f_branch2b (BatchNormalizati	(None, 10, 10, 256)	1024	res4f_branch2b[0][0]
activation_39 (Activation)	(None, 10, 10, 256)	0	bn4f_branch2b[0][0]
res4f_branch2c (Conv2D)	(None, 10, 10, 1024)	263168	activation_39[0][0]
bn4f_branch2c (BatchNormalizati	(None, 10, 10, 1024)	4096	res4f_branch2c[0][0]
add_13 (Add)	(None, 10, 10, 1024)	0	bn4f_branch2c[0][0] activation_37[0][0]
activation_40 (Activation)	(None, 10, 10, 1024)	0	add_13[0][0]
res5a_branch2a (Conv2D)	(None, 5, 5, 512)	524800	activation_40[0][0]
bn5a_branch2a (BatchNormalizati	(None, 5, 5, 512)	2048	res5a_branch2a[0][0]
activation_41 (Activation)	(None, 5, 5, 512)	0	bn5a_branch2a[0][0]
res5a_branch2b (Conv2D)	(None, 5, 5, 512)	2359808	activation_41[0][0]
bn5a_branch2b (BatchNormalizati	(None, 5, 5, 512)	2048	res5a_branch2b[0][0]
activation_42 (Activation)	(None, 5, 5, 512)	0	bn5a_branch2b[0][0]
res5a_branch2c (Conv2D)	(None, 5, 5, 2048)	1050624	activation_42[0][0]
res5a_branch1 (Conv2D)	(None, 5, 5, 2048)	2099200	activation_40[0][0]
bn5a_branch2c (BatchNormalizati	(None, 5, 5, 2048)	8192	res5a_branch2c[0][0]
bn5a_branch1 (BatchNormalizatio	(None, 5, 5, 2048)	8192	res5a_branch1[0][0]
add_14 (Add)	(None, 5, 5, 2048)	0	bn5a_branch2c[0][0] bn5a_branch1[0][0]
activation_43 (Activation)	(None, 5, 5, 2048)	0	add_14[0][0]
res5b_branch2a (Conv2D)	(None, 5, 5, 512)	1049088	activation_43[0][0]
bn5b_branch2a (BatchNormalizati	(None, 5, 5, 512)	2048	res5b_branch2a[0][0]
activation_44 (Activation)	(None, 5, 5, 512)	0	bn5b_branch2a[0][0]
res5b_branch2b (Conv2D)	(None, 5, 5, 512)	2359808	activation_44[0][0]
bn5b_branch2b (BatchNormalizati	(None, 5, 5, 512)	2048	res5b_branch2b[0][0]
activation_45 (Activation)	(None, 5, 5, 512)	0	bn5b_branch2b[0][0]
res5b_branch2c (Conv2D)	(None, 5, 5, 2048)	1050624	activation_45[0][0]
bn5b_branch2c (BatchNormalizati	(None, 5, 5, 2048)	8192	res5b_branch2c[0][0]
add_15 (Add)	(None, 5, 5, 2048)	0	bn5b_branch2c[0][0]

activation_43[0][0]			
activation_46 (Activation)	(None, 5, 5, 2048)	0	add_15[0][0]
res5c_branch2a (Conv2D)	(None, 5, 5, 512)	1049088	activation_46[0][0]
bn5c_branch2a (BatchNormalizati	(None, 5, 5, 512)	2048	res5c_branch2a[0][0]
activation_47 (Activation)	(None, 5, 5, 512)	0	bn5c_branch2a[0][0]
res5c_branch2b (Conv2D)	(None, 5, 5, 512)	2359808	activation_47[0][0]
bn5c_branch2b (BatchNormalizati	(None, 5, 5, 512)	2048	res5c_branch2b[0][0]
activation_48 (Activation)	(None, 5, 5, 512)	0	bn5c_branch2b[0][0]
res5c_branch2c (Conv2D)	(None, 5, 5, 2048)	1050624	activation_48[0][0]
bn5c_branch2c (BatchNormalizati	(None, 5, 5, 2048)	8192	res5c_branch2c[0][0]
add_16 (Add)	(None, 5, 5, 2048)	0	bn5c_branch2c[0][0] activation_46[0][0]
activation_49 (Activation)	(None, 5, 5, 2048)	0	add_16[0][0]
=====			
Total params: 23,587,712			
Trainable params: 53,120			
Non-trainable params: 23,534,592			

In [21]: # Want to use the base model and add a fully connected layer as well as a sigmoid
activation layer for our artist classification

```
# base_model.trainable=False

modelRN50t = models.Sequential()
modelRN50t.add(base_model)
modelRN50t.add(layers.Flatten())
modelRN50t.add(layers.Dense(64, activation='relu'))
modelRN50t.add(layers.Dense(1, activation='sigmoid'))

modelRN50t.compile(loss='binary_crossentropy',
                    optimizer=optimizers.RMSprop(lr=2e-5),
                    metrics=['acc'])

modelRN50t.summary()
```

Layer (type)	Output Shape	Param #
=====	=====	=====
resnet50 (Model)	(None, 5, 5, 2048)	23587712
flatten_7 (Flatten)	(None, 51200)	0
dense_13 (Dense)	(None, 64)	3276864
dense_14 (Dense)	(None, 1)	65
=====	=====	=====
Total params: 26,864,641		
Trainable params: 3,330,049		
Non-trainable params: 23,534,592		

```
In [22]: train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40, # this will rotate the image within a range of 40deg
    width_shift_range=0.2, # the next two will stretch/compress the images
    height_shift_range=0.2,
    shear_range=0.2, # will shear the image
    zoom_range=0.2, # zoom in on image
    horizontal_flip=True,) # can flip the image along the horizontal axis

# Validation set remains the same
val_datagen = ImageDataGenerator(rescale=1./255)

train_dir = artist_dir + 'train_data/'
val_dir = artist_dir + 'val_data/'

train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(150, 150),
    batch_size=20,
    class_mode='binary')

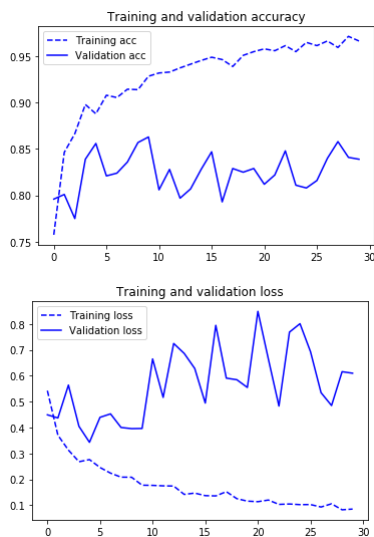
val_generator = val_datagen.flow_from_directory(
    val_dir,
    target_size=(150, 150),
    batch_size=20,
    class_mode='binary')
```

Found 1000 images belonging to 2 classes.
Found 400 images belonging to 2 classes.

```
In [23]: historyRN = modelRN50t.fit_generator(
    train_generator,
    steps_per_epoch=100,
    epochs=30,
    validation_data=val_generator,
    validation_steps=50,
    workers=12) # also added workers to reduce up CPU bottlene
```

```
Epoch 1/30
100/100 [=====] - 19s 188ms/step - loss: 0.5424 - acc: 0.7575 - val_loss: 0.4492 - val_acc: 0.7960
Epoch 2/30
100/100 [=====] - 11s 114ms/step - loss: 0.3704 - acc: 0.8465 - val_loss: 0.4370 - val_acc: 0.8010
Epoch 3/30
100/100 [=====] - 12s 116ms/step - loss: 0.3129 - acc: 0.8665 - val_loss: 0.5641 - val_acc: 0.7750
Epoch 4/30
100/100 [=====] - 11s 114ms/step - loss: 0.2681 - acc: 0.8980 - val_loss: 0.4048 - val_acc: 0.8390
Epoch 5/30
100/100 [=====] - 11s 114ms/step - loss: 0.2764 - acc: 0.8880 - val_loss: 0.3430 - val_acc: 0.8560
Epoch 6/30
100/100 [=====] - 11s 115ms/step - loss: 0.2457 - acc: 0.9080 - val_loss: 0.4395 - val_acc: 0.8210
Epoch 7/30
100/100 [=====] - 11s 115ms/step - loss: 0.2240 - acc: 0.9055 - val_loss: 0.4529 - val_acc: 0.8240
Epoch 8/30
100/100 [=====] - 11s 114ms/step - loss: 0.2085 - acc: 0.9145 - val_loss: 0.4003 - val_acc: 0.8360
Epoch 9/30
100/100 [=====] - 12s 115ms/step - loss: 0.2082 - acc: 0.9140 - val_loss: 0.3958 - val_acc: 0.8570
Epoch 10/30
100/100 [=====] - 11s 114ms/step - loss: 0.1774 - acc: 0.9285 - val_loss: 0.3966 - val_acc: 0.8630
Epoch 11/30
100/100 [=====] - 11s 115ms/step - loss: 0.1767 - acc: 0.9320 - val_loss: 0.6650 - val_acc: 0.8060
Epoch 12/30
100/100 [=====] - 11s 115ms/step - loss: 0.1749 - acc: 0.9330 - val_loss: 0.5165 - val_acc: 0.8280
Epoch 13/30
100/100 [=====] - 12s 116ms/step - loss: 0.1741 - acc: 0.9375 - val_loss: 0.7248 - val_acc: 0.7970
Epoch 14/30
100/100 [=====] - 12s 116ms/step - loss: 0.1418 - acc: 0.9415 - val_loss: 0.6863 - val_acc: 0.8070
Epoch 15/30
100/100 [=====] - 12s 115ms/step - loss: 0.1469 - acc: 0.9455 - val_loss: 0.6282 - val_acc: 0.8280
Epoch 16/30
100/100 [=====] - 12s 115ms/step - loss: 0.1371 - acc: 0.9490 - val_loss: 0.4947 - val_acc: 0.8470
Epoch 17/30
100/100 [=====] - 12s 115ms/step - loss: 0.1360 - acc: 0.9465 - val_loss: 0.7949 - val_acc: 0.7930
Epoch 18/30
100/100 [=====] - 11s 114ms/step - loss: 0.1524 - acc: 0.9390 - val_loss: 0.5909 - val_acc: 0.8290
Epoch 19/30
100/100 [=====] - 12s 115ms/step - loss: 0.1254 - acc: 0.9510 - val_loss: 0.5847 - val_acc: 0.8250
Epoch 20/30
100/100 [=====] - 12s 117ms/step - loss: 0.1159 - acc: 0.9550 - val_loss: 0.5549 - val_acc: 0.8290
Epoch 21/30
100/100 [=====] - 12s 117ms/step - loss: 0.1137 - acc: 0.9580 - val_loss: 0.8488 - val_acc: 0.8120
Epoch 22/30
100/100 [=====] - 12s 117ms/step - loss: 0.1201 - acc: 0.9560 - val_loss: 0.6639 - val_acc: 0.8220
Epoch 23/30
100/100 [=====] - 12s 115ms/step - loss: 0.1032 - acc: 0.9615 - val_loss: 0.4831 - val_acc: 0.8480
Epoch 24/30
100/100 [=====] - 12s 115ms/step - loss: 0.1048 - acc: 0.9550 - val_loss: 0.7686 - val_acc: 0.8110
Epoch 25/30
100/100 [=====] - 12s 116ms/step - loss: 0.1023 - acc: 0.9650 - val_loss: 0.8012 - val_acc: 0.8080
Epoch 26/30
100/100 [=====] - 12s 116ms/step - loss: 0.1026 - acc: 0.9615 - val_loss: 0.6929 - val_acc: 0.8160
Epoch 27/30
100/100 [=====] - 12s 116ms/step - loss: 0.0931 - acc: 0.9665 - val_loss: 0.5348 - val_acc: 0.8400
Epoch 28/30
100/100 [=====] - 11s 114ms/step - loss: 0.1056 - acc: 0.9595 - val_loss: 0.4850 - val_acc: 0.8580
Epoch 29/30
100/100 [=====] - 11s 115ms/step - loss: 0.0824 - acc: 0.9715 - val_loss: 0.6158 - val_acc: 0.8410
Epoch 30/30
100/100 [=====] - 12s 117ms/step - loss: 0.0852 - acc: 0.9665 - val_loss: 0.6099 - val_acc: 0.8390
```

```
In [24]: plot_training(historyRN)
```



```
In [25]: perf_eval(test_dir, modelRN50t)
```

Found 591 images belonging to 2 classes.

Test Classification Results:

```
Pred. VanGogh Correct - 129
Pred. Picasso Correct - 410
Pred. VanGogh Miss - 37
Pred. Picasso Miss - 15
```

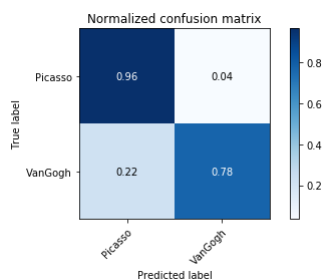
Test Accuracy: 0.9120135363790186

VanGogh Accuracy: 0.7771084337349398

Picasso Accuracy: 0.9647058823529412

F1 Score: 0.832258064516129

Normalized confusion matrix



```
In [26]: # Save Model
temp_model.save('Artists_RN50t.h5')
```

>90% Test Accuracy w/ Pre-Trained ResNet50 CNN

Awesome - we can do even better by fine-tuning the classification layers of a pre-trained ResNet50 CNN. Looking at the training curves, there is still room for improvement though! In the future, I would add some dropout before the classification layers to regularize and would also try unfreezing some of the ResNet layers to allow the convolutional layers to better extract the features relevant to our paintings.