From a given image, the model classifies if the image is a Dog or a Cat

(Using google colab to work on the problem)

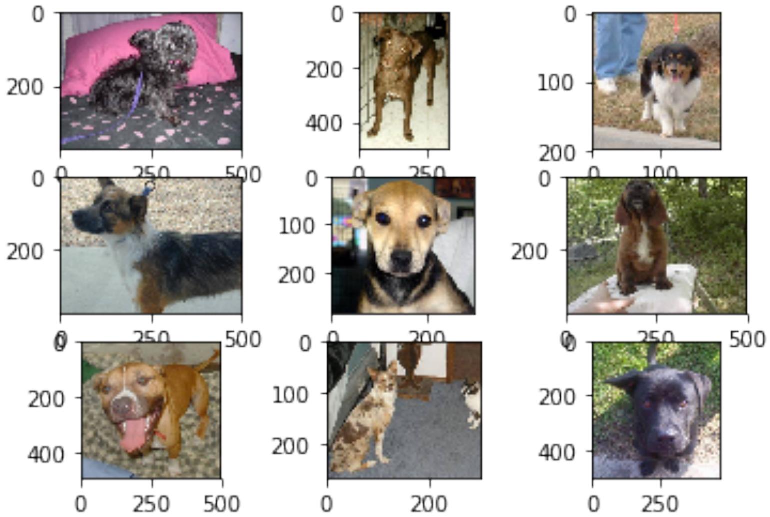
In [2]:
```
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/


!chmod 600 ~/.kaggle/kaggle.json

!kaggle datasets download -d bohraboxer/cattyvsdoggy
!ls
```

```
Downloading cattyvsdoggy.zip to /content
 96% 521M/543M [00:08<00:00, 68.7MB/s]
100% 543M/543M [00:08<00:00, 67.8MB/s]
cattyvsdoggy.zip  kaggle.json  sample_data
```

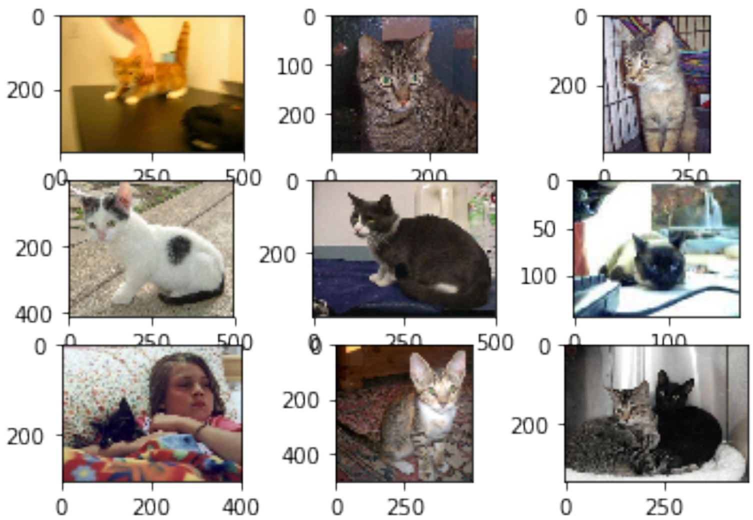
Exploratory Data analysis

Images of dogs

In [4]:
```
# From the image, we see that the image is not of same length

## packages to plot image
from matplotlib import pyplot
from matplotlib.image import imread
# define location of dataset
folder = 'train/'
# plotting of first 9 images of dog
for i in range(9):
    pyplot.subplot(330 + 1 + i)
    # defining filename
    filename = folder + 'dog.' + str(i) + '.jpg'
    # load of image pixels
    image = imread(filename)
    # plot of raw pixel data
    pyplot.imshow(image)
pyplot.show()
```



In [5]:
```
# From the image, we see that the image is not of same length

# packages to plot image
from matplotlib import pyplot
from matplotlib.image import imread
# define location of dataset
folder = 'train/'
# plot first 9 cat images
for i in range(9):
    pyplot.subplot(330 + 1 + i)
    # define filename
    filename = folder + 'cat.' + str(i) + '.jpg'
    # load image pixels
    image = imread(filename)
    # plot raw pixel data
    pyplot.imshow(image)
pyplot.show()
```



From the above plots we see that the image is not of same length. To train the model with the training data, we need to have images of same

Data Preparation

In [6]:
```
# loading the dogs vs cats dataset.
# Reshaping the image and saving to a new file

## Importing of required packages
from os import listdir
from numpy import asarray
from numpy import save
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array


# define location of dataset
folder = 'train/'
photos, labels = list(), list()
# enumerate files in the directory
for file in listdir(folder):
    # determine class
    output = 0.0
    if file.startswith('cat'):
        output = 1.0
    # load image
    photo = load_img(folder + file, target_size=(100, 100))
    # convert to numpy array
    photo = img_to_array(photo)
    # store
    photos.append(photo)
    labels.append(output)
# convert to a numpy arrays
# numpy array is stored in "photos" and labelling is stored in "labels
photos = asarray(photos)
labels = asarray(labels)
print(photos.shape, labels.shape)
```

```
Using TensorFlow backend.

(25000, 100, 100, 3) (25000,)
```

The raw image data is reshaped into (100 * 100).

The Cat image is labeled as 1 and Dog image is labeled as 0

The image is converted to an array

In [0]:
```
#Importing the required packages
from os import makedirs
from os import listdir
from shutil import copyfile
from random import seed
from random import random


# creating the directories
dataset_home = 'dataset_dogs_vs_cats/'
subdirs = ['train/', 'test/']
for subdir in subdirs:
    # creating label subdirectories
    labeldirs = ['dogs/', 'cats/']
    for labldir in labeldirs:
        newdir = dataset_home + subdir + labldir
        makedirs(newdir, exist_ok=True)

# seed random number generator
seed(1)
# define ratio of pictures to use for validation
val_ratio = 0.25
# copy training dataset images into subdirectories
src_directory = 'train/'
for file in listdir(src_directory):
    src = src_directory + '/' + file
    dst_dir = 'train/'
    if random() < val_ratio:
        dst_dir = 'test/'
    if file.startswith('cat'):
        dst = dataset_home + dst_dir + 'cats/'  + file
        copyfile(src, dst)
    elif file.startswith('dog'):
        dst = dataset_home + dst_dir + 'dogs/'  + file
        copyfile(src, dst)
```

The data is split into train and test directory with both folders containing Cat and Dog images separately.

Model building

In [0]:
```
# importing the required packages

import sys
from keras.layers import Conv2D
from matplotlib import pyplot
from keras.utils import to_categorical
from keras.applications.vgg16 import VGG16
from keras.models import Model
from keras.layers import Dense
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.optimizers import SGD
from keras.models import Sequential
from keras.preprocessing.image import ImageDataGenerator
from keras.layers import Dropout
from keras.preprocessing.image import ImageDataGenerator
```

In [0]:
```
# function to plot Loss and Accurcay of both train and test data

def summarize_diagnostics(history):
    # plot loss
    pyplot.subplot(211)
    pyplot.title('Cross Entropy Loss')
    pyplot.plot(history.history['loss'], color='blue', label='train')
    pyplot.plot(history.history['val_loss'], color='orange', label='te
    # plot accuracy
    pyplot.subplot(212)
    pyplot.title('Classification Accuracy')
    pyplot.plot(history.history['acc'], color='blue', label='train')
    pyplot.plot(history.history['val_acc'], color='orange', label='tes
    pyplot.show()
```

1. CNN with 1 hidden layer(32).

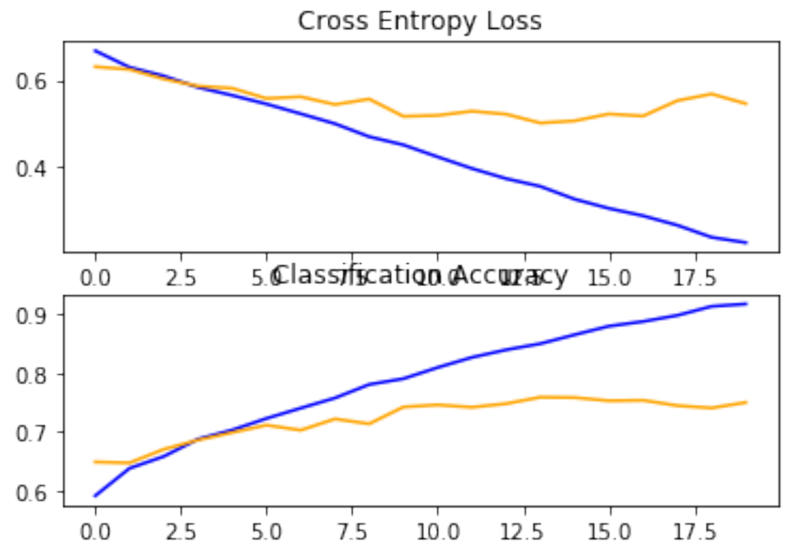
In [0]:
```
# defining a cnn model
def define_model():
    model = Sequential()
    model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer
    model.add(MaxPooling2D((2, 2)))
    model.add(Flatten())
    model.add(Dense(128, activation='relu', kernel_initializer='he_uni
    model.add(Dense(1, activation='sigmoid'))
    # compile model
    opt = SGD(lr=0.001, momentum=0.9)
    model.compile(optimizer=opt, loss='binary_crossentropy', metrics=[
    return model
```

In [24]:
```
# run the test harness for evaluating a model
def run_test_harness():
    # define model
```

```
    model = define_model()
    # rescaling the image by divining each pixel by 255
    datagen = ImageDataGenerator(rescale=1.0/255.0)
    # prepare iterators and resizing the image to (100*100)
    train_it = datagen.flow_from_directory('dataset_dogs_vs_cats/train
        class_mode='binary', batch_size=64, target_size=(100, 100))
    test_it = datagen.flow_from_directory('dataset_dogs_vs_cats/test/'
        class_mode='binary', batch_size=64, target_size=(100, 100))
    # fitting of model
    history = model.fit_generator(train_it, steps_per_epoch=len(train_
        validation_data=test_it, validation_steps=len(test_it), epochs
    # evaluate model
    _, acc = model.evaluate_generator(test_it, steps=len(test_it), verb
    print('accuracy is > %.3f' % (acc * 100.0))
    # learning curves
    summarize_diagnostics(history)

# entry point, run the test harness
run_test_harness()
```

```
Found 18697 images belonging to 2 classes.
Found 6303 images belonging to 2 classes.
Epoch 1/20

293/293 [==============================] - 72s 244ms/step - loss: 0.
6674 - acc: 0.5914 - val_loss: 0.6306 - val_acc: 0.6491
Epoch 2/20
293/293 [==============================] - 71s 242ms/step - loss: 0.
6294 - acc: 0.6384 - val_loss: 0.6245 - val_acc: 0.6475
Epoch 3/20
293/293 [==============================] - 69s 237ms/step - loss: 0.
6093 - acc: 0.6584 - val_loss: 0.6026 - val_acc: 0.6705
Epoch 4/20
293/293 [==============================] - 69s 236ms/step - loss: 0.
5832 - acc: 0.6880 - val_loss: 0.5863 - val_acc: 0.6862
Epoch 5/20
293/293 [==============================] - 70s 238ms/step - loss: 0.
5654 - acc: 0.7031 - val_loss: 0.5813 - val_acc: 0.6989
Epoch 6/20
293/293 [==============================] - 68s 233ms/step - loss: 0.
5449 - acc: 0.7229 - val_loss: 0.5579 - val_acc: 0.7114
Epoch 7/20
293/293 [==============================] - 70s 238ms/step - loss: 0.
5222 - acc: 0.7406 - val_loss: 0.5618 - val_acc: 0.7028
Epoch 8/20
293/293 [==============================] - 70s 238ms/step - loss: 0.
4998 - acc: 0.7574 - val_loss: 0.5439 - val_acc: 0.7219
Epoch 9/20
293/293 [==============================] - 71s 241ms/step - loss: 0.
4710 - acc: 0.7799 - val_loss: 0.5565 - val_acc: 0.7136
Epoch 10/20
293/293 [==============================] - 70s 238ms/step - loss: 0.
4510 - acc: 0.7903 - val_loss: 0.5169 - val_acc: 0.7422
Epoch 11/20
293/293 [==============================] - 71s 242ms/step - loss: 0.
```

```
4239 - acc: 0.8089 - val_loss: 0.5190 - val_acc: 0.7457
Epoch 12/20
293/293 [==============================] - 69s 236ms/step - loss: 0.
3969 - acc: 0.8263 - val_loss: 0.5286 - val_acc: 0.7417
Epoch 13/20
293/293 [==============================] - 69s 234ms/step - loss: 0.
3736 - acc: 0.8387 - val_loss: 0.5217 - val_acc: 0.7477
Epoch 14/20
293/293 [==============================] - 69s 236ms/step - loss: 0.
3566 - acc: 0.8487 - val_loss: 0.5016 - val_acc: 0.7587
Epoch 15/20
293/293 [==============================] - 70s 240ms/step - loss: 0.
3275 - acc: 0.8638 - val_loss: 0.5065 - val_acc: 0.7581
Epoch 16/20
293/293 [==============================] - 71s 243ms/step - loss: 0.
3052 - acc: 0.8789 - val_loss: 0.5222 - val_acc: 0.7527
Epoch 17/20
293/293 [==============================] - 70s 239ms/step - loss: 0.
2886 - acc: 0.8872 - val_loss: 0.5175 - val_acc: 0.7535
Epoch 18/20
293/293 [==============================] - 71s 242ms/step - loss: 0.
2666 - acc: 0.8975 - val_loss: 0.5528 - val_acc: 0.7444

Epoch 19/20
293/293 [==============================] - 70s 238ms/step - loss: 0.
2401 - acc: 0.9117 - val_loss: 0.5681 - val_acc: 0.7404
Epoch 20/20
293/293 [==============================] - 71s 241ms/step - loss: 0.
2274 - acc: 0.9161 - val_loss: 0.5459 - val_acc: 0.7498
99/99 [==============================] - 16s 161ms/step
```



The model built with 1 hidden layer gives an accuracy of 75%. In the model, there is not much changes in the test data after 7 to 10 epochs.

2. CNN with 3 hidden layers (32,64,128)

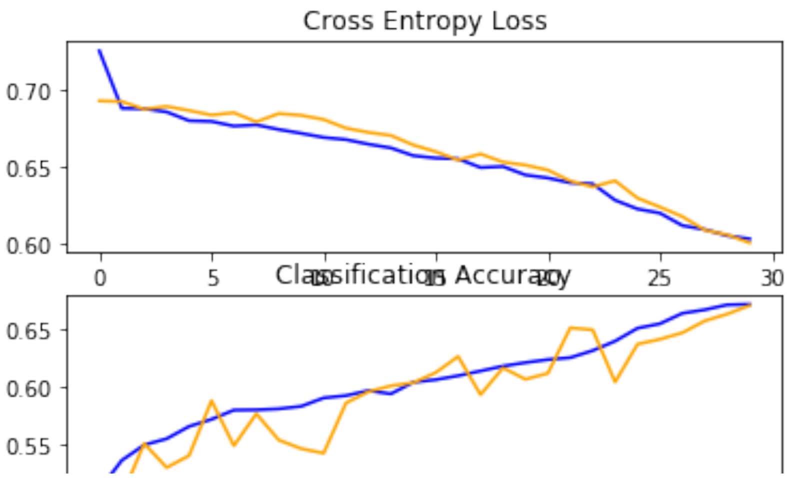
In [0]:
```
# define cnn model
def define_model():
    model = Sequential()
    model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer
    model.add(MaxPooling2D((2, 2)))
    model.add(Dropout(0.25))
    model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer
    model.add(MaxPooling2D((2, 2)))
    model.add(Dropout(0.25))
    model.add(Conv2D(128, (3, 3), activation='relu', kernel_initialize
    model.add(MaxPooling2D((2, 2)))
    model.add(Dropout(0.25))
    model.add(Flatten())
    model.add(Dense(128, activation='relu', kernel_initializer='he_uni
    model.add(Dropout(0.5))
    model.add(Dense(1, activation='sigmoid'))
    # compile model
    opt = SGD(lr=0.001, momentum=0.9)
    model.compile(optimizer=opt, loss='binary_crossentropy', metrics=[
    return model
```

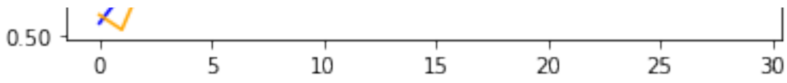
In [37]:
```
def run_test_harness():
    # define model
    model = define_model()
    # create data generators
    train_datagen = ImageDataGenerator(rescale=1.0/255.0,
        width_shift_range=0.1, height_shift_range=0.1, horizontal_flip
    test_datagen = ImageDataGenerator(rescale=1.0/255.0)
    # prepare iterators
    train_it = train_datagen.flow_from_directory('dataset_dogs_vs_cats
        class_mode='binary', batch_size=64, target_size=(100, 100))
    test_it = test_datagen.flow_from_directory('dataset_dogs_vs_cats/t
        class_mode='binary', batch_size=64, target_size=(100, 100))
    # fit model
    history = model.fit_generator(train_it, steps_per_epoch=len(train_
        validation_data=test_it, validation_steps=len(test_it), epochs
    # evaluate model
    _, acc = model.evaluate_generator(test_it, steps=len(test_it), verb
    print('> %.3f' % (acc * 100.0))
    # learning curves
    summarize_diagnostics(history)

# entry point, run the test harness
run_test_harness()
```

```
Found 12607 images belonging to 2 classes.
```

```
Found 18697 images belonging to 2 classes.
Found 6303 images belonging to 2 classes.
Epoch 1/30
293/293 [==============================] - 109s 373ms/step - loss: 0
.7247 - acc: 0.5121 - val_loss: 0.6923 - val_acc: 0.5186
Epoch 2/30
293/293 [==============================] - 106s 363ms/step - loss: 0
.6873 - acc: 0.5372 - val_loss: 0.6919 - val_acc: 0.5058
Epoch 3/30
293/293 [==============================] - 105s 359ms/step - loss: 0
.6872 - acc: 0.5498 - val_loss: 0.6869 - val_acc: 0.5513
Epoch 4/30
293/293 [==============================] - 106s 363ms/step - loss: 0
.6853 - acc: 0.5551 - val_loss: 0.6887 - val_acc: 0.5305
Epoch 5/30
293/293 [==============================] - 106s 363ms/step - loss: 0
.6795 - acc: 0.5654 - val_loss: 0.6860 - val_acc: 0.5409
Epoch 6/30
293/293 [==============================] - 105s 358ms/step - loss: 0
.6787 - acc: 0.5722 - val_loss: 0.6831 - val_acc: 0.5883
Epoch 7/30
293/293 [==============================] - 105s 357ms/step - loss: 0
.6761 - acc: 0.5798 - val_loss: 0.6846 - val_acc: 0.5494
Epoch 8/30
293/293 [==============================] - 105s 358ms/step - loss: 0
.6770 - acc: 0.5803 - val_loss: 0.6787 - val_acc: 0.5770
Epoch 9/30
293/293 [==============================] - 104s 354ms/step - loss: 0
.6740 - acc: 0.5805 - val_loss: 0.6840 - val_acc: 0.5543
Epoch 10/30
293/293 [==============================] - 105s 358ms/step - loss: 0
.6711 - acc: 0.5837 - val_loss: 0.6829 - val_acc: 0.5469
Epoch 11/30
293/293 [==============================] - 105s 359ms/step - loss: 0
.6687 - acc: 0.5909 - val_loss: 0.6802 - val_acc: 0.5429
Epoch 12/30
293/293 [==============================] - 104s 356ms/step - loss: 0
.6669 - acc: 0.5929 - val_loss: 0.6746 - val_acc: 0.5864
Epoch 13/30
293/293 [==============================] - 105s 358ms/step - loss: 0
.6640 - acc: 0.5975 - val_loss: 0.6718 - val_acc: 0.5961
Epoch 14/30
293/293 [==============================] - 104s 356ms/step - loss: 0
.6616 - acc: 0.5944 - val_loss: 0.6698 - val_acc: 0.6011
Epoch 15/30
293/293 [==============================] - 105s 357ms/step - loss: 0
.6566 - acc: 0.6038 - val_loss: 0.6636 - val_acc: 0.6038
Epoch 16/30
293/293 [==============================] - 105s 360ms/step - loss: 0
.6553 - acc: 0.6066 - val_loss: 0.6593 - val_acc: 0.6126
Epoch 17/30
293/293 [==============================] - 104s 353ms/step - loss: 0
.6542 - acc: 0.6104 - val_loss: 0.6538 - val_acc: 0.6265
Epoch 18/30
```

```
293/293 [==============================] - 105s 357ms/step - loss: 0
.6487 - acc: 0.6142 - val_loss: 0.6578 - val_acc: 0.5935
Epoch 19/30
293/293 [==============================] - 105s 360ms/step - loss: 0
.6500 - acc: 0.6183 - val_loss: 0.6525 - val_acc: 0.6167
Epoch 20/30
293/293 [==============================] - 105s 357ms/step - loss: 0
.6438 - acc: 0.6214 - val_loss: 0.6505 - val_acc: 0.6069
Epoch 21/30
293/293 [==============================] - 104s 356ms/step - loss: 0
.6419 - acc: 0.6243 - val_loss: 0.6473 - val_acc: 0.6119
Epoch 22/30
293/293 [==============================] - 107s 365ms/step - loss: 0
.6391 - acc: 0.6250 - val_loss: 0.6402 - val_acc: 0.6513
Epoch 23/30
293/293 [==============================] - 105s 358ms/step - loss: 0
.6384 - acc: 0.6317 - val_loss: 0.6364 - val_acc: 0.6495
Epoch 24/30
293/293 [==============================] - 104s 356ms/step - loss: 0
.6274 - acc: 0.6399 - val_loss: 0.6403 - val_acc: 0.6045
Epoch 25/30
293/293 [==============================] - 107s 365ms/step - loss: 0
.6228 - acc: 0.6500 - val_loss: 0.6290 - val_acc: 0.6372
Epoch 26/30
293/293 [==============================] - 105s 358ms/step - loss: 0
.6196 - acc: 0.6539 - val_loss: 0.6233 - val_acc: 0.6414
Epoch 27/30
293/293 [==============================] - 104s 354ms/step - loss: 0
.6112 - acc: 0.6639 - val_loss: 0.6170 - val_acc: 0.6470
Epoch 28/30
293/293 [==============================] - 106s 361ms/step - loss: 0
.6083 - acc: 0.6672 - val_loss: 0.6082 - val_acc: 0.6573
Epoch 29/30
293/293 [==============================] - 105s 358ms/step - loss: 0
.6053 - acc: 0.6702 - val_loss: 0.6052 - val_acc: 0.6632
Epoch 30/30
293/293 [==============================] - 104s 356ms/step - loss: 0
.6029 - acc: 0.6710 - val_loss: 0.6000 - val_acc: 0.6706
99/99 [==============================] - 17s 175ms/step
> 67.111
```





The model built with 3 hidden layer gives an accuracy of 67%. In the model, the accuracy keeps getting better with increase in epcohs. To increase the accuracy, we need to increase to number of epochs to get the better accuracy.

3. Transfer Learning (VGG16)

To train a model, we need alot of data and computational resources to build a very good performing model. Instead of building a model form scratch, we can use the pre-trained models to extract features from the image and thereby reducing the time to train model.

we choose pretrained model of VGG16 and only use aur training data in the last layer.

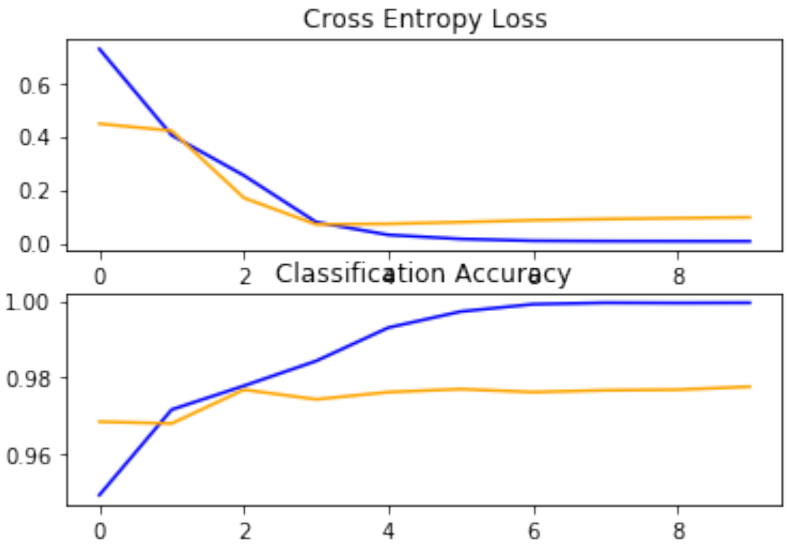
In [0]:
```
# define cnn model
def define_model():
    # load model
    model = VGG16(include_top=False, input_shape=(224, 224, 3))
    # mark loaded layers as not trainable
    for layer in model.layers:
        layer.trainable = False
    # add new classifier layers
    flat1 = Flatten()(model.layers[-1].output)
    class1 = Dense(128, activation='relu', kernel_initializer='he_unif
    output = Dense(1, activation='sigmoid')(class1)
    # define new model
    model = Model(inputs=model.inputs, outputs=output)
    # compile model
    opt = SGD(lr=0.001, momentum=0.9)
    model.compile(optimizer=opt, loss='binary_crossentropy', metrics=[
    return model
```

In [11]:
```
# run the test harness for evaluating a model
def run_test_harness():
    # define model
    model = define_model()
    # create data generator
    datagen = ImageDataGenerator(featurewise_center=True)
    # specify imagenet mean values for centering
    datagen.mean = [123.68, 116.779, 103.939]
    # prepare iterator
    train_it = datagen.flow_from_directory('dataset_dogs_vs_cats/train
```

```
        class_mode='binary', batch_size=64, target_size=(224, 224))
    test_it = datagen.flow_from_directory('dataset_dogs_vs_cats/test/'
        class_mode='binary', batch_size=64, target_size=(224, 224))
    # fit model
    history = model.fit_generator(train_it, steps_per_epoch=len(train_
        validation_data=test_it, validation_steps=len(test_it), epochs
    # evaluate model
    _, acc = model.evaluate_generator(test_it, steps=len(test_it), verb
    print('> %.3f' % (acc * 100.0))
    # learning curves
    summarize_diagnostics(history)

# entry point, run the test harness
run_test_harness()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tenso
rflow/python/framework/op_def_library.py:263: colocate_with (from te
nsorflow.python.framework.ops) is deprecated and will be removed in
a future version.
Instructions for updating:
Colocations handled automatically by placer.
Downloading data from https://github.com/fchollet/deep-learning-mode
ls/releases/download/v0.1/vgg16_weights_tf_dim_ordering_tf_kernels_n
otop.h5 (https://github.com/fchollet/deep-learning-models/releases/d
ownload/v0.1/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5)
58892288/58889256 [==============================] - 2s 0us/step
Found 18697 images belonging to 2 classes.
Found 6303 images belonging to 2 classes.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tenso
rflow/python/ops/math_ops.py:3066: to_int32 (from tensorflow.python.
ops.math_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/10
293/293 [==============================] - 144s 493ms/step - loss: 0
.7250 - acc: 0.9491 - val_loss: 0.4471 - val_acc: 0.9683
Epoch 2/10
293/293 [==============================] - 131s 448ms/step - loss: 0
.4027 - acc: 0.9715 - val_loss: 0.4207 - val_acc: 0.9678
Epoch 3/10
293/293 [==============================] - 130s 445ms/step - loss: 0
.2526 - acc: 0.9778 - val_loss: 0.1692 - val_acc: 0.9767
Epoch 4/10
293/293 [==============================] - 130s 445ms/step - loss: 0
.0781 - acc: 0.9843 - val_loss: 0.0696 - val_acc: 0.9741
Epoch 5/10
293/293 [==============================] - 132s 449ms/step - loss: 0
.0304 - acc: 0.9930 - val_loss: 0.0718 - val_acc: 0.9760
Epoch 6/10
293/293 [==============================] - 131s 446ms/step - loss: 0
.0151 - acc: 0.9972 - val_loss: 0.0783 - val_acc: 0.9768
Epoch 7/10
293/293 [==============================] - 132s 449ms/step - loss: 0
.0084 - acc: 0.9991 - val_loss: 0.0853 - val_acc: 0.9760
```

```
Epoch 8/10
293/293 [==============================] - 131s 446ms/step - loss: 0
.0070 - acc: 0.9995 - val_loss: 0.0898 - val_acc: 0.9765
Epoch 9/10
293/293 [==============================] - 131s 447ms/step - loss: 0
.0067 - acc: 0.9995 - val_loss: 0.0932 - val_acc: 0.9767
Epoch 10/10
293/293 [==============================] - 132s 449ms/step - loss: 0
.0065 - acc: 0.9995 - val_loss: 0.0962 - val_acc: 0.9775
> 97.636
```



The model with transfer learning gives an accuracy of 97%.

Conclusion

In [2]:
```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["MLP_MODEL","Epochs", "TRAIN_ACCURACY", "TEST_ACCURAC

x.add_row(["CNN with 1 conv layers and kernel size of 3*3",20, 0.91, 0
x.add_row(["CNN with 3 conv layers and kernel size of 3*3 with dropout
x.add_row(["CNN with transfer learning",10, 0.9995, 0.9775])

print('\t\t\tConvolutional Neural Network ')
print(x)
```

```
                        Convolutional Neural Network
+--------------------------------------------------------------------
+--------+----------------+---------------+
|                              MLP_MODEL
| Epochs | TRAIN_ACCURACY | TEST_ACCURACY |
+--------------------------------------------------------------------
+--------+----------------+---------------+
|           CNN with 1 conv layers and kernel size of 3*3
|   20   |      0.91      |      0.74     |
| CNN with 3 conv layers and kernel size of 3*3 with dropout layers
|   30   |      0.67      |      0.67     |
|                     CNN with transfer learning
|   10   |     0.9995     |     0.9775    |
+--------------------------------------------------------------------
+--------+----------------+---------------+
```