Type *Markdown* and LaTeX: α^2

CNN for lesion classification

1. Brief CNN theory

Theory same as in last notebook

2. We build one using keras and tensorflow

2.1 Preparation

In [1]:

```
# setup code for this notebook
import numpy as np
import matplotlib.pyplot as plt
from functions import data, Timer
timer = Timer()

# This makes matplotlib figures appear inline in the notebook
# rather than in a new window.
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# Make the notebook reload external python modules;
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

The ultra sound scan data

- 163 scans total, clinically confirmed as having either bening or malignant (cancerous) lesions
- 100 scans for training, 63 for testing
- Training data was passed through 7 transformations to give us 800 training images total
- We balanced the training data to have half malignant and half benign
- Since the malignant cases were less than benign cases, we use only 528 images for training
- Emperically we have found this improves our overall performance
- Testing images not transformed
- Both training and testing images were resized to 224X224
- Raw pngs then converted to numpy arrays and saved

In [2]:

```
# Import keras libraries
from keras.models import Sequential
from keras.layers.core import Dense, Dropout, Activation, Flatten
from keras.layers.convolutional import Conv2D
from keras.layers.pooling import MaxPooling2D
from keras import backend as K
```

```
Using TensorFlow backend.
```

In [3]:

```
img_rows, img_cols = 224, 224 # 224, 224 resized down from 360, 528
color_channels = 3

if K.image_data_format() == 'channels_first':
    input_shape = (color_channels, img_rows, img_cols)
else:
    input_shape = (img_rows, img_cols, color_channels)

print('Input shape', input_shape)
```

```
Input shape (224, 224, 3)
```

2.2 A CNN

In [4]:

```
# values for the convnet

# number of convolutional filters to use
filters = 64
# size of pooling area
pooling_area = 2
# conv kernel size
conv_kernel = 3
```

In [5]:

```
# We define the cnn model
def buildModelStructure():
    model = Sequential()

    model.add(Conv2D(filters, (conv_kernel, conv_kernel), padding='valid',
                     input_shape=input_shape))
    model.add(Activation('relu'))
    model.add(MaxPooling2D(pool_size=(pooling_area, pooling_area)))

    model.add(Conv2D(filters, (conv_kernel, conv_kernel)))
    model.add(Activation('relu'))
    model.add(MaxPooling2D(pool_size=(pooling_area, pooling_area)))

    model.add(Conv2D(64, (conv_kernel, conv_kernel)))
    model.add(Activation('relu'))
    model.add(MaxPooling2D(pool_size=(pooling_area, pooling_area)))

    model.add(Flatten())
    model.add(Dense(64))
    model.add(Activation('relu'))
    model.add(Dropout(0.5))
    model.add(Dense(1))
    model.add(Activation('sigmoid'))

    return model
```

In [6]:

```
# Visualize
from IPython.display import SVG
from keras.utils.vis_utils import model_to_dot

def visualize(model):
    model.summary()
    SVG(model_to_dot(model).create(prog='dot', format='svg'))
```

In [7]:

```
# generator helpers
from keras.preprocessing.image import ImageDataGenerator
```

In [8]:

```
# data readers
base = "J:\\final year project\\code and models\\data\\augmented\\"
train_directory = base+'training'
validation_directory = base+'validation'

batch_size = 32

# normalization
train_generator = ImageDataGenerator(rescale=1./255)
validation_generator = ImageDataGenerator(rescale=1./255)

# this is a generator that will read scans found in
# the train directory, and indefinitely generate
# batches of image data
train_generator = train_generator.flow_from_directory(
        train_directory,
        target_size=(img_rows, img_cols),
        batch_size=batch_size,
        class_mode='binary')

# A  similar generator, for validation data
validation_generator = validation_generator.flow_from_directory(
        validation_directory,
        target_size=(img_rows, img_cols),
        batch_size=batch_size,
        class_mode='binary')
```

```
Found 400 images belonging to 2 classes.
Found 128 images belonging to 2 classes.
```

In [9]:

```
def plot(network_history):
    plt.figure()
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.plot(network_history.history['loss'])
    plt.plot(network_history.history['val_loss'])
    plt.legend(['Training', 'Validation'])

    plt.figure()
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.plot(network_history.history['acc'])
    plt.plot(network_history.history['val_acc'])
    plt.legend(['Training', 'Validation'], loc='lower right')
```

In [10]:

```
# helpers for checkpointing and early stopping
from keras.callbacks import ModelCheckpoint, EarlyStopping

best_model_file = '4.3.h5'
early_stop = EarlyStopping(monitor='val_loss', patience=7, verbose=True)
best_model = ModelCheckpoint(best_model_file, verbose=True, save_best_only=True)

def testModel(optimizer='adagrad', epochs=10, text="Training model"):
    # build model
    model = buildModelStructure()

    # Compile it
    model.compile(loss='binary_crossentropy',
              optimizer=optimizer,
              metrics=['accuracy'])
    timer.start()
    network_history = model.fit_generator(
            train_generator,
            steps_per_epoch=800,
            epochs=epochs,
            validation_data = validation_generator,
            validation_steps=256,
            verbose=True,
            callbacks=[best_model, early_stop])
    timer.stop(text)
    plot(network_history)
```

In [11]:

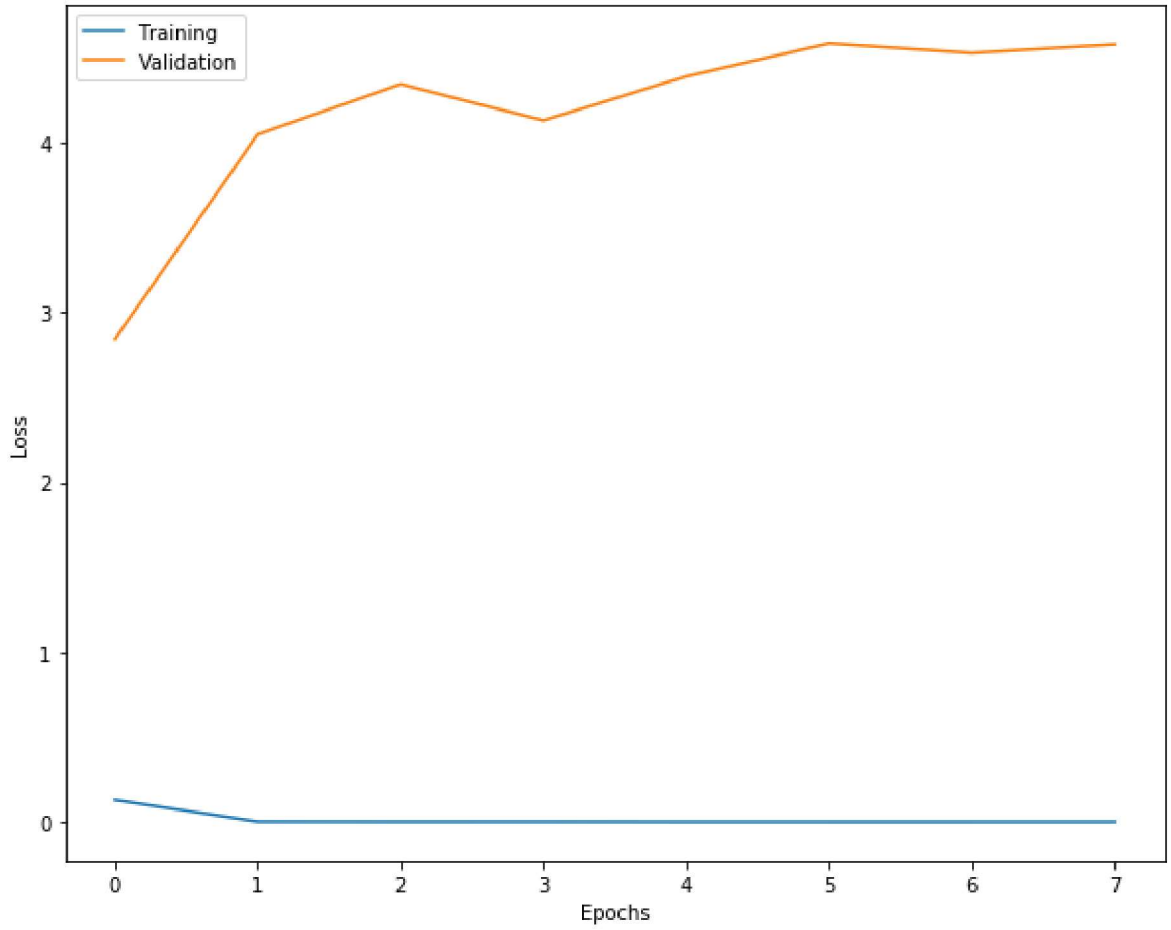
```
print(9)
```

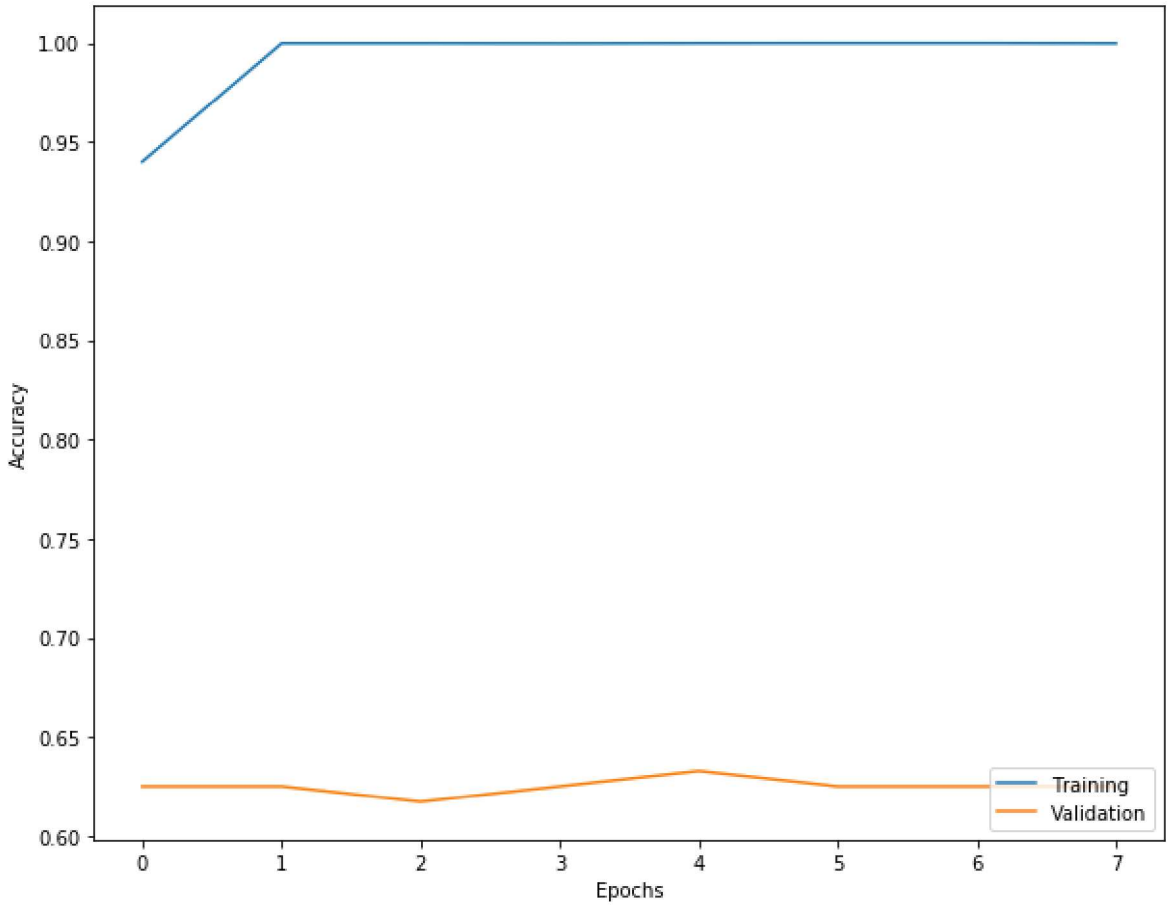
```
9
```

In [12]:

```
#Adagrad
epochs = 20
testModel('adagrad', epochs, "training model with adagrad")
```

```
Epoch 1/20
800/800 [==============================] - 303s 379ms/step - loss: 0.1290 -
acc: 0.9397 - val_loss: 2.8452 - val_acc: 0.6250

Epoch 00001: val_loss improved from inf to 2.84515, saving model to 4.3.h5
Epoch 2/20
800/800 [==============================] - 296s 370ms/step - loss: 9.9990e-0
4 - acc: 0.9999 - val_loss: 4.0509 - val_acc: 0.6250

Epoch 00002: val_loss did not improve
Epoch 3/20
800/800 [==============================] - 295s 369ms/step - loss: 5.5027e-0
4 - acc: 0.9999 - val_loss: 4.3462 - val_acc: 0.6172

Epoch 00003: val_loss did not improve
Epoch 4/20
800/800 [==============================] - 294s 368ms/step - loss: 6.1481e-0
4 - acc: 0.9998 - val_loss: 4.1326 - val_acc: 0.6250

Epoch 00004: val_loss did not improve
Epoch 5/20
800/800 [==============================] - 292s 366ms/step - loss: 2.4799e-0
4 - acc: 1.0000 - val_loss: 4.3924 - val_acc: 0.6328

Epoch 00005: val_loss did not improve
Epoch 6/20
800/800 [==============================] - 293s 366ms/step - loss: 1.7267e-0
4 - acc: 1.0000 - val_loss: 4.5862 - val_acc: 0.6250

Epoch 00006: val_loss did not improve
Epoch 7/20
800/800 [==============================] - 293s 366ms/step - loss: 1.9681e-0
4 - acc: 1.0000 - val_loss: 4.5303 - val_acc: 0.6250

Epoch 00007: val_loss did not improve
Epoch 8/20
800/800 [==============================] - 294s 368ms/step - loss: 2.6304e-0
4 - acc: 0.9999 - val_loss: 4.5803 - val_acc: 0.6250

Epoch 00008: val_loss did not improve
Epoch 00008: early stopping
Timing:: took 39 minutes training model with adagrad
---------------------------------
```


Training
Validation
Loss
Epochs
0
1
2
3
4
5
6
7


Accuracy
Epochs
Training
Validation
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60

2.3 Evaluating the CNNs performance

In [1]:

```
# Get test data
from functions import data
x_test, y_test = data.getTestData()
print('Test data shape: ', x_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
Test data shape:  (63, 224, 224, 3)
Test labels shape:  (63, 1)
```

In [2]:

```
# normalize data
X_test = x_test/255
```

In [3]:

```
# load and evaluate best model
from keras.models import load_model
best_model = load_model('4.3.h5')
best_model.summary()
```

```
Using TensorFlow backend.
```

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 222, 222, 32)	896
activation_1 (Activation)	(None, 222, 222, 32)	0
max_pooling2d_1 (MaxPooling2	(None, 111, 111, 32)	0
conv2d_2 (Conv2D)	(None, 109, 109, 32)	9248
activation_2 (Activation)	(None, 109, 109, 32)	0
max_pooling2d_2 (MaxPooling2	(None, 54, 54, 32)	0
conv2d_3 (Conv2D)	(None, 52, 52, 64)	18496
activation_3 (Activation)	(None, 52, 52, 64)	0
max_pooling2d_3 (MaxPooling2	(None, 26, 26, 64)	0
flatten_1 (Flatten)	(None, 43264)	0
dense_1 (Dense)	(None, 64)	2768960
activation_4 (Activation)	(None, 64)	0
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 1)	65
activation_5 (Activation)	(None, 1)	0

```
Total params: 2,797,665
Trainable params: 2,797,665
Non-trainable params: 0
```

In [4]:

```
best_model.predict_classes(x_test)
```

Out[4]:

```
array([[1],
       [1],
       [1],
       [0],
       [1],
       [0],
       [1],
       [1],
       [0],
       [1],
       [1],
       [1],
       [1],
       [1],
       [1],
       [1],
       [0],
       [0],
       [0],
       [1],
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       [1],
       [1],
       [1],
       [0],
       [1],
       [1],
       [0],
       [1],
       [1],
       [0],
```

```
       [1],
       [1],
       [1],
       [1],
       [1],
       [0],
       [1],
       [1]])
```

In [5]:

```
def printMetrics(fn, tp):
    sensitivity = tp/(tp+fn)

    print("True Positive Rate (TPR) or Hit Rate or Recall or Sensitivity: "
          , sensitivity)
```

tn is the true negative. These are scans classified correctly as not having malignant lesions.

fn is the false negative. These are scans classified incorrectly as having malignant lesions yet they are benign.

fn is the false negatives. These are images predicted as not having malignant lesions yet they do. This should be low.

tp is the true positive. These are correctly predicted to have malignant lesions.

Sensitivity is a function of false negatives and true positives two variables. Because we are dealing with cancer, false negatives should be very low and true positives high. Low number of false negatives and a high number of true positives gives a high sensitivity. A high sensitivity is desired in a good model

In [6]:

```
# Evaluate all
from sklearn.metrics import confusion_matrix
expected = y_test
prediction = best_model.predict_classes(x_test)
tn,fp,fn,tp = confusion_matrix(y_test, prediction).ravel()
print("false negatives: ", fn)
print("true positives: ", tp)
print("true negatives: ", tn)
print("false positives: ", fp)
printMetrics(fn, tp)
```

```
false negatives:  5
true positives:  16
true negatives:  12
false positives:  30
True Positive Rate (TPR) or Hit Rate or Recall or Sensitivity:  0.7619047619
05
```

Not much improvement from our best performing model which uses fewer training steps per epoch

References for images and some content:

[1] https://adeshpande3.github.io/adeshpande3.github.io/ ()
[2] "Neural Networks and Deep Learning" (http://neuralnetworksanddeeplearning.com/) by Michael Nielsen.
[3] Deep learning with TensorFlow and Keras by Valerio Maggio

In [ ]: