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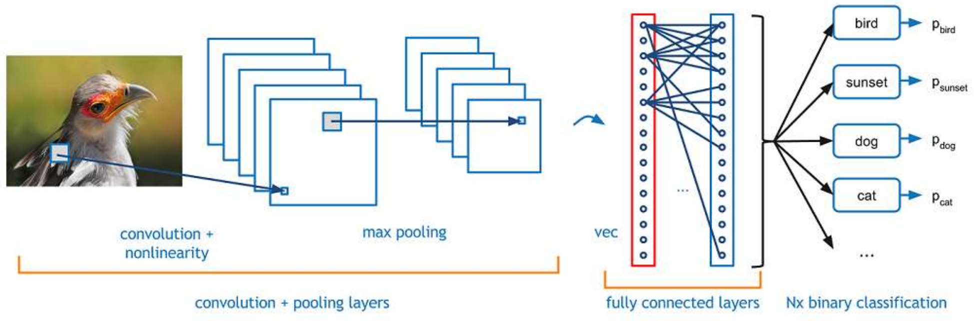
CNN for lesion classification

1. Brief CNN theory

A Convolutional Neural Network (CNN, or ConvNet) is a type of **feed-forward** artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex.



> source: https://flickrcode.files.wordpress.com/2014/10/conv-net2.png (https://flickrcode.files.wordpress.com/2014/10/conv-net2.png)

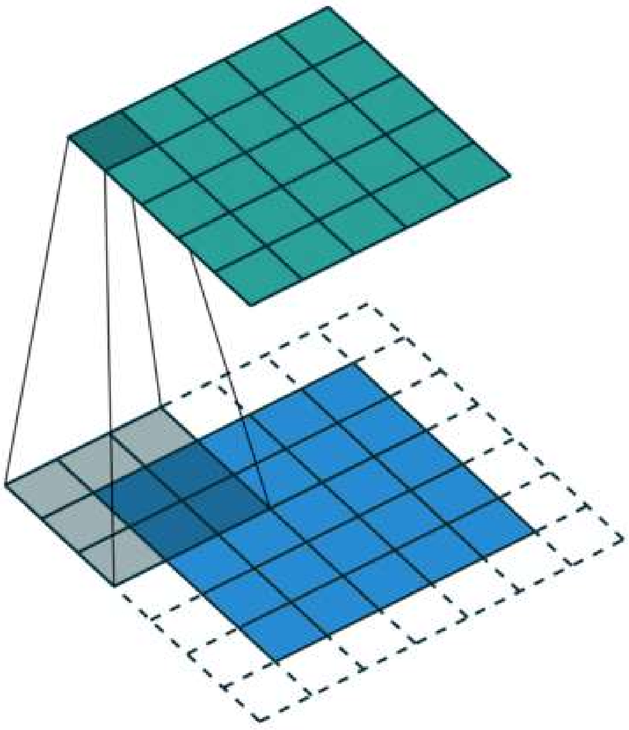
1.1 Structure of a CNN

> A more detailed overview of what CNNs do would be that you take the image, pass it through a series of convolutional, nonlinear, pooling (downsampling), and fully connected layers, and get an output. As we said earlier, the output can be a single class or a probability of classes that best describes the image.

source: [1]

Convolutional Layer

The first layer in a CNN is always a **Convolutional Layer**.



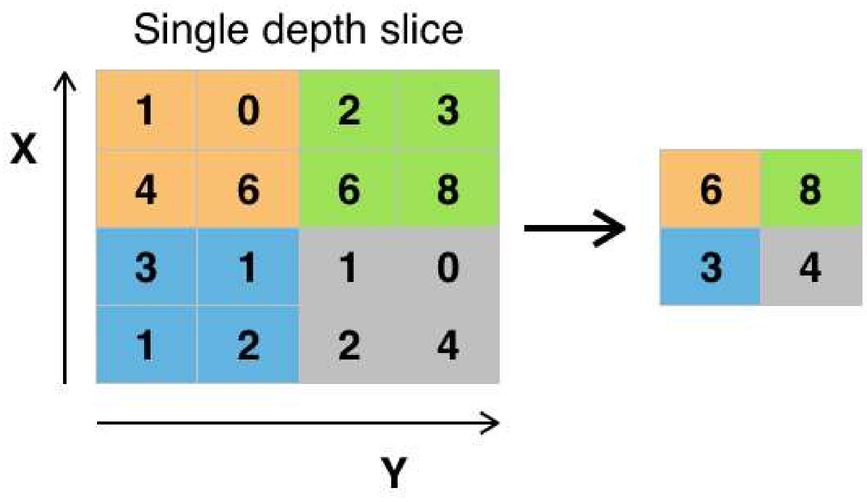
Typical CNN Structure

A traditional CNN architecture consists of other layers interspaced between convolution layers

Input -> Conv -> ReLU -> Conv -> ReLU -> Pool -> ReLU -> Conv -> ReLU -> Pool -> Fully Connected

Pooling layer

After some ReLu layers, **pooling layer** is typically applied.



Example of Maxpool with a 2x2 filter and a stride of 2

Pooling reduces the amount of parameters (helping with computional efficiency) and controls overfitting

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 = 32
# 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]:

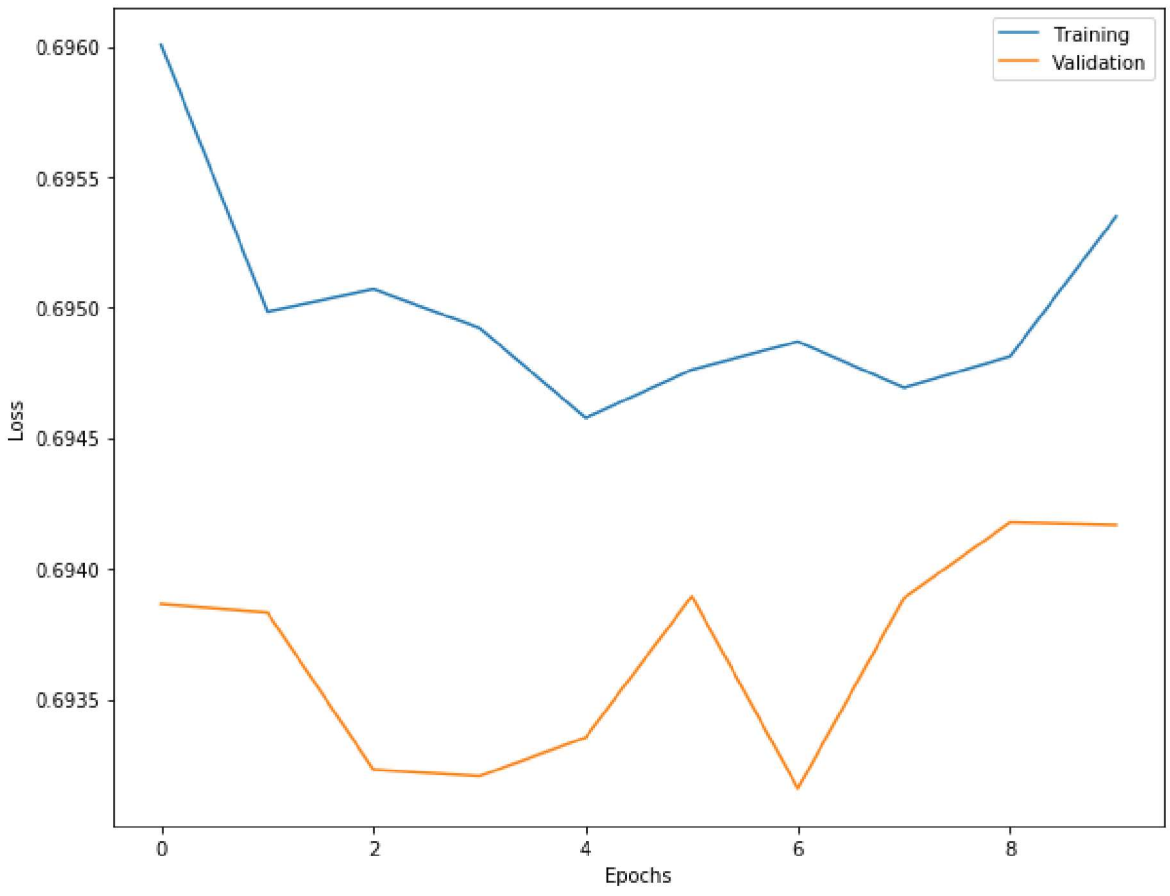
```
# helpers for checkpointing and early stopping
from keras.callbacks import ModelCheckpoint # , EarlyStopping

best_model_file = 'best_cnn_dgen_model.h5'
# early_stop = EarlyStopping(monitor='val_loss', patience=5, verbose=1)
best_model = ModelCheckpoint(best_model_file, verbose=True, save_best_only=True)

def testModel(optimizer='rmsprop', epochs=2, 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=400,
            epochs=epochs,
            validation_data = validation_generator,
            validation_steps=128,
            verbose=True,
            callbacks=[best_model])
    timer.stop(text)
    plot(network_history)
```

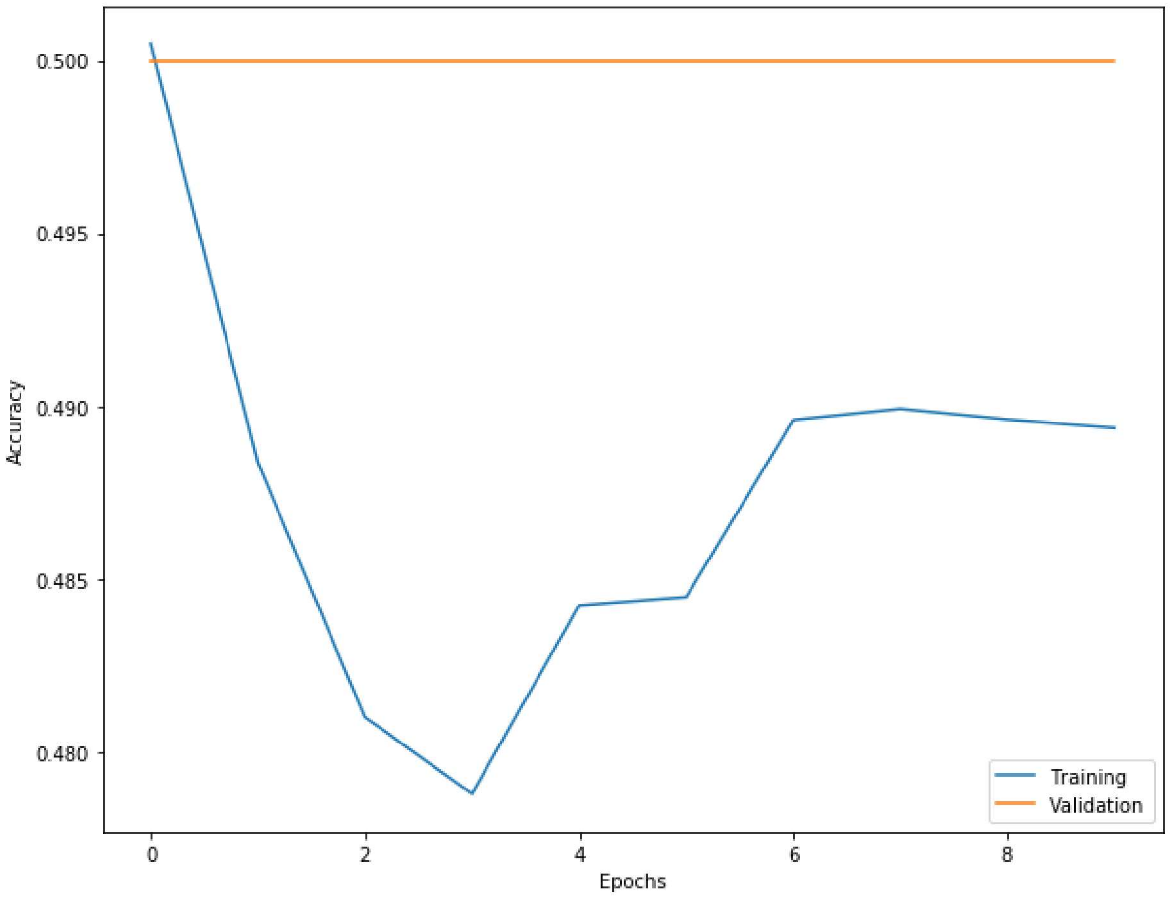
In [11]:

```python
# We test SGD
from keras.optimizers import SGD
epochs = 10
sgd = SGD(lr=0.1, decay=1e-6, momentum=0.9, nesterov=True)
testModel(sgd, epochs)
```

```
Epoch 1/10
400/400 [==============================] - 164s 409ms/step - loss: 0.6959 -
acc: 0.5004 - val_loss: 0.6939 - val_acc: 0.5000

Epoch 00001: val_loss improved from inf to 0.69386, saving model to best_cnn
_dgen_model.h5
Epoch 2/10
400/400 [==============================] - 143s 358ms/step - loss: 0.6950 -
acc: 0.4877 - val_loss: 0.6938 - val_acc: 0.5000

Epoch 00002: val_loss improved from 0.69386 to 0.69383, saving model to best
_cnn_dgen_model.h5
Epoch 3/10
400/400 [==============================] - 144s 360ms/step - loss: 0.6950 -
acc: 0.4814 - val_loss: 0.6932 - val_acc: 0.5000

Epoch 00003: val_loss improved from 0.69383 to 0.69323, saving model to best
_cnn_dgen_model.h5
Epoch 4/10
400/400 [==============================] - 143s 357ms/step - loss: 0.6949 -
acc: 0.4800 - val_loss: 0.6932 - val_acc: 0.5000

Epoch 00004: val_loss improved from 0.69323 to 0.69320, saving model to best
_cnn_dgen_model.h5
Epoch 5/10
400/400 [==============================] - 143s 358ms/step - loss: 0.6946 -
acc: 0.4835 - val_loss: 0.6934 - val_acc: 0.5000

Epoch 00005: val_loss did not improve
Epoch 6/10
400/400 [==============================] - 144s 359ms/step - loss: 0.6947 -
acc: 0.4858 - val_loss: 0.6939 - val_acc: 0.5000

Epoch 00006: val_loss did not improve
Epoch 7/10
400/400 [==============================] - 142s 356ms/step - loss: 0.6949 -
acc: 0.4904 - val_loss: 0.6932 - val_acc: 0.5000

Epoch 00007: val_loss improved from 0.69320 to 0.69316, saving model to best
_cnn_dgen_model.h5
Epoch 8/10
400/400 [==============================] - 142s 356ms/step - loss: 0.6946 -
acc: 0.4904 - val_loss: 0.6939 - val_acc: 0.5000

Epoch 00008: val_loss did not improve
Epoch 9/10
400/400 [==============================] - 142s 356ms/step - loss: 0.6947 -
acc: 0.4904 - val_loss: 0.6942 - val_acc: 0.5000

Epoch 00009: val_loss did not improve
Epoch 10/10
400/400 [==============================] - 142s 355ms/step - loss: 0.6954 -
acc: 0.4894 - val_loss: 0.6942 - val_acc: 0.5000
```

```
Epoch 00010: val_loss did not improve
Timing:: took 24 minutes Training model
-----------------------------------
```

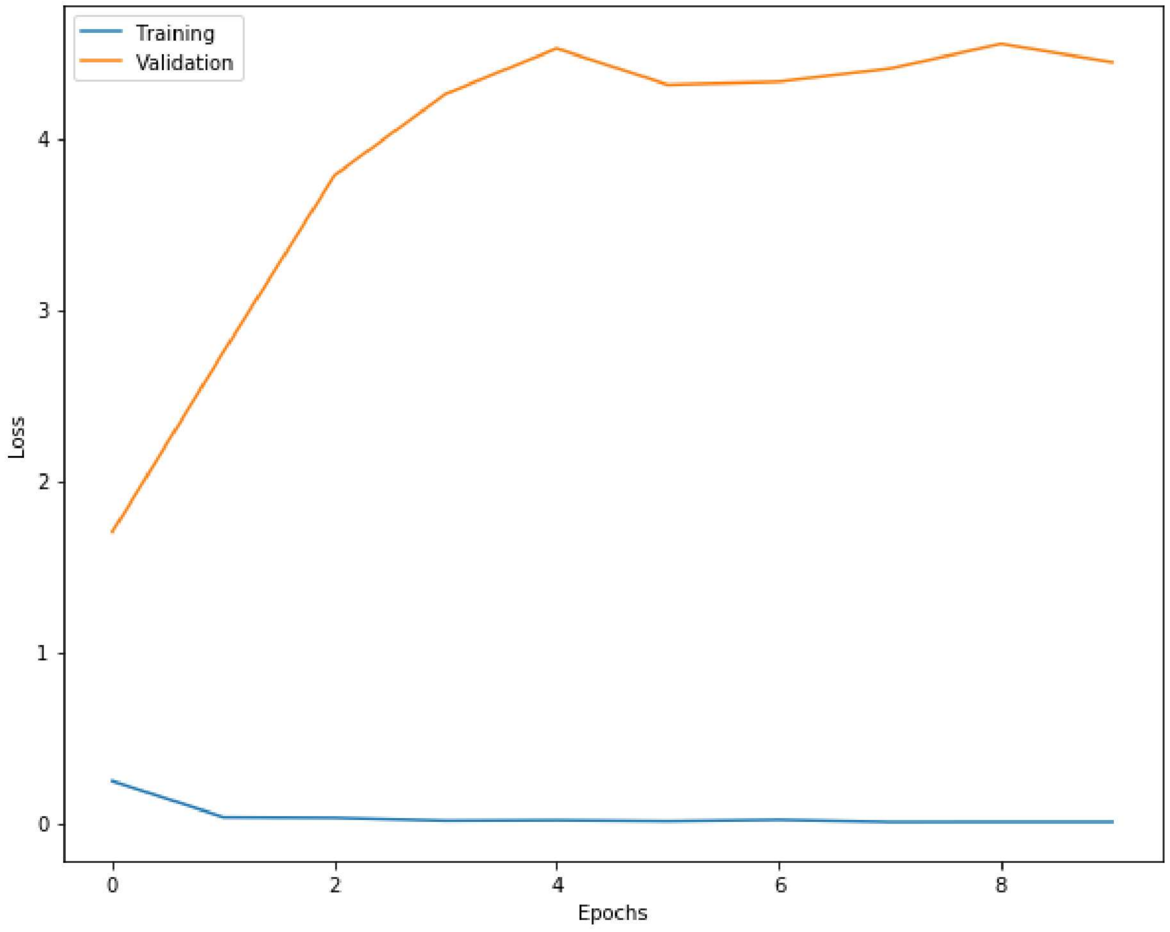


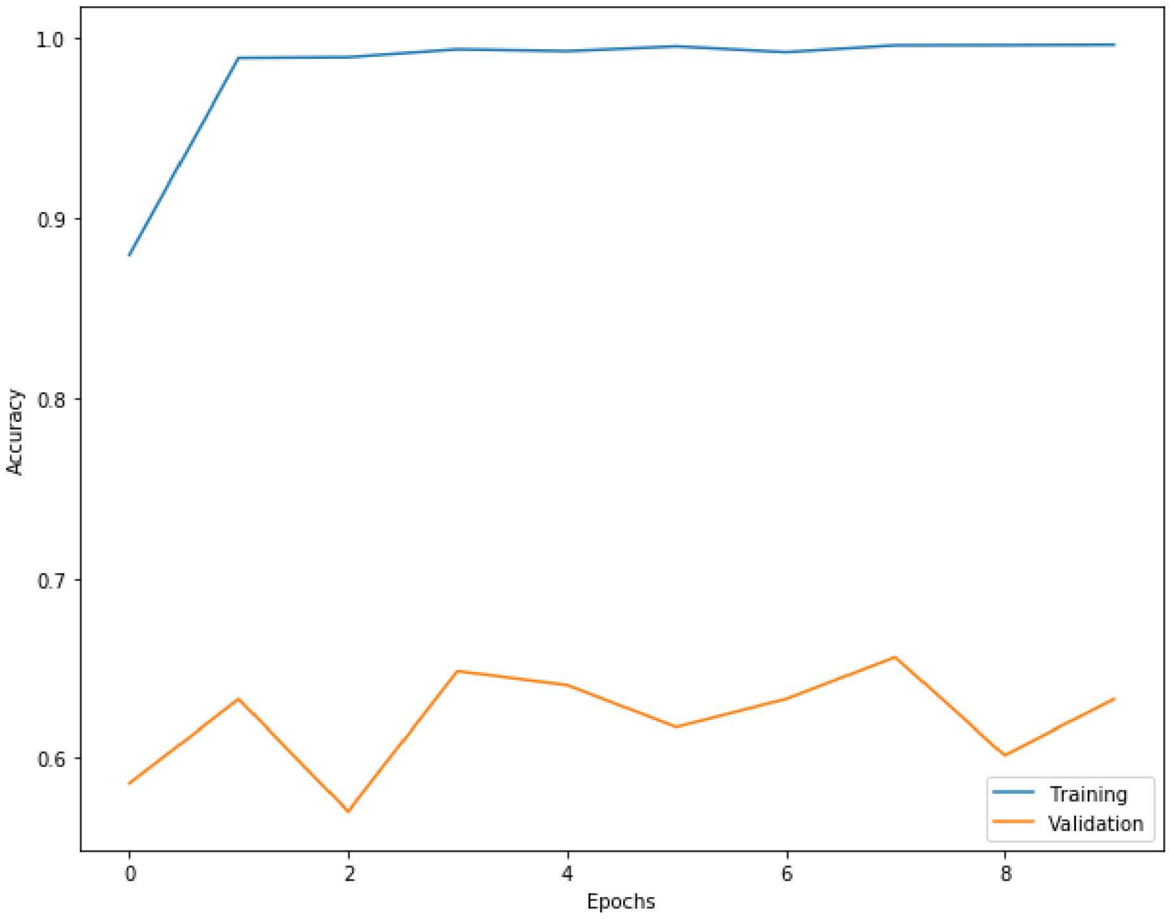


In [12]:

```
#Adam
epochs = 10
testModel('adam', epochs, "training model with adam")
```

```
Epoch 1/10
400/400 [==============================] - 152s 380ms/step - loss: 0.2467 -
acc: 0.8794 - val_loss: 1.7016 - val_acc: 0.5859

Epoch 00001: val_loss did not improve
Epoch 2/10
400/400 [==============================] - 150s 375ms/step - loss: 0.0353 -
acc: 0.9892 - val_loss: 2.7529 - val_acc: 0.6328

Epoch 00002: val_loss did not improve
Epoch 3/10
400/400 [==============================] - 154s 385ms/step - loss: 0.0320 -
acc: 0.9895 - val_loss: 3.7833 - val_acc: 0.5703

Epoch 00003: val_loss did not improve
Epoch 4/10
400/400 [==============================] - 149s 372ms/step - loss: 0.0153 -
acc: 0.9941 - val_loss: 4.2580 - val_acc: 0.6484

Epoch 00004: val_loss did not improve
Epoch 5/10
400/400 [==============================] - 148s 371ms/step - loss: 0.0177 -
acc: 0.9931 - val_loss: 4.5229 - val_acc: 0.6406

Epoch 00005: val_loss did not improve
Epoch 6/10
400/400 [==============================] - 149s 372ms/step - loss: 0.0128 -
acc: 0.9955 - val_loss: 4.3113 - val_acc: 0.6172

Epoch 00006: val_loss did not improve
Epoch 7/10
400/400 [==============================] - 148s 370ms/step - loss: 0.0205 -
acc: 0.9923 - val_loss: 4.3292 - val_acc: 0.6328

Epoch 00007: val_loss did not improve
Epoch 8/10
400/400 [==============================] - 148s 369ms/step - loss: 0.0078 -
acc: 0.9960 - val_loss: 4.4059 - val_acc: 0.6562

Epoch 00008: val_loss did not improve
Epoch 9/10
400/400 [==============================] - 147s 369ms/step - loss: 0.0079 -
acc: 0.9963 - val_loss: 4.5496 - val_acc: 0.6016

Epoch 00009: val_loss did not improve
Epoch 10/10
400/400 [==============================] - 147s 369ms/step - loss: 0.0078 -
acc: 0.9966 - val_loss: 4.4435 - val_acc: 0.6328

Epoch 00010: val_loss did not improve
Timing:: took 24 minutes training model with adam
-----------------------------------
```

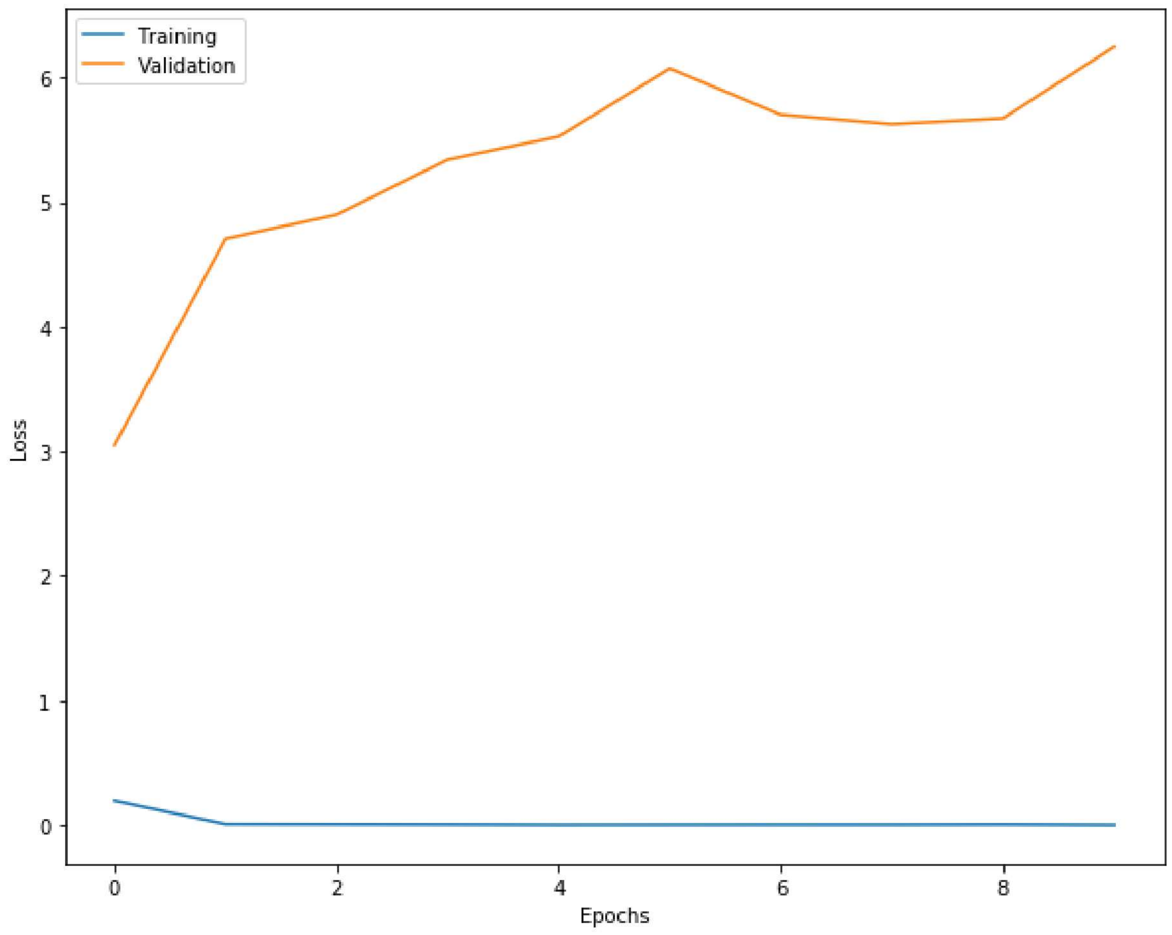

Training
Validation
Loss
Epochs
0
1
2
3
4
0
2
4
6
8

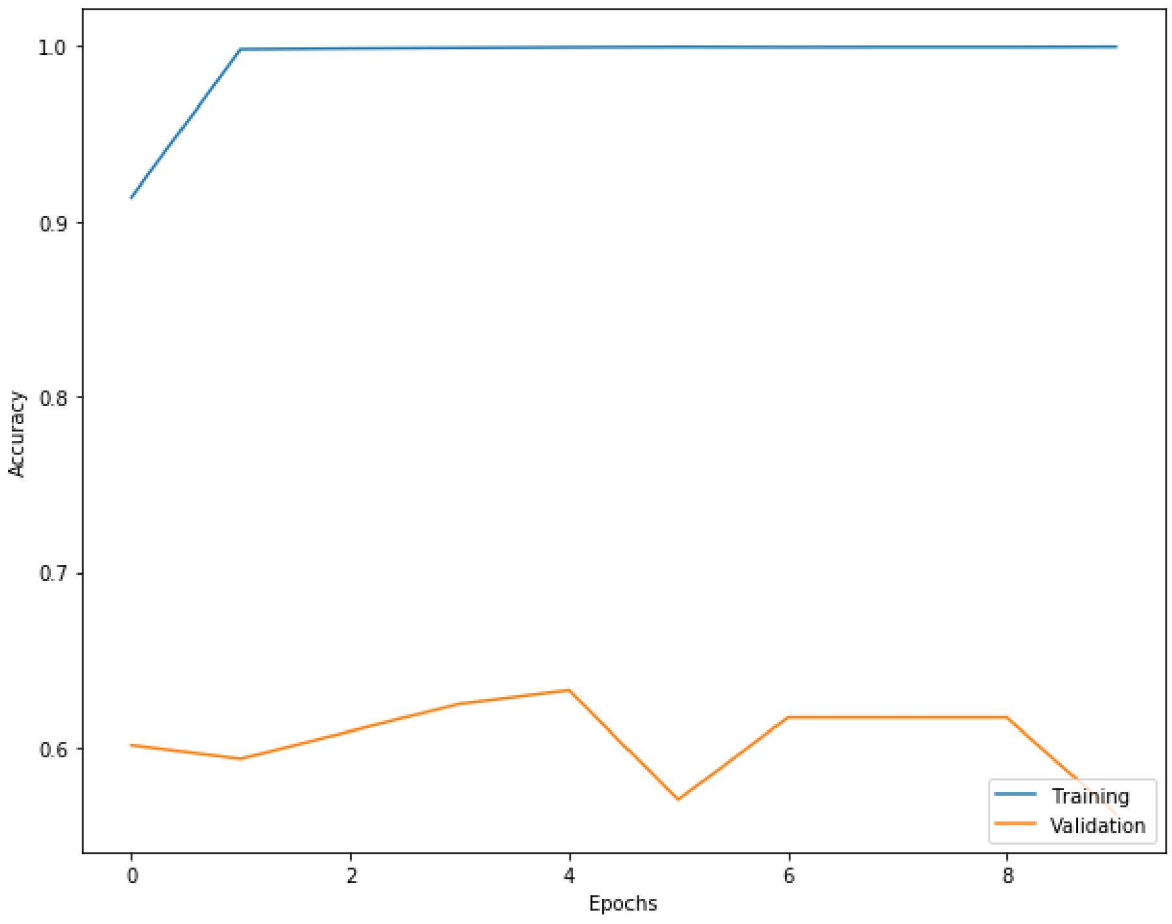

Training
Validation
Accuracy
Epochs
1.0
0.9
0.8
0.7
0.6
0
2
4
6
8

In [13]:

```
#Rmsprop
epochs = 10
testModel('rmsprop', epochs, "training model with rmsprop")
```

```
Epoch 1/10
400/400 [==============================] - 152s 379ms/step - loss: 0.1935 -
acc: 0.9142 - val_loss: 3.0490 - val_acc: 0.6016

Epoch 00001: val_loss did not improve
Epoch 2/10
400/400 [==============================] - 148s 371ms/step - loss: 0.0070 -
acc: 0.9982 - val_loss: 4.7061 - val_acc: 0.5938

Epoch 00002: val_loss did not improve
Epoch 3/10
400/400 [==============================] - 147s 367ms/step - loss: 0.0056 -
acc: 0.9988 - val_loss: 4.8994 - val_acc: 0.6094

Epoch 00003: val_loss did not improve
Epoch 4/10
400/400 [==============================] - 149s 372ms/step - loss: 0.0039 -
acc: 0.9991 - val_loss: 5.3412 - val_acc: 0.6250

Epoch 00004: val_loss did not improve
Epoch 5/10
400/400 [==============================] - 147s 368ms/step - loss: 0.0015 -
acc: 0.9995 - val_loss: 5.5268 - val_acc: 0.6328

Epoch 00005: val_loss did not improve
Epoch 6/10
400/400 [==============================] - 151s 377ms/step - loss: 0.0021 -
acc: 0.9997 - val_loss: 6.0726 - val_acc: 0.5703

Epoch 00006: val_loss did not improve
Epoch 7/10
400/400 [==============================] - 148s 371ms/step - loss: 0.0027 -
acc: 0.9995 - val_loss: 5.7015 - val_acc: 0.6172

Epoch 00007: val_loss did not improve
Epoch 8/10
400/400 [==============================] - 148s 371ms/step - loss: 0.0024 -
acc: 0.9996 - val_loss: 5.6260 - val_acc: 0.6172

Epoch 00008: val_loss did not improve
Epoch 9/10
400/400 [==============================] - 146s 366ms/step - loss: 0.0055 -
acc: 0.9995 - val_loss: 5.6722 - val_acc: 0.6172

Epoch 00009: val_loss did not improve
Epoch 10/10
400/400 [==============================] - 146s 365ms/step - loss: 8.8241e-0
4 - acc: 0.9998 - val_loss: 6.2457 - val_acc: 0.5625

Epoch 00010: val_loss did not improve
Timing:: took 24 minutes training model with rmsprop
-----------------------------------
```

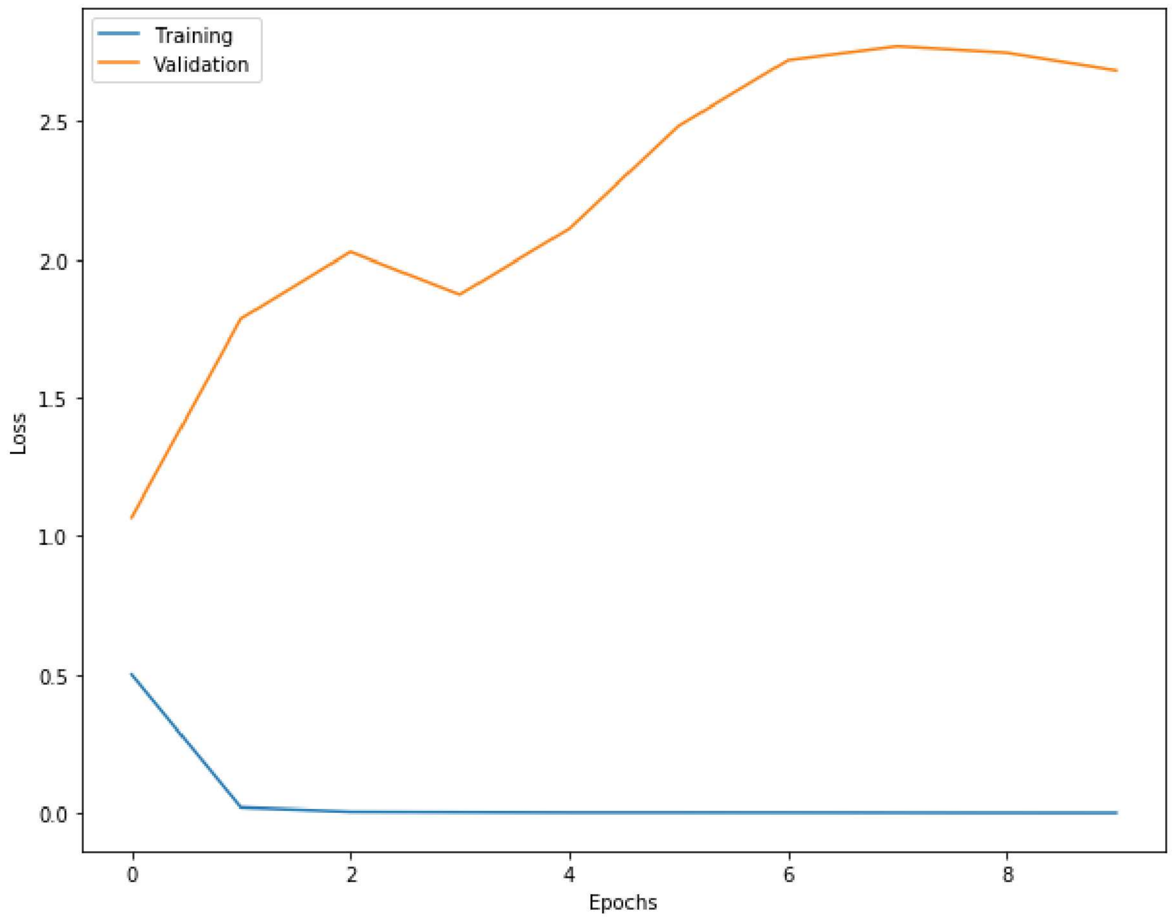

Training
Validation
Loss
Epochs
0
1
2
3
4
5
6
0
2
4
6
8

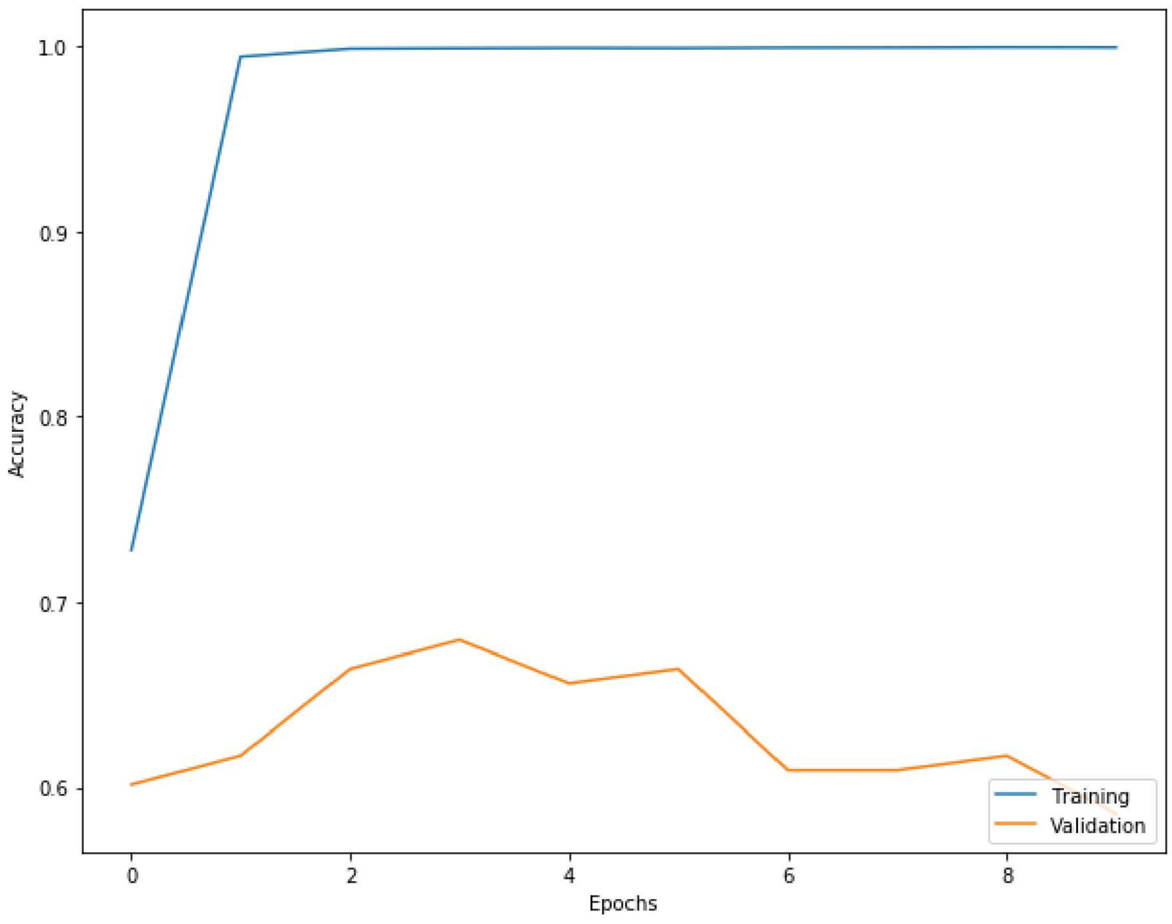

Training
Validation
Accuracy
Epochs
0.6
0.7
0.8
0.9
1.0
0
2
4
6
8

In [14]:

```
#Adagrad
epochs = 10
testModel('adagrad', epochs, "training model with adagrad")
```

```
Epoch 1/10
400/400 [==============================] - 174s 436ms/step - loss: 0.4993 -
acc: 0.7275 - val_loss: 1.0676 - val_acc: 0.6016

Epoch 00001: val_loss did not improve
Epoch 2/10
400/400 [==============================] - 1711s 4s/step - loss: 0.0198 - ac
c: 0.9945 - val_loss: 1.7856 - val_acc: 0.6172

Epoch 00002: val_loss did not improve
Epoch 3/10
400/400 [==============================] - 942s 2s/step - loss: 0.0047 - ac
c: 0.9988 - val_loss: 2.0273 - val_acc: 0.6641

Epoch 00003: val_loss did not improve
Epoch 4/10
400/400 [==============================] - 148s 370ms/step - loss: 0.0036 -
acc: 0.9991 - val_loss: 1.8733 - val_acc: 0.6797

Epoch 00004: val_loss did not improve
Epoch 5/10
400/400 [==============================] - 147s 368ms/step - loss: 0.0024 -
acc: 0.9992 - val_loss: 2.1108 - val_acc: 0.6562

Epoch 00005: val_loss did not improve
Epoch 6/10
400/400 [==============================] - 147s 369ms/step - loss: 0.0023 -
acc: 0.9992 - val_loss: 2.4827 - val_acc: 0.6641

Epoch 00006: val_loss did not improve
Epoch 7/10
400/400 [==============================] - 147s 368ms/step - loss: 0.0021 -
acc: 0.9995 - val_loss: 2.7202 - val_acc: 0.6094

Epoch 00007: val_loss did not improve
Epoch 8/10
400/400 [==============================] - 148s 370ms/step - loss: 0.0018 -
acc: 0.9995 - val_loss: 2.7712 - val_acc: 0.6094

Epoch 00008: val_loss did not improve
Epoch 9/10
400/400 [==============================] - 149s 373ms/step - loss: 0.0015 -
acc: 0.9995 - val_loss: 2.7473 - val_acc: 0.6172

Epoch 00009: val_loss did not improve
Epoch 10/10
400/400 [==============================] - 148s 371ms/step - loss: 0.0012 -
acc: 0.9996 - val_loss: 2.6830 - val_acc: 0.5859

Epoch 00010: val_loss did not improve
Timing:: took 64 minutes training model with adagrad
-----------------------------------
```


Training
Validation
Loss
Epochs
0.0
0.5
1.0
1.5
2.0
2.5
0
2
4
6
8


Training
Validation
Accuracy
Epochs
0.6
0.7
0.8
0.9
1.0
0
2
4
6
8

2.3 Evaluating the Learning performance

Adagrad best

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 [ ]:
```